
Inexact Primal-Dual Path-Following Algorithms for Certain Quadratic SDPs

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SDPT3

The code **SDPT3** is joint work of Kim Toh, National University of Singapore, Reha Tütüncü, Goldman-Sachs, and me.

SDPT3: Primal-Dual Predictor-Corrector Interior-Point Method for SQLP.

Available from <http://www.math.nus.edu.sg/~mattohkc/sdpt3.html>.

Matlab-based (like SeDuMi), using **C** for computationally intensive parts (like CSDP), exploits **sparsity** (based on ideas from SDPA).

Obtains relatively **high-precision** solutions but is computationally **expensive**.

SDP: dense: $n \leq 500$; sparse $n \leq 2000$.

SOCP: sparse: $n \leq 150,000$.

LP: ditto.

QSDP

The focus of this talk: application to the **quadratic SDP**:

$$\begin{aligned} (QSDP) \quad \min_X \quad & \frac{1}{2} X \bullet Q(X) + C \bullet X \\ & \mathcal{A}(X) = b, \quad X \succeq 0, \end{aligned} \tag{1}$$

where $Q : \mathcal{S}^n \rightarrow \mathcal{S}^n$ is a given self-adjoint positive semidefinite operator on \mathcal{S}^n and $\mathcal{A} : \mathcal{S}^n \rightarrow \mathbb{R}^m$ is a linear map, with $(\mathcal{A}(X))_i = A_i \bullet X$ for each i .

Its **dual** is

$$\begin{aligned} (QSDD) \quad \max_{X,y,S} \quad & -\frac{1}{2} X \bullet Q(X) + b^T y \\ & \mathcal{A}^T(y) - Q(X) + S = C, \quad S \succeq 0. \end{aligned} \tag{2}$$

Note: the quadratic term involves the **matrix** variable X not the **vector** variable y .

Outline

- Application
- Newton systems
- Preconditioned SQMR
- Computational results

Applications

Consider the **semidefinite least-squares problem**:

$$\begin{aligned} \min_X \quad & \|\mathcal{L}(X) - \hat{K}\|_F \\ (SDLS) \quad & \mathcal{A}(X) = b, \\ & X \succeq 0, \end{aligned}$$

i.e., find a feasible psd X such that $\mathcal{L}(X)$ is as close as possible to \hat{K} .

This includes the **closest correlation matrix problem** and the **nearest Euclidean distance matrix problem** for a weighted graph.

Often $\mathcal{L}(X) = U^{1/2} X U^{1/2}$, and then $\mathcal{Q} = U \circledast U$,

where $U \circledast U(Z) := U Z U^T$ when $Z \in \mathcal{S}^n$, $U \in \mathbb{R}^{n \times n}$.

Newton Systems

At a given iteration of a predictor-corrector algorithm, given the current solution X, y, S , we need to solve for the **search directions** from

$$\begin{aligned} -Q(\Delta X) + \mathcal{A}^T(\Delta y) + \Delta S &= R_d \\ \mathcal{A}(\Delta X) &= r_p \\ \mathcal{E}(\Delta X) + \mathcal{F}(\Delta S) &= R_c, \end{aligned} \tag{3}$$

where \mathcal{E} and \mathcal{F} are linear operators on \mathcal{S}^n that depend on X and S and the symmetrization scheme chosen. If we eliminate ΔS and set

$$\mathcal{H} = \mathcal{F}^{-1}\mathcal{E} + Q, \tag{4}$$

this reduces to ...

Newton Systems, II

$$\begin{bmatrix} -\mathcal{H} & \mathcal{A}^T \\ \mathcal{A} & 0 \end{bmatrix} \begin{bmatrix} \Delta X \\ \Delta y \end{bmatrix} = \begin{bmatrix} R_h \\ r_p \end{bmatrix}. \quad (5)$$

By further eliminating ΔX , we get the **Schur complement equation** of dimension m below:

$$M\Delta y := \mathcal{A}\mathcal{H}^{-1}\mathcal{A}^T\Delta y = h. \quad (6)$$

[Note: if Q is zero and instead (QSDD) has objective function $b^T y - y^T Q y / 2$, then we must solve $M\Delta y = h$ where

$$M = \mathcal{A}\mathcal{E}^{-1}\mathcal{F}\mathcal{A}^T + Q, \quad (7)$$

and this is much easier.]

Form of \mathcal{H}

If we use Nesterov-Todd scaling and $\mathcal{Q} = U \circledast U$, then

$$\mathcal{H} = W^{-1} \circledast W^{-1} + U \circledast U, \quad (8)$$

where W is the Nesterov-Todd scaling matrix. Note: this form of \mathcal{H} also arises from a **linear SDP with a simple upper bound on X** :

$$\min C \bullet X, \quad \mathcal{A}(X) = b, \quad 0 \preceq X \preceq U. \quad (9)$$

After adding a slack matrix, formulating the Newton equations, and simplifying, we find we need to solve

$$\mathcal{A}(\mathcal{F}_1^{-1} \mathcal{E}_1 + \mathcal{F}_2^{-1} \mathcal{E}_2)^{-1} \mathcal{A}^T \Delta y = h \quad (10)$$

for suitable \mathcal{E}_i and \mathcal{F}_i : if we use Nesterov-Todd scaling we get a similar form.

Computational problem

For \mathcal{H} as above, we find

$$\mathcal{H}^{-1} = (P \circledast P) \left(\mathcal{I} + D \circledast D \right)^{-1} (P \circledast P)^T, \quad (11)$$

for an easily computed $P \in \mathbb{R}^{n \times n}$ and diagonal D , so that

$$(\mathcal{A}\mathcal{H}^{-1}\mathcal{A}^T)_{ij} = A_i \bullet (P \circledast P) \left(\mathcal{I} + D \circledast D \right)^{-1} (P \circledast P)^T A_j. \quad (12)$$

This is **too expensive** to compute for **each** i, j in the large sparse setting. Why? If the diagonal term were missing, we would only have to compute the entries of $(PP^T)A_j(PP^T)$ corresponding to **nonzero** entries of A_i . So the **diagonal operator** is the **culprit!**

So we **use preconditioned SQMR**. We need to be able to compute Mv for an arbitrary v , and solve $\widehat{M}w = g$ for an arbitrary g , where $\widehat{M} \approx M$.

Approximation of M , I

We have two ways to approximate M . The first uses

$$\left(\mathcal{I} + D \circledast D\right)^{-1} \approx \sum_{k=1}^q \alpha_k \Lambda_k \circledast \Lambda_k, \quad (13)$$

where each α_k is a scalar and each Λ_k is a diagonal matrix. This is done via an eigenvalue computation. Then M is approximated by the preconditioner

$$\widehat{M} := \sum_{k=1}^q \alpha_k \mathcal{A}(V_k \circledast V_k) \mathcal{A}^T. \quad (14)$$

with $V_k = P \Lambda_k P^T$. Unfortunately, this may not be positive definite.

Approximation of M , II

The second method approximates

$$\mathcal{H} = W^{-1} \circledast W^{-1} + U \circledast U \quad (15)$$

by $V \circledast V$.

We do not know how to solve this problem exactly, but when “ \circledast ” is replaced by “ \otimes ” the solution is easily obtained by solving a 2×2 eigenvalue problem. With this V , we set the preconditioner to be

$$\widehat{M} = \mathcal{A}(V^{-1} \circledast V^{-1})\mathcal{A}^T. \quad (16)$$

This approximation is always positive definite. [Actually, we find it preferable to approximate $I \circledast I + D \circledast D$ in this way, and hence obtain an approximation of \mathcal{H}^{-1} — see (11).]

Computational Results

The next slides give some results for four classes of problems (the first three are nearest correlation matrix problems with a certain \hat{K} and U , and the last linear SDPs with upper bounds) and four algorithms:

A1: **Direct** solution of the Schur complement equation;

A2: Solution of the equation using **unpreconditioned SQMR**;

A3: Solution of the equation using **preconditioned SQMR**:

the preconditioner is the **first** if it is positive definite, otherwise the second;

and

A4: Solution of the equation using **preconditioned SQMR**,

using the **second** preconditioner.

The **dimension n** varies from **200** to **2000**. The column “psqmr” gives the average number of PSQMR iterations to solve each Schur complement equation.

	n	A1			A2				A3			
		it	ϕ	Time (s)	it	ϕ	Time (s)	psqmr	it	ϕ	Time (s)	psqmr
E3	200	12	1.8e-08	26.5	12	2.5e-08	6.5	1.7	12	1.8e-08	7.7	1.0
	400	12	1.6e-08	269.6	12	2.1e-08	37.6	1.6	12	1.6e-08	44.3	1.0
	800	13	1.4e-08	3245.9	13	1.5e-08	269.0	1.7	13	5.2e-08	338.5	1.0
	1600				14	6.8e-09	1932.0	1.7	14	6.7e-09	2302.3	1.1
	2000				14	1.1e-08	3582.9	1.6	14	1.0e-08	4347.9	1.1
E6	200	20	1.2e-08	54.2	21	9.6e-09	32.1	32.9	20	1.2e-08	13.4	1.1
	400	21	1.4e-08	487.7	23	2.5e-08	218.3	39.5	21	1.4e-08	76.7	1.0
	800	22	5.5e-08	5633.7	24	4.9e-08	1544.3	43.7	22	5.5e-08	522.6	1.0
	1600				27	8.6e-08	16579.6	63.9	25	2.4e-08	4223.8	1.0
	2000				28	8.0e-08	30566.7	62.1	26	1.1e-08	8632.0	1.0
E9	200	12	2.0e-08	34.5	13	4.8e-08	17.1	41.4	12	2.0e-08	8.3	1.0
	400	13	1.8e-08	330.4	14	2.6e-08	119.8	45.9	13	1.8e-08	53.1	1.0
	800	13	9.5e-08	3623.9	14	9.4e-08	815.6	45.4	13	9.5e-08	359.4	1.0
	1600	15	2.5e-08	50155.2	16	2.1e-08	7243.8	46.9	15	2.5e-08	2964.0	1.0
	2000				16	2.7e-08	13428.5	47.3	15	4.6e-08	5549.2	1.0
E10	200	14	5.5e-08	55.2	15	6.1e-08	71.1	76.1	14	5.2e-08	18.5	1.0
	400	14	7.1e-08	325.2	14	6.9e-08	335.8	96.0	14	7.5e-08	106.7	1.4
	800	15	6.6e-08	3955.8	15	1.1e-07	4312.7	236.4	15	1.4e-07	508.8	1.3
	1600	17	2.7e-07	56457.0	17	3.3e-07	62418.6	440.9	17	1.3e-07	5818.5	1.3
	2000				18	1.4e-06	136231.9	520.2	17	1.2e-07	9128.1	1.1

A2				A3				A4			
it	ϕ	Time (s)	psqmr	it	ϕ	Time (s)	psqmr	it	ϕ	Time (s)	psqmr
12	2.5e-08	6.5	1.7	12	1.8e-08	7.7	1.0	12	4.6e-08	6.9	1.6
12	2.1e-08	37.6	1.6	12	1.6e-08	44.3	1.0	12	1.7e-08	39.1	1.6
13	1.5e-08	269.0	1.7	13	5.2e-08	338.5	1.0	13	1.4e-08	276.7	1.7
14	6.8e-09	1932.0	1.7	14	6.7e-09	2302.3	1.1	14	6.7e-09	1974.7	1.7
14	1.1e-08	3582.9	1.6	14	1.0e-08	4347.9	1.1	14	1.0e-08	3761.2	1.7
21	9.6e-09	32.1	32.9	20	1.2e-08	13.4	1.1	20	1.3e-08	19.0	14.7
23	2.5e-08	218.3	39.5	21	1.4e-08	76.7	1.0	21	4.2e-08	111.0	15.4
24	4.9e-08	1544.3	43.7	22	5.5e-08	522.6	1.0	22	7.3e-08	696.0	13.6
27	8.6e-08	16579.6	63.9	25	2.4e-08	4223.8	1.0	25	9.6e-08	6759.0	20.6
28	8.0e-08	30566.7	62.1	26	1.1e-08	8632.0	1.0	27	7.1e-08	14097.6	21.7
13	4.8e-08	17.1	41.4	12	2.0e-08	8.3	1.0	13	1.3e-08	8.2	6.2
14	2.6e-08	119.8	45.9	13	1.8e-08	53.1	1.0	14	9.8e-09	53.9	7.2
14	9.4e-08	815.6	45.4	13	9.5e-08	359.4	1.0	15	1.3e-08	401.7	8.2
16	2.1e-08	7243.8	46.9	15	2.5e-08	2964.0	1.0	16	2.0e-08	3185.9	9.7
16	2.7e-08	13428.5	47.3	15	4.6e-08	5549.2	1.0	17	1.0e-08	6379.2	10.2
15	6.1e-08	71.1	76.1	14	5.2e-08	18.5	1.0	14	8.2e-08	61.1	69.2
14	6.9e-08	335.8	96.0	14	7.5e-08	106.7	1.4	14	1.0e-07	313.7	66.6
15	1.1e-07	4312.7	236.4	15	1.4e-07	508.8	1.3	15	9.1e-08	650.8	12.9
17	3.3e-07	62418.6	440.9	17	1.3e-07	5818.5	1.3	17	7.7e-08	3917.3	6.4
18	1.4e-06	136231.9	520.2	17	1.2e-07	9128.1	1.1	17	8.6e-08	7046.7	5.4