Bad semidefinite programs: they all look the same

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A pair of Semidefinite Programs (SDP)

$$egin{aligned} \sup_x \ c^T x & \inf_Y \ Bullet Y \ s.t. \ \sum_{i=1}^m x_i A_i \preceq B & Y \succeq 0 \ A_i ullet Y = c_i \ (i=1,\ldots,m). \end{aligned}$$

Here

- A_i, B are symmetric matrices, $c, x \in \mathbb{R}^m$.
- $A \leq B$ means that B A is symmetric positive semidefinite (psd).
- $A \bullet B = \sum_{i,j} a_{ij} b_{ij}$.

Conic LPs and SDPs

• Common framework for LP and SDP: both \mathbb{R}^n_+ and psd matrices are closed convex cones.

• A set C is a cone, if $x \in C, \lambda \ge 0 \Rightarrow \lambda x \in C$.

• Linear objective, conic constraint both in LP and SDP, and many other interesting problems, notably SOCPs.

Why is SDP important: applications in

- 0–1 Integer programming.
- Approx algorithms
- Chemical engineering
- Chemistry
- Coding theory
- Control theory
- Combinatorial opt
- Discrete geometry
- Eigenvalue optimization
- Facility planning
- Finance
- Geometric optimization

- Global optimization
- Graph visualization
- Inventory theory
- Machine learning
- Matrix analysis
- PDEs
- Probability theory
- Robust optimization
- Signal processing
- Statistics
- Structural optimization

SDP theory and applications

- Nice duality theory: see later
- Applications: see textbooks by
 - Boyd-Vandenberghe
 - Ben-Tal-Nemirovskii
- Algebraic geometry:
 - Nie-Sturmfels 2010
 - von Bothmer-Ranestad 2009
 - Gouveia, Parrilo, Thomas, 2010
 - Book by Blekherman, et al, 2013
- Polynomial optimization:
 - Lasserre 2000 –
 - Parrilo 2000 –
 - Nie 2000 –
 - Helton-Vinnikov 2003

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But: in SDP, unlike in LP pathological phenomena occur: nonattainment, positive gaps.

This is bad, since we would like a certificate of optimality.

Primal:

 $\sup 2x_1 \qquad \Leftrightarrow \ \sup 2x_1 \ s.t. \ x_1 \begin{pmatrix} 0 \ 1 \ 0 \end{pmatrix} \preceq \begin{pmatrix} 1 \ 0 \ 0 \end{pmatrix} \qquad s.t. \ \begin{pmatrix} 1 \ -x_1 \ -x_1 \end{pmatrix} \succeq 0$

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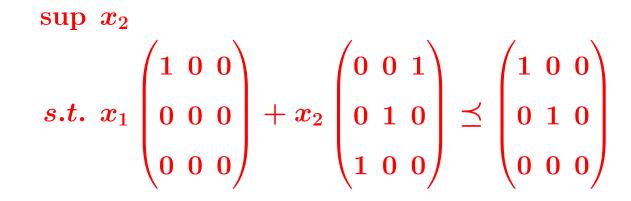
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Here $\inf = 0$, but not attained: Any $y_{11} > 0$, $y_{22} = 1/y_{11}$ is feasible, but $y_{11} = 0$ is not.

Pathology # 2: positive duality gap

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$$\begin{array}{c} \sup \ x_2 \\ s.t. \ x_1 \begin{pmatrix} 1 \ 0 \ 0 \\ 0 \ 0 \ 0 \\ 0 \ 0 \ 0 \end{pmatrix} + x_2 \begin{pmatrix} 0 \ 0 \ 1 \\ 0 \ 1 \ 0 \\ 1 \ 0 \ 0 \end{pmatrix} \preceq \begin{pmatrix} 1 \ 0 \ 0 \\ 0 \ 1 \ 0 \\ 0 \ 0 \ 0 \end{pmatrix}$$

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Dual value is 1, and it is attained.

Terminology

Definition:

• The system $P_{SD} = \{ x \mid \sum_{i=1}^{m} x_i A_i \preceq B \}$ is well-behaved, if for all c such that

 $\sup\{ c^T x \, | \, x \in P_{SD} \}$ is finite,

the dual program has the same value, and it attains.

- Badly behaved, otherwise.
- We would like to understand well/badly behaved systems.

Some literature

- Conic LPs may be badly behaved when K is not polyhedral.
- Borwein-Wolkowicz 1981 Facial reduction: theoretical construction of well behaved system
- Ramana 1995 Extended dual for SDP
- Ramana, Tunçel, Wolkowicz, 1997 Facial reduction implies correctness of extended dual
- Klep, Schweighofer, 2013 Related duals based on algebraic geometry.
- Waki, Muramatsu, 2013; Pataki 2013: Simpler facial reduction algorithms.
- P 2007 Closedness of linear image of a closed, convex cone

Motivation

The systems

$$x_1 egin{pmatrix} 0 & 1 \ 1 & 0 \end{pmatrix} \preceq egin{pmatrix} 1 & 0 \ 0 & 0 \end{pmatrix}$$

and

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are both badly behaved.

Curious similarity:

- "Hanging off" diagonals;
- if we delete 2nd row and 2nd column in all matrices in the second system, and delete the first matrix, we get back the first system.

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• W.l.o.g. the max (rank) slack is

$$Z = egin{pmatrix} I_r & 0 \ 0 & 0 \end{pmatrix}.$$

$$V = egin{pmatrix} \stackrel{r}{\overbrace{V_{11}}} V_{12} \ V_{12} \ V_{12}^T \ V_{22} \end{pmatrix}, ext{ where } V_{22} \succeq 0, ext{ R}(V_{12}^T)
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• Ex:
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• Ex:
$$x_1 \overbrace{\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}}^V \preceq \overbrace{\begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}}^Z$$

What is missing?

- Matrices Z, V prove that (P_{SD}) is badly behaved.
- But: this is not yet a poly time, or easy to verify proof of bad behavior

Reformulations of

 $(P_{SD}) \sum_{i=1}^m x_i A_i \preceq B$

are obtained by a sequence of:

• Rotate all matrices by
$$T = \begin{pmatrix} I_r & 0 \\ 0 & M \end{pmatrix}$$
, M orthogonal.

$$ullet$$
 $B \leftarrow B + \sum_{i=1}^m \mu_i A_i$

•
$$A_i \leftarrow \sum_{j=1}^m \lambda_j A_j$$
 where $\lambda_i \neq 0$

Reformulations preserve well/badly behaved status; preserve max slack; provide an equivalence relation

Theorem: (P_{SD}) is badly behaved \Leftrightarrow it has a reformulation:

$$(P_{SD,bad}) \ \sum_{i=1}^k x_i egin{pmatrix} F_i & 0 \ 0 & 0 \end{pmatrix} + \sum_{i=k+1}^m x_i egin{pmatrix} F_i & G_i \ G_i^T & H_i \end{pmatrix} \ \preceq \ egin{pmatrix} I_r & 0 \ 0 & 0 \end{pmatrix} = Z,$$

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where
$$1) \mathbf{Z} \text{ is max slack; } 2) \begin{pmatrix} G_i \\ H \end{pmatrix} \text{ lin. indep. } 3) \mathbf{H}_m \succeq \mathbf{0}$$

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Proof that $(P_{SD,bad})$ is badly behaved:

x feas. with slack $S \Rightarrow \operatorname{supp}(S) \subseteq \operatorname{supp}(Z)$

 $\Rightarrow x_{k+1} = \cdots = x_m = 0 \Rightarrow \sup -x_m = 0$

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Proof that $(P_{SD,bad})$ is badly behaved:

$$egin{aligned} Y \succeq 0, Y ullet Z = 0 \ \Rightarrow & Y = egin{pmatrix} 0 & 0 \ 0 & Y_{22} \end{pmatrix} \ & \Rightarrow & Y ullet egin{pmatrix} F_m & G_m \ G_m^T & H_m \end{pmatrix} \geq 0 \end{aligned}$$

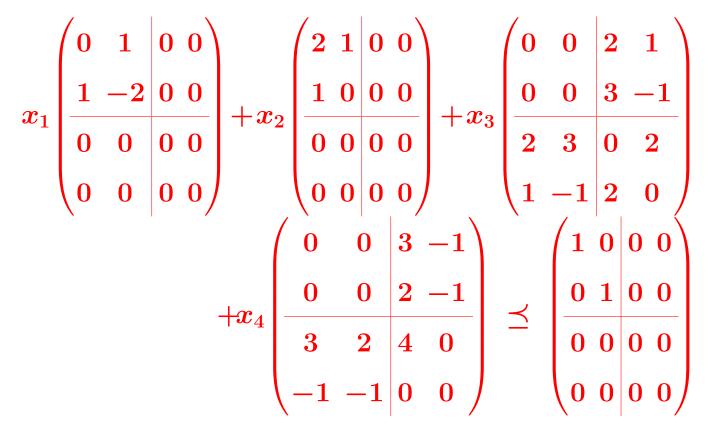
 \Rightarrow no dual soln with value 0

Example: before reformulation

$$x_{1} \begin{pmatrix} 54 & 46 & 50 & 4 \\ 46 & -38 & 87 & -106 \\ 50 & 87 & -60 & 296 \\ 4 & -106 & 296 & -368 \end{pmatrix} + x_{2} \begin{pmatrix} 110 & 91 & 105 & -6 \\ 91 & -72 & 171 & -210 \\ 105 & 171 & -72 & 528 \\ -6 & -210 & 528 & -672 \end{pmatrix} + x_{3} \begin{pmatrix} 42 & 35 & 40 & 0 \\ 35 & -28 & 67 & -82 \\ 40 & 67 & -36 & 216 \\ 0 & -82 & 216 & -272 \end{pmatrix} \\ + x_{4} \begin{pmatrix} 36 & 30 & 35 & -2 \\ 30 & -24 & 57 & -70 \\ 35 & 57 & -24 & 176 \\ -2 & -70 & 176 & -224 \end{pmatrix} \preceq \begin{pmatrix} 389 & 323 & 370 & -12 \\ 323 & -257 & 610 & -748 \\ 370 & 610 & -288 & 1920 \\ -12 & -748 & 1920 & -2432 \end{pmatrix}$$

Hard to tell if well or badly behaved

Example: after reformulation



As before: $x_3 = x_4 = 0 \Rightarrow \sup -x_4 = 0$

But: no dual solution with value 0

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where

1) \mathbf{Z} is max slack; 2) \mathbf{H}_i lin. indep. 3) $\mathbf{H}_i \bullet \mathbf{I} = \mathbf{0} \forall i$

Corollaries:

• The question:

Is (P_{SD}) well behaved?

is in $NP \cap coNP$ in real number model of computing.

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- Certificate: reformulation, and proof that Z is max rank slack.
- (P_{SD}) well behaved \Rightarrow for all c with a finite obj. value \exists optimal

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- Corollary: we can generate all linear maps under which the image of the psd cone is closed.
- Proof: $\{(A_i \bullet Y)_{i=1}^m | Y \succeq 0\}$ is closed $\Leftrightarrow \sum_{i=1}^m x_i A_i \preceq 0$ is well behaved.

Broader framework: Well- and badly behaved conic LPs

• Conic linear system, with K closed, convex cone:

 $(P) \quad Ax \leq_K b \qquad (\Leftrightarrow b - Ax \in K)$

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where (D_c) is dual program. Badly behaved if not well behaved.

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• Known:

K polyhedral \Rightarrow (P) is well-behaved. (P) Slater, i.e., $\exists x : b - Ax \in \operatorname{ri} K \Rightarrow (P)$ is well-behaved.

Given K closed, convex cone

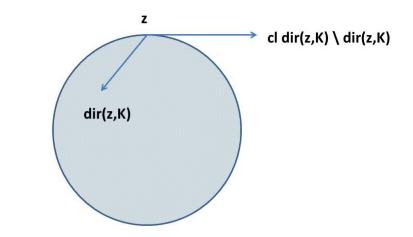
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- polyhedral, semidefinite, second order cones are nice.
- set of feasible directions at $z \in K$ maybe not closed: $\operatorname{dir}(z, K) = \{ y \mid \exists \epsilon > 0 \text{ s.t. } z + \epsilon y \in K \}$



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- \Rightarrow is true, even if K is not nice
- K polyhedral, or (P) Slater $(z \in riK) \Rightarrow dir(z, K)$ closed.

The difference set

• So, the set

 $\operatorname{cl}\,\operatorname{dir}({m z},{m K})\setminus\operatorname{dir}({m z},{m K})$

helps us understand conic duality.

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 $\operatorname{cl}\,\operatorname{dir}({m z},{m K})\setminus\operatorname{dir}({m z},{m K})$

helps us understand conic duality.

• Example:

$$Z=egin{pmatrix} I_r & 0\ 0 & 0 \end{pmatrix}.$$

Then

$$V \in \operatorname{cl}\,\operatorname{dir}(Z,PSD) \setminus \operatorname{dir}(Z,PSD)$$

 \mathbf{iff}

$$V = egin{pmatrix} \stackrel{r}{V_{11}} V_{12} \ V_{12} \ V_{12}^T V_{22} \end{pmatrix}, ext{ where } V_{22} \succeq 0, ext{ R}(V_{12}^T)
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- More generally: conditions for well and badly behaved nature of a conic linear system
- Exact characterization when K is nice.
- Latest version of paper is on Optimization Online.

Thank you!