Combinatorial characterizations in semidefinite programming duality

Gábor Pataki

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Talk at Danish Technical University

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: B A is positive semidefinite (psd).
- $A \bullet B = \sum_{i,j} a_{ij} b_{ij}$.

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- $A \leq B$ means: B A is positive semidefinite (psd).
- $A \bullet B = \sum_{i,j} a_{ij} b_{ij}$.
- $Y \succeq 0 \stackrel{\text{def}}{\Leftrightarrow}$ all principal subdeterminants are nonnegative.
- Equivalently, if $v^T Y v \ge 0 \, \forall v \in \mathbb{R}^n$.

Why is SDP important: LP \subseteq SDP \subseteq Convex Optimization

LP as SDP:

- If A_i and B are diagonal \Rightarrow so is $B \sum_{i=1}^m x_i A_i$.
- So it is psd iff diagonal elements are nonnegative.
- So LP can be modeled as SDP: make A_i , B diagonal.

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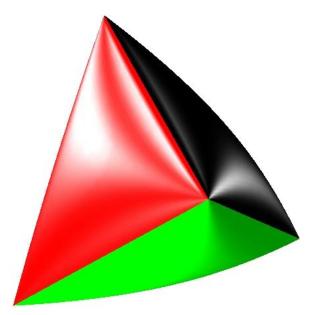
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SDP is a convex problem:

• Feasible set is convex, since set of psd matrices is.

3 by 3 correlation matrices

The set
$$\{ (x, y, z) \mid \begin{pmatrix} 1 & x & y \\ x & 1 & z \\ y & z & 1 \end{pmatrix} \succeq 0 \}$$



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
- Several thousand papers on SDP in the last 10 years.

The primal-dual pair of SDPs:

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Ideal situation: $\exists \bar{x}, \exists \bar{Y} : c^T \bar{x} = B \bullet \bar{Y}.$

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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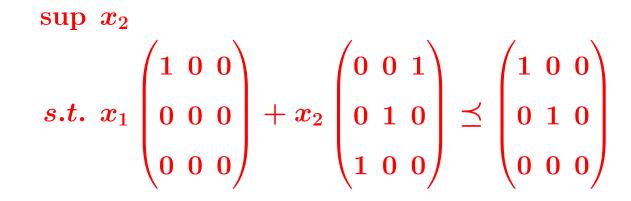
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Unattained inf = 0 : $y_{11} > 0$ is feasible, but $y_{11} = 0$ is not.

Pathology # 2: positive duality gap

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

Only feasible x_2 is $x_2 = 0$.

Pathology # 2: positive duality gap

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Only feasible x_2 is $x_2 = 0$.

Dual value is 1, and it is attained.

Terminology

Definition:

• The system

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

is well-behaved, if for all c such that

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

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

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

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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Curious similarity – of these, and about 20 others in the literature

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

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

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- But: this is not yet a poly time, or easy to verify proof of bad behavior
- Aside: how do we prove that Ax = b is infeasible? \rightarrow row echelon form.
- We will borrow ideas from the row echelon form to produce easy-to-verify certificates.

Reformulations of

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

are obtained by a sequence of:

- Apply a rotation $V^T()V$ to all matrices, where V is invertible.
- $B \leftarrow B + \sum_{i=1}^m \mu_i A_i$

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

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

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

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W

 $\langle H_i \rangle$

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

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

x feas. with slack $S \Rightarrow \text{last} \quad n - r \text{ cols of } S$ are zero

$$egin{array}{ccc} \Rightarrow & x_{k+1} = \cdots = x_m = \ \Rightarrow & \sup - x_m = 0 \end{array}$$

0

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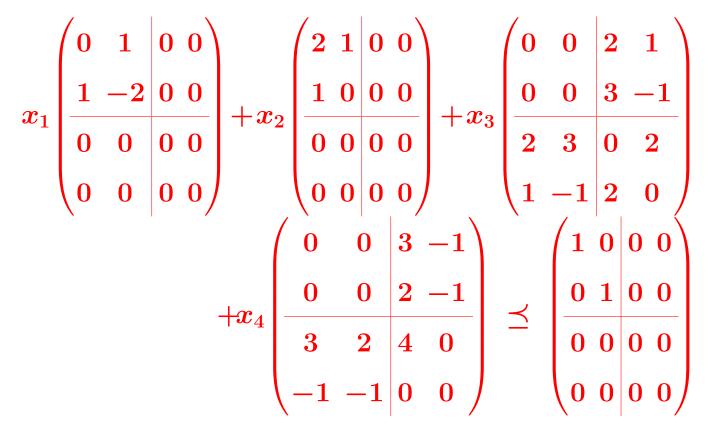
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Example: before reformulation

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

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

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

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where

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

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• The question:

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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.

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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.

How about proving infeasibility? This part is joint with Minghui Liu. Semidefinite System (spectrahedron)

$$egin{aligned} A_i ullet X &= b_i \, (i=1,\ldots,m) \ X \succeq 0 \end{aligned}$$

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Here

- A_i are symmetric matrices.
- $A \bullet B = \sum_{i,j} a_{ij} b_{ij}$.

Farkas' Lemma for SDP

- $(1) \Rightarrow (2)$:
- (1) $\sum_{i=1}^{m} y_i A_i \succeq 0$, $\sum_{i=1}^{m} y_i b_i = -1$ (P_{alt}) is feasible.
- (2) $A_i \bullet X = b_i \forall i, X \succeq 0$ (**P**) is infeasible.

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- **Proof:** One line.

Farkas' Lemma for SDP

- (1) \Rightarrow (2): (1) $\sum_{i=1}^{m} y_i A_i \succeq 0$, $\sum_{i=1}^{m} y_i b_i = -1$ (P_{alt}) is feasible. (2) $A_i \bullet X = b_i \forall i, X \succeq 0$ (P) is infeasible.
- **Proof:** One line.
- However: (2) \Rightarrow (1): (P_{alt}) is not an exact certificate of infeasibility.

Literature: exact certificates of infeasibility

- Ramana 1995
- Klep, Schweighofer 2013
- Waki, Muramatsu 2013: variant of facial reduction of
- Borwein, Wolkowicz 1981
- Also: Ramana, Tuncel, Wolkowicz, 1997

Literature: exact certificates of infeasibility

• Ramana's dual, and certificate of infeasibility: needs O(n) copies of the system, extra variables, and constraints like $U_{i+1} \succeq W_i W_i^T$

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- Ramana's dual, and certificate of infeasibility: needs O(n) copies of the system, extra variables, and constraints like $U_{i+1} \succeq W_i W_i^T$
- Goal: Find an exact certificate of infeasibility that is "almost" as simple as Farkas' Lemma.

Infeasible example, and proof of infeasibility

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• Suppose X feasible
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• Suppose X feasible
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• Main idea: We will find such a structure in every infeasible semidefinite system.

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- We obtain a reformulation of (P) by a sequence of the following:
- (1) Elementery row operations on the equations. (2) $A_i \leftarrow V^T A_i V \ (i = 1, ..., m)$, where V is invertible.

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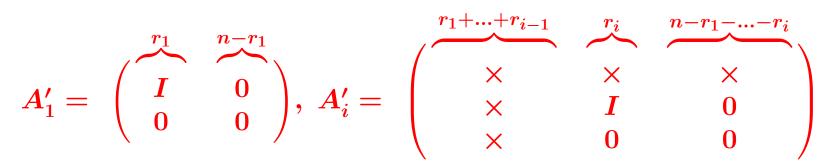
- We obtain a reformulation of (P) by a sequence of the following:
- (1) Elementery row operations on the equations. (2) $A_i \leftarrow V^T A_i V \ (i = 1, ..., m)$, where V is invertible.
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- Fact: Reformulations preserve (in)feasibility.

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where $k \geq 0$, and for $i = 1, \ldots, k + 1$ the A'_i look like



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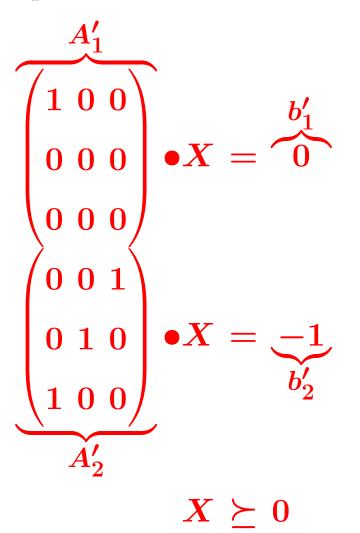
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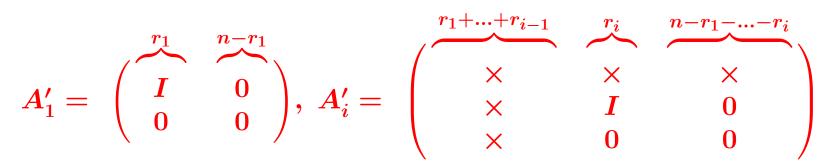
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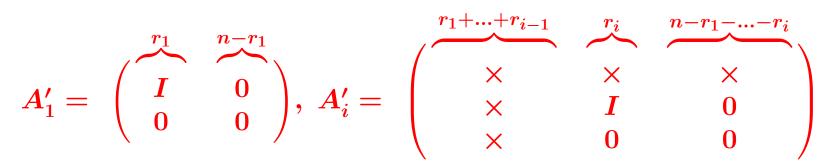
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• $k = 0 \rightarrow$ original Farkas' lemma.

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- Using this result, we can generate all infeasible SDP problems, as:
- (1) Generate a system like (P_{ref}) .
- (2) Reformulate it.

Proof outline

• Based on simplified facial reduction algorithm: construct the A'_i one by one.

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- "Difficult" direction is about 1.5 pages.
- Alternative: adapt a traditional facial reduction algorithm, the closest one is by Waki and Muramatsu.

Computational use

- Infeasible instances with this basic structure are very challenging for SDP solvers!
- Even more so, if we apply random elementary row ops and rotations.

Papers

- P: On the closedness of the linear image of a closed convex cone, Math of OR, 2007
- P: Bad semidefinite programs: they all look the same, under review.
- Liu-P: Exact duality in semidefinite programming based on elementary reformulations, SIOPT 2015
- Liu-P: Exact duals and short certificates fo infeasibility and weak infeasibility in conic linear programming, under review

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- (P_{ref}) being infeasible is almost a tautology.
- Algorithm to systematically generate all infeasible SDPs.

Thank you!