# On positive duality gaps in semidefinite programming

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Talk at RICAM, 2019

## A pair of Semidefinite Programs (SDP)

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

#### 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).
- $A \bullet B = \sum_{i,j} a_{ij} b_{ij}$ .

$$\sup_{x} c^{T}x \qquad \inf_{Y} B \bullet Y$$
 $(P) \quad s.t. \ \sum_{i=1}^{m} x_{i}A_{i} \preceq B \qquad Y \succeq 0 \qquad (D)$ 
 $A_{i} \bullet Y = c_{i} orall i.$ 

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**Easy:** If x and Y are feasible, then  $c^T x \leq B \bullet Y$ .

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But: pathologies occur, as nonattainment, positive gaps.

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Easy: If x and Y are feasible, then  $c^T x \leq B \bullet Y$ . Ideally:  $\exists x^*, \exists Y^* : c^T x^* = B \bullet Y^*$ .

But: pathologies occur, as nonattainment, positive gaps.  $\rightarrow$  in such cases we cannot certify optimality.

**Primal:** 



Primal:

$$\sup x_2 = x_1 \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} + x_2 \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} \preceq \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

 $x_2 = 0$  identically.

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$$\Rightarrow y_{11} = 0 \Rightarrow Y = egin{pmatrix} 0 & 0 & 0 \\ 0 & y_{22} & y_{23} \\ 0 & y_{23} & y_{33} \end{pmatrix}$$

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$$ext{1st dual constraint} \Rightarrow ext{ } y_{11} = 0 \ \Rightarrow Y = egin{pmatrix} 0 & 0 & 0 \ 0 & y_{22} & y_{23} \ 0 & y_{23} & y_{33} \end{pmatrix}$$

2nd dual constraint  $\Rightarrow y_{22} = 1 \Rightarrow \text{dual opt} = 1$ 

### Primal:

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

Looks quite odd:  $x_1$  "only exists" to create a zero block in the dual matrix.

# Positive gaps

- Maybe the "worst/most interesting" pathology.
- Solvers fail, or report a wrong solution.
- Good model of positive gaps in more general convex programs

## Literature

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- It does not distinguish among bad objective functions.
- Positive gaps related to complementarity in homogeneous systems: Tuncel, Wolkowicz, 2012
- Weak infeasibility: Lourenco, Muramatsu, Tsuchiya, 2014
- Infeasibility, weak infeasibility: Liu, P 2015, 2017

Literature: how to solve some pathological SDPs

- Facial reduction of Borwein-Wolkowicz, Waki-Muramatsu, Pataki: implemented by Permenter, Parrilo 2014; Permenter, Friberg, Andersen 2015
- Very simple facial reduction (just inspect the constraints): Zhu, P, Tran Dinh (Sieve-SDP) 2017
- SPECTRA, exact arithmetic SDP solver Henrion-Naldi-El Din 2016
- Douglas-Rachford splitting: Liu, Ryu, Yin 2017
- Homotopy method Hauenstein, Liddell, Zhang 2018

### Main ideas

- Look at small instances.
- Proposition: positive gap  $\Rightarrow m \geq 2$ .
- Fully characterize the m = 2 case.

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- Precisely: the structure that causes positive gap when m = 2 often does the same when m > 2.

### Main ideas

• Look at small instances.

Proposition: positive gap  $\Rightarrow m \geq 2$ .

- Fully characterize the m = 2 case.
- Show that the m = 2 case sheds light on larger m.
- Precisely: the structure that causes positive gap when m = 2 does the same in many cases even if m > 2.
- Reformulate
- Borrow ideas from linear system of equations: to show Ax = b is infeasible, we create an equation  $\langle 0, x \rangle = 1$ .

**Recall:** a pair of Semidefinite Programs (SDPs)

$$\sup_{x} c^T x \qquad \inf_{Y} B ullet Y$$
 $(P) \quad s.t. \ \sum_{i=1}^m x_i A_i \preceq B \qquad Y \succeq 0 \qquad (D)$ 
 $A_i ullet Y = c_i orall i.$ 

Reformulations of (P) - (D) are obtained by

• Choose *T* invertible, and

$$B \leftarrow T^T BT, A_i \leftarrow T^T A_i T \forall i.$$

- Elementary row operations on (D): e.g., exchange two constraints  $A_i \bullet Y = c_i$  and  $A_j \bullet Y = c_j$ .
- Choose  $\mu \in \mathbb{R}^m$  and

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

Reformulations preserve positive gaps (if any).



where  $\Lambda \succ 0, \ M \neq 0, \ c_2' > 0, s \ge 0.$ 



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#### Proof of $\Leftarrow$

This is the easy direction.

Essentially reuse the argument from before.



where  $\Lambda \succ 0, \, M 
eq 0, \, c_2' > 0, s \geq 0.$ 

**Proof of**  $\Leftarrow M \neq 0 \Rightarrow x_2 = 0 \Rightarrow \text{primal} = 0.$ 



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Proof of  $\Leftarrow$  Dual matrix  $Y \succeq 0$ 

1st dual constraint  $\Rightarrow \Lambda \bullet Y(1:p,1:p) = 0$ 



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**Proof of**  $\leftarrow$  Dual matrix  $Y \succeq 0$ 

1st dual constraint  $\Rightarrow \Lambda \bullet Y(1:p,1:p) = 0$ 

$$\Rightarrow Y(1:p,1:p) = 0$$

 $\Rightarrow$  1st *p* rows and columns of *Y* are zero.



where  $\Lambda \succ 0, \, M \neq 0, \, c_2' > 0, s \geq 0.$ 

$$imes ext{ dual is } egin{array}{c} ext{if } & egin{pmatrix} I_{r-p} & 0 \ 0 & 0 \end{pmatrix} ullet Y' \ 0 & 0 \end{pmatrix} ullet Y' \ S.t. egin{pmatrix} \Sigma & 0 \ 0 & -I_s \end{pmatrix} ullet Y' = c_2' > 0 \ Y' \succeq 0, \end{array}$$



where  $\Lambda \succ 0, \ M 
eq 0, \ c_2' > 0, s \geq 0.$ 

 $\Rightarrow$  dual optimal value > 0.

Simple certificate of the positive pap

When does the underlying system admit a gap? Given

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

is there  $c \in \mathbb{R}^m$  such that there is a positive gap?

# Suppose m = 2. Then $\exists (c_1, c_2)$ with positive gap $\Leftrightarrow (P_{SD})$ has reformulation



where  $\Lambda \succ 0, \ M \neq 0, \ s \geq 0$ .

How about m > 2?





Primal = 0.

$$\sup x_3 = x_3 = x_1 \begin{pmatrix} 1 & & \ & 0 & & \ & 0 & & \ & & 0 & & \ & & 0 & & \ & & 0 & & \ & & 1 & & \ & & 0 & & \ & & 1 & & \ & & 0 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 0 & & \ & & 1 & & 0 \end{pmatrix} + x_3 \begin{pmatrix} 0 & & & & \ & 0 & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & \ & & 1 & & 0 \end{pmatrix} \preceq \begin{pmatrix} 1 & & & & \ & 1 & & & \ & & 1 & & \ & & 1 & & \ & & 0 \end{pmatrix}.$$

Primal = 0.

Dual : Variable  $Y = (y_{ij}) \succeq 0$ 

$$\sup x_3 = x_3$$
  
 $s.t. \ x_1 egin{pmatrix} 1 & & \ 0 & & \ 0 & & \ & 0 & & \ & 1 & & \ & 1 & & \ & 0 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & 0 \end{pmatrix} + x_3 egin{pmatrix} 0 & & & \ 0 & & 1 & & \ & 0 & & 1 & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 0 & \end{pmatrix} ext{.}$ 

Primal = 0.

Dual : Variable  $Y = (y_{ij}) \succeq 0$ 

1st two dual constraints  $\Rightarrow$  1st two rows and columns of Y are zero.

$$\sup x_3 = x_3 = x_1 \begin{pmatrix} 1 & & \ 0 & & \ & 0 & & \ & 0 & & \ & 0 & & \ & 0 & & \ & 1 & & \ & 0 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 0 & & \ & 1 & & 0 \end{pmatrix} + x_3 \begin{pmatrix} 0 & & & \ & 0 & & 1 & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & 0 \end{pmatrix} \preceq \begin{pmatrix} 1 & & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 0 \end{pmatrix}.$$

### Primal = 0.

 $\Rightarrow$  Dual is equivalent to:

$$\begin{array}{l} \inf \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \bullet Y' \\ s.t. \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \bullet Y' = 1 \\ Y' \succeq 0, \end{array}$$

Same structure as in the 2 variable case

$$\sup x_3 = x_3 = x_1 \begin{pmatrix} 1 & & \ 0 & & \ & 0 & & \ & 0 & & \ & 0 & & \ & 0 & & \ & 1 & & \ & 0 & & \ & 1 & & \ & 0 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 0 & & \ & 1 & & 0 \end{pmatrix} + x_3 \begin{pmatrix} 0 & & & \ & 0 & & 1 & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & 0 \end{pmatrix} \preceq \begin{pmatrix} 1 & & & \ & 1 & & \ & 1 & & \ & 1 & & \ & 1 & & 0 \end{pmatrix}.$$

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Same structure as in the 2 variable case

We can create such an instance for any  $m = 2, 3, 4, \ldots$  with n = m + 1

**Name:** single sequence SDPs

Objective is  $\sup x_m$ .

Sparsity structure when m = 2, 3, 4 (n = m + 1)



Sparsity structure when m = 2, 3, 4 (n = m + 1)



Blue stripe in  $A_{i+1}$ : If  $Y \succeq 0$ ,  $A_1 \bullet Y = \ldots A_i \bullet Y = 0$ , then these parts of Y are zero.

# How do we get these instances? Background: facial reduction

Given H affine subspace, K closed convex cone s.t.  $H \cap K \neq \emptyset$ , a facial reduction algorithm (FRA) works as:

(1) If ri  $K \cap H = \emptyset$ , find  $y \in H^{\perp} \cap (K^* \setminus K^{\perp})$ . (2) Replace K by  $K \cap y^{\perp}$ . Goto (1).

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## **Facial reduction sequence:**

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# Singularity degree:

Is the smallest number of FRA steps, until the FRA stops. So we can talk about the singularity degree of an SDP.

### Back to m = 2 example:



Here  $(A_1)$  is a facial reduction sequence for (D).

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### Back to larger example:



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Here  $(A_1, A_2)$  is a facial reduction sequence for (D).

 $A_1 \bullet Y = A_2 \bullet Y = 0$  proves that dual matrix must look like

### **Theorem:**

- sing(D)  $\leq m$ .
- =  $m \Rightarrow$  no gap. (Easy)
- $\forall m \geq 2, \forall g > 0 \exists$  instance s.t.

sing(D) = m - 1 and gap is g.

# Indeed, the single sequence SDPs have sing(D) = m - 1



We also look at the homogeneous dual

 $egin{aligned} A_i ullet Y &= 0 \, orall i \ B ullet Y &= 0 \, (HD) \ Y &\succeq 0 \end{aligned}$ 

### **Theorem:**

- $sing(HD) \le m + 1$ . (Easy)
- =  $m + 1 \Rightarrow$  no gap.
- $\forall m \geq 2, \forall g > 0 \exists$  instance s.t.

sing(D) = m - 1 and sing(HD) = m and gap is g.

### **Theorem:**

- $sing(HD) \le m + 1$ . (Easy)
- =  $m + 1 \Rightarrow$  no gap.
- ∀m ≥ 2, ∀g > 0∃ instance s.t.
   sing(D) = m 1 and sing(HD) = m and gap is g.
   Proof: the double sequence SDPs



Surprising connection between singularity degrees

$$\underbrace{\operatorname{sing}(\operatorname{HD}) = m + 1}_{(\text{maximal})} \Rightarrow \underbrace{\operatorname{sing}(\operatorname{D}) = 0}_{(\text{minimal})}$$

sing(D) = 0 means it satisfies Slater's condition

## **Problem library and computational results**

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- Instances with  $m = 2, 3, \ldots, 11$ ; gap = 10.
- Integral data. Gap can be verified by hand, in exact arithmetic.
- Four categories:
  - $-\operatorname{gap\_single\_finite\_clean\_m}$
  - $-gap\_single\_finite\_messy\_m$
  - $-gap\_single\_inf\_clean\_m,$
  - $-gap\_single\_inf\_messy\_m.$
- Messy means we applied a similarity transformation  $T^{T}()T$ .

# Results

	GAP, SINGLE, FINITE		GAP, SINGLE, INFINITE	
	CLEAN	MESSY	CLEAN	MESSY
MOSEK	1	1	0	0
SDPA-GMP	1	1	0	0
PP+MOSEK	10	1	10	0
SIEVE-SDP + MOSEK	10	1	10	0

PP: preprocessor of Permenter and Parrilo
Sieve-SDP: preprocessor of Zhu, Pataki, Tran-Dinh Note: SPECTRA works when m = 2.

## Summary:

- Positive gaps: "worst/most interesting" pathology of SDPs.
- Complete characterization for m = 2 by reformulation.
- Complete characterization of positive gap systems with m = 2.

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- Positive gaps: "worst/most interesting" pathology of SDPs.
- Complete characterization for m = 2 by reformulation.
- Complete characterization of positive gap systems with m = 2.
- Similarly structured positive gap SDPs in any dimension.
- Highest singularity degree that leads to a positive gap.
- Challenging problem library.

# Papers

- **P**: Bad semidefinite programs: they all look the same, **2010–SIOPT 2017**
- **P**: Characterizing bad semidefinite programs: normal forms and short proofs

### SIAM Review, 2019

• **P**: On positive duality gaps in semidefinite programming, submitted.

# Thank you!