On the complexity of computing the handicap of a sufficient matrix

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Convex Optimization and Algebraic Geometry, IPAM, October 1, 2010

Sufficient and \mathcal{P} -matrices

We look at several matrix classes related to positive semidefinite (PSD) matrices.

Definition (Sufficient matrices)

A matrix $M \in \mathbb{R}^{n \times n}$ is a column sufficient matrix if for all $x \in \mathbb{R}^n$

$$x_i(Mx)_i \leq 0 \ \forall \ i = 1, \ldots, n$$
 implies $x_i(Mx)_i = 0 \ \forall \ i = 1, \ldots, n$,

and row sufficient if M^T is column sufficient. Matrix M is sufficient if it is both row and column sufficient.

Definition (P-matrices)

A matrix $M \in \mathbb{R}^{n \times n}$ is a \mathcal{P} -matrix (resp. \mathcal{P}_0 -matrix) if all its principal minors are positive (resp. nonnegative).

$\mathcal{P}_*(\kappa)$ -matrices

Definition ($\mathcal{P}_*(\kappa)$ -matrix)

Let $\kappa \geq 0$ be a nonnegative number. A matrix $M \in \mathbb{R}^{n \times n}$ is a $\mathcal{P}_*(\kappa)$ -matrix if for all $x \in \mathbb{R}^n$

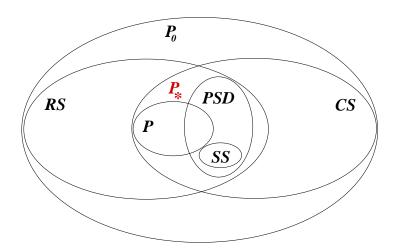
$$x^{T}Mx + 4\kappa \sum_{i \in \mathcal{I}_{+}(x)} x_{i}(Mx)_{i} \ge 0, \tag{1}$$

where

$$\mathcal{I}_{+}(x) := \{1 \leq i \leq n : x_{i}(Mx)_{i} > 0\}.$$

- Note that $\mathcal{P}_*(0)$ are the positive semidefinite (PSD) matrices.
- Define $\mathcal{P}_* := \bigcup_{\kappa > 0} \mathcal{P}_*(\kappa)$.
- The \mathcal{P}_* and sufficient matrices are the same [Kojima et al. (1991), Guu and Cottle (1995), Väliaho (1996)].

Matrix classes: Venn diagram



 $\mathsf{CS} = \mathsf{column} \ \mathsf{sufficient}, \ \mathsf{RS} = \mathsf{row} \ \mathsf{sufficient}, \ \mathsf{SS} = \mathsf{skew\text{-}symmetric}, \ \mathsf{PSD} = \mathsf{positive} \ \mathsf{semidefinite}.$

Matrix classes: membership problem

Theorem (Tseng (2000))

The membership decision problem is co-NP complete in the Turing model for:

- \mathcal{P} and \mathcal{P}_0 matrices;
- Column sufficient matrices;
- Row sufficient matrices.

P. Tseng. Co-NP-completeness of some matrix classification problems. *Mathematical Programming*, 88:183–192, 2000.

The linear complementarity problem (LCP)

LCP

Given $M \in \mathbb{R}^{n \times n}$ and $q \in \mathbb{R}^n$, find $x \in \mathbb{R}^n$ and $s \in \mathbb{R}^n$ such that

$$-Mx + q = s$$
, $x_i \ge 0$, $s_i \ge 0$, $x_i s_i = 0$ $(i = 1, ..., n)$.

Turing model complexity of LCP

Matrix class	Complexity of LCP	Reference
PSD	Р	Kojima et al (1989)
\mathcal{P}	not NP-hard, unless NP=co-NP	Megiddo (1988)
\mathcal{P}_*	unknown	
\mathcal{P}_0	NP-complete	Kojima et al (1991)

Complexity of LCP with sufficient matrices

- LCP is NP-hard for general M, but ...
- ... may be solved by interior point methods if M is sufficient.
- The complexity is then polynomial in n, the bitsize of (M, q), and the handicap of M:

Definition (Handicap of a sufficient matrix)

Let $M \in \mathbb{R}^{n \times n}$. The handicap of M is:

$$\hat{\kappa}(M) := \inf\{\kappa \mid M \in \mathcal{P}_*(\kappa)\}.$$

F. A. Potra and X. Liu. Predictor-corrector methods for sufficient linear complementarity problems in a wide neighborhood of the central path. *Optimization Methods & Software*, 20(1):145–168, 2005.

- We will show that the handicap of M can be exponential in its bit size ...
- ... proving that the best known complexity bounds for LCP with sufficient *M* are exponential in the input size.

Properties of the handicap

Definition

A principal pivotal transformation of a matrix $A = \begin{pmatrix} A_{\mathcal{J}\mathcal{J}} & A_{\mathcal{J}\mathcal{K}} \\ A_{\mathcal{K}\mathcal{J}} & A_{\mathcal{K}\mathcal{K}} \end{pmatrix}$ where $\mathcal{J} \cup \mathcal{K} = \{1, \dots, n\}$ and $A_{\mathcal{J}\mathcal{J}}$ is nonsingular, is the matrix

$$\begin{pmatrix} A_{\mathcal{J}\mathcal{J}}^{-1} & -A_{\mathcal{J}\mathcal{J}}^{-1} A_{\mathcal{J}\mathcal{K}} \\ A_{\mathcal{K}\mathcal{J}} A_{\mathcal{J}\mathcal{J}}^{-1} & A_{\mathcal{K}\mathcal{K}} - A_{\mathcal{K}\mathcal{J}} A_{\mathcal{J}\mathcal{J}}^{-1} A_{\mathcal{J}\mathcal{K}} \end{pmatrix}.$$

Theorem (Guu and Cottle (1995), Kojima et al. (1991), Väliaho (1997))

Let $M \in \mathbb{R}^{n \times n}$ be a sufficient matrix. Then:

- The handicaps of M and all its principal pivotal transforms are the same.
- The handicap of M is at least as large as that of any of its proper principal submatrices.
- $\hat{\kappa} \begin{pmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{pmatrix} = \frac{1}{4} \left[\frac{m_{21}^2}{\left(\sqrt{m_{11} m_{22}} + \sqrt{m_{11} m_{22} m_{12} m_{21}} \right)^2} 1 \right].$

Size of the handicap

Theorem (De Klerk-Nagy)

There exists an $M \in \mathcal{P}$ with $\hat{\kappa}(M) > 2^{\sqrt{L(M)}}$, where L(M) is the bitsize of M.

Proof sketch: Let

$$M = \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ -1 & 1 & 0 & 0 & \dots & 0 & 0 \\ -1 & -1 & 1 & 0 & \dots & 0 & 0 \\ & & & & & & \\ \vdots & & & & \ddots & & \\ -1 & -1 & -1 & -1 & \dots & -1 & 1 \end{pmatrix}$$

then $\hat{\kappa}(M) \geq 2^{2n-8} - \frac{1}{4}$ (via the theorem on the previous slide).



Complexity of computing the handicap

Consider the following decision problem:

Decision problem

- **Input:** an integer n > 0, an integer $n \times n$ matrix M with bit size L(M), and a positive integer t;
- **Question:** Is $\hat{\kappa}(M) > t$?

Conjecture

If M is sufficient, there is an upper bound on $\hat{\kappa}(M)$ with bit size polynomial in L(M).

Theorem (De Klerk-Nagy)

The decision problem is in NP in the Turing model. If the conjecture holds, the decision problem is NP-complete.

Computing the handicap

There is an algorithm to compute the handicap of a sufficient M:

H. Väliaho. Determining the handicap of a sufficient matrix. *Linear Algebra and Its Applications*, 253:279–298, 1997.

Theorem (De Klerk-Nagy)

The complexity of the Väliaho algorithm is lower bounded by $\frac{1}{5}6^n$.

- In practice, the algorithm is prohibitively slow if $n \geq 7$...
- this motivates an alternative approach using sum-of-squares of polynomials and semidefinite programming.

Computing the handicap (ctd.)

Recall that, if $M \in \mathcal{P}_*(\kappa)$ then

$$x^{T}Mx + 4\kappa \sum_{i \in \mathcal{I}_{+}(x)} x_{i}(Mx)_{i} \geq 0 \ \forall x \in \mathbb{R}^{n},$$

where

$$\mathcal{I}_{+}(x) := \{1 \leq i \leq n : x_{i}(Mx)_{i} > 0\}.$$

Lemma

Let $M \in \mathbb{R}^{n \times n}$ and

$$p_{\kappa}(x,\alpha) := x^{T} M x + 4 \kappa \sum_{i=1}^{n} \alpha_{i}.$$

One has:

$$\hat{\kappa}(M) = \inf \{ \kappa \geq 0 : p_{\kappa}(x, \alpha) \geq 0, \ \forall (x, \alpha) \in \mathcal{K} \},$$

where $\mathcal{K} := \{(x, \alpha) : \|x\| = 1, \ \alpha \ge x \circ Mx, \ \|\alpha\| \le \|M\|_2, \ \alpha \ge 0\}.$

Computing the handicap (ctd.)

Lemma

Let $M \in \mathbb{R}^{n \times n}$ a \mathcal{P} -matrix and

$$p_{\kappa}(x,\alpha) := x^{T} M x + 4 \kappa \sum_{i=1}^{n} \alpha_{i}.$$

One has:

$$\hat{\kappa}(M) = \inf \left\{ \kappa \geq 0 : \; p_{\kappa}(x, \alpha) > 0, \; \forall (x, \alpha) \in \mathcal{K} \right\},$$

where
$$\mathcal{K}:=\left\{(x,\alpha):\ \|x\|=1,\ \alpha\geq x\circ Mx,\ \|\alpha\|\leq \|M\|_2,\ \alpha\geq 0\right\}.$$

- Now we can use Putinar's *positivstellensatz* for polynomials positive on compact semialgebraic sets ...
- ... and Lasserre's approach to obtain semidefinite programming approximations.

Putinar's positivstellensatz

Consider *semi-algebraic set* defined by polynomials g_i (i = 1, ..., m):

$$K = \{x \in \mathbb{R}^k : g_i(x) \ge 0 \ (i = 1, ..., m)\}.$$

Quadratic module:

The *quadratic module* generated by functions g_1, \ldots, g_m is defined as

$$\mathcal{M}(g_1,\ldots,g_m) = \left\{ s_0 + \sum_{j=1}^m s_j g_j : \ s_j \ \text{sums of squares}, \ \ j=0,\ldots,m
ight\}.$$

Theorem (Putinar):

For a given polynomial p one has p(x) > 0 for all $x \in \mathcal{K}$ iff $p \in \mathcal{M}(g_1, \dots, g_m)$, provided that $\mathcal{M}(g_1, \dots, g_m)$ is Archimedean.

M. Putinar. Positive polynomials on compact semi-algebraic sets. *Ind. Univ. Math. J.* 42:969–984, 1993.

Lasserre's approach

Truncated quadratic module:

Given an integer t > 0, the *truncated quadratic module of degree* 2t generated by functions g_1, \ldots, g_m is defined as

$$\mathcal{M}_t(g_1,\ldots,g_m) := \left\{ s_0 + \sum_{j=1}^m s_j g_j : s_j \text{ sums of squares}, \ (j=0,\ldots,m) \right\}$$
 $\deg \operatorname{ree}(g_j s_j) \leq 2t \ (j=0,\ldots,m), \ \deg \operatorname{ree}(s_0) \leq 2t.$

Approach of Lasserre:

For a given polynomial p the question: "Is $p \in \mathcal{M}_t(g_1, \dots, g_m)$?", may be formulated as a semidefinite program (SDP).

J.B. Lasserre. Global optimization with polynomials and the problem of moments. SIOPT, 11:296-817, 2001.

SDP formulation

$$\kappa^{(t)} := \inf \kappa$$

subject to

$$\begin{split} x^T M x + 4\kappa \sum_{i=1}^n \alpha_i &= s_0(x,\alpha) + \sum_{j=1}^n \left(\alpha_j - x_j(Mx)_j\right) s_j(x,\alpha) \\ &+ \left. + \sum_{j=1}^n \alpha_j \, s_{n+j}(x,\alpha) + \left(\|M\|_2^2 - \sum_{i=1}^n \alpha_i^2\right) s_{2n+1}(x,\alpha) \right. \\ &+ \left. \left(1 - \sum_{i=1}^n x_i^2\right) r(x,\alpha) \right. \\ &s_j(x,\alpha) \qquad \text{sums of squares,} \quad j = 0,\dots,2n+1 \\ &\deg(s_0) &\leq 2t, \\ &\deg(s_j) &\leq 2t-2, \quad j = 1,\dots,2n+1 \\ &r \in \mathbb{R}[x,\alpha], \, \deg(r) \leq 2t-2 \end{split}$$

SDP approximation of the handicap: properties

For fixed t, $\kappa^{(t)}$ may be computed in polynomial time within any fixed accuracy.

Theorem (De Klerk-Nagy)

Let $M \in \mathbb{R}^{n \times n}$ with handicap $\hat{\kappa}(M)$ Then:

- $\kappa^{(t)} = \infty$ for all $t \in \mathbb{N}$ if M is not sufficient;
- \bullet $\hat{\kappa}(M) = \lim_{t \to \infty} \kappa^{(t)}$ if M is a \mathcal{P} -matrix;
- **1** $0 = \hat{\kappa}(M) = \kappa^{(1)}$ if M is PSD;
- **3** $\hat{\kappa}(M) = \kappa^{(1)}$ if n = 2;
- **1** $\kappa^{(1)} < \infty$ iff \exists a diagonal matrix D (positive diagonal entries) such that DM is PSD.

Numerical examples

- We compared our approach numerically to the algorithm of Väliaho for small matrices $(n \le 7)$.
- The SDP problems with optimal values $\kappa^{(t)}$ $(t=1,2,\ldots)$ were solved using SeDumi and Gloptipoly.
- D. Henrion, J. B. Lasserre, J. Loefberg. GloptiPoly 3: moments, optimization and semidefinite programming. *Optimization Methods and Software*, **24**:4-5, 761–779, 2009.
 - The test matrices were all \mathcal{P} -matrices (with finite handicap).
 - s = 1 in the next table means Gloptipoly could verify global optimality, i.e. the handicap is obtained exactly.

Numerical examples

	Order of SOS	Väliaho's	
Matrix	1	2	algorithm
$M_2 (n = 3)$	$s=0$ $\kappa^{(1)} = 6$ 0.2s	$s=1$ $\kappa^{(2)} = 6$ 0.6s	$\hat{\kappa}=6$ 0.3s
$M_3 \ (n=3)$	$ s=-1 $ $ \kappa^{(1)} = \infty $ (infeasible) $ 0.2s $	$\kappa^{(2)} = 0.91886 \ 0.5 \mathrm{s}$	$\hat{\kappa}=0.91886$ 0.3s
$M_4 \ (n=3)$	$ \kappa^{(1)} = 0.08986 $ 0.1s	$ \kappa^{(2)} = 0.08986 $ 0.4s	$\hat{\kappa}=0.08986$ 0.6s
$M_5 (n = 3)$	s=0 $\kappa^{(1)} = 0.03987$ 0.2s	$s=1$ $\kappa^{(2)} = 0.03987$ 0.4s	$\hat{\kappa}=0.03987$ 0.6s
$M_6 \ (n=6)$	$ s=0 $ $ \kappa^{(1)} = 15.75 $ 0.3s	$ s=1 $ $ \kappa^{(2)} = 15.75 $ 138.7s	$\hat{\kappa}=15.75$ 1737.7s
$M_7 \ (n=7)$	$s=0 \ \kappa^{(1)} = 0.039866 \ 0.3s$	$s=1$ $\kappa^{(2)} = 0.039866$ 413.1s	 > 12h

Conclusions and summary

- We have shown that the handicap of a sufficient matrix M may be exponential in the bit size of M ...
- matrices are exponential in the input size.

that implies the best known complexity bounds for LCP's with sufficient

- Lasserre's sum-of-squares approach may be used to compute the handicap ...
- and is a better choice in practice than Väliaho's algorithm.

Almost the End

Further reading:

Preprint at Optimization Online.

One more conjecture ...

A conjecture by Monique Laurent and myself

Identity:

$$x_1x_2 + \frac{1}{8} = \frac{1}{2}(x_1 + x_2 - \frac{1}{2})^2 + \frac{1}{2}(x_1 - x_1^2) + \frac{1}{2}(x_2 - x_2^2).$$

Thus $x_1x_2 + \frac{1}{8}$ belongs to the truncated quadratic module of degree 2 generated by $x_1 - x_1^2$, $x_2 - x_2^2$.

Question:

What is the smallest constant $C_n > 0$ so that $\prod_{i=1}^n x_i + C_n$ belongs to the truncated quadratic module of degree n generated by $x_1 - x_1^2, \dots, x_n - x_n^2$?

Conjecture: $C_n = \frac{1}{n(n+2)}$. (We know that $C_n \leq 1$.)

Conjecture from:

E. de Klerk, M. Laurent. Error bounds for some semidefinite programming approaches to polynomial minimization on the hypercube. *SIOPT*, to appear.