Paula Amaral

Dep. Mathematics and CMA

University Nova de Lisboa



### Outline

Infeasibility

Optimal correction of an infeasible system

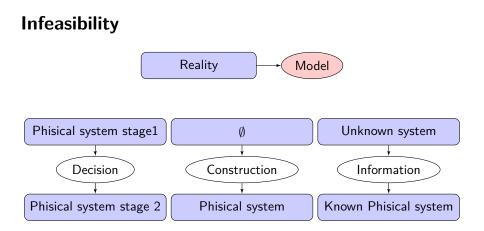
**Fractional Quadratic Problem** 

**Copositive Formulation** 

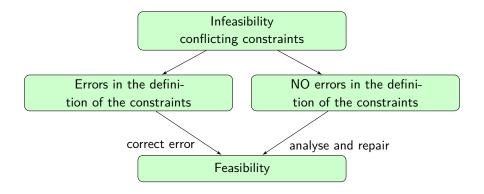
Duality

Size reduction, from  $n^2$  to  $(n-m)^2$ 

**Computational results** 



 $\begin{array}{l} {\sf Restrictions} \hookrightarrow {\sf constraints} \\ {\sf Performance} \hookrightarrow {\sf objective function} \end{array}$ 

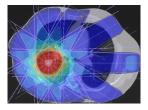


#### Radiation Treatment Planning IMRT (Intensity-modulated rad. Therapy)

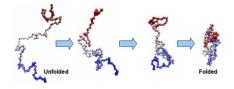
- small individual beams of radiation of adjustable angles and intensity are directed through the body.
- Body modeled as a collection of voxels (volume pixels).

• Constraints 
$$A_1 x \leq u, A_2 x \geq u, x \geq 0.$$

infeasible



Prediction of the three-dimensional protein folding pattern from its amino acid sequence



- protein energy models. (hundred of millions of constraints).
- energy function is a linear combination of basis functions.
- comparing the energy of a misfolded shape to the energy of the native shape.
- native shapes always have a lower energy than a misfolded shape.

- given a set of similar decoy structures to compare against, energy inequalities can be constructed.
- constraints  $E_{misfolded}(x) E_{native}(x) \ge \epsilon, \ x \ge 0.$
- *x* parameters (hundred)
- MAXFS helps defining the region for the correct native structure.

### Digital Video Broadcasting (Amaldi 2005)

Given m square areas, representing test points for signal reception, and n transmitters, determine the transmission power of each transmitter so that the signal reception at each test point is acceptable.

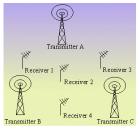


Figure 1: Example of a DVB-T network

- there may be interference in each test point due large delays is signal arrival from different transmitters.
- $x_j$  is the unknown power of the transmitter j.
- constraints  $\sum_{i} a_{ij} x_j \ge b_i$  representing the total signal strength at point j
- $a_{ij}$  is positive if the signal is useful and negative if it interferes.
- $b_i$  is the minimum signal streight needed at test point i to provide adequate signal strength with 95% probability.
- complete coverage of a large number of test points is not usually possible.
- find maximal number of constraints satisfied.

### Post-infeasibiity analysis

- detecting feasibility status
- retrieve valuable information regarding the inconsistency
  - identication of conficting sets of constraints
  - irreducible inconsistent sets (IIS)
- achieving feasibility
  - removing constraints
  - changing the coefficients of the constraints

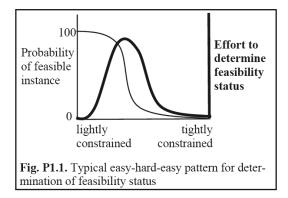


Figure 1: Picture from - Feasibility and infeasibility in Optimization: algorithms and computational methods, John W Chinneck.

# Optimal correction of an infeasible system

Given linear system of inequalities

 $Ax \le b \to (A+H)x \le (b+p)$ 

Optimal correction p and H, respectively, of the vector b and the matrix A:

Minimize 
$$\varphi(H, p)$$
 (1)

subject to 
$$(A+H)x \le b+p$$
 (2)

$$x \in \mathcal{X}, H \in \mathcal{R}^{m \times n}, p \in \mathcal{R}^m,$$
 (3)

where  $\mathcal{X} \subseteq \mathcal{R}^n$  is a convex set and  $\varphi$  is an appropriate matrix norm.

#### For

• 
$$\varphi = \| \cdot \|_{l_1}$$
,  $(\|A\|_{l_1} = \sum_{ij} |a_{ij}|)$ 

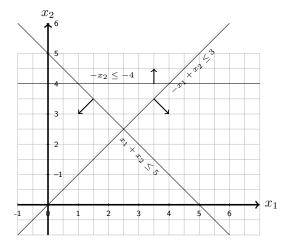
• 
$$\varphi = \|\cdot\|_{l_{\infty}}$$
,  $(\|A\|_{l_{\infty}} = \max_{ij} |a_{ij}|)$ 

• 
$$\varphi = \|\cdot\|_{\infty}$$
, ( $\|A\|_{\infty} = \max_i \sum_j |a_{ij}|$ )

Vatolin (1980) find an optimal correction by solving a set of linear programming problems and that the number of linear programming problems to be solved is

• 
$$l_1 \rightarrow 2n+1$$

- $\bullet \quad \infty \to 2n+1$
- $l_{\infty} \to 2^n$



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$$\begin{bmatrix} 0 & -1 \\ -1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \le \begin{bmatrix} -4 \\ 0 \\ 5 \end{bmatrix}$$
$$\| \cdot \|_{l_{\infty}}, (\|A\|_{l_{\infty}} = \max_{ij} |a_{ij}|) \rightarrow \begin{bmatrix} -0.1579 & -0.1579 & 0.1579 \\ -0.1579 & -0.1579 & 0.1579 \\ -0.1579 & -0.1579 & 0.1579 \end{bmatrix}$$
$$\| \cdot \|_{l_1}, (\|A\|_{l_1} = \sum_{ij} |a_{ij}|) \rightarrow \begin{bmatrix} -0.6 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \text{ or } \begin{bmatrix} 0 & -0.6 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$\| \cdot \|_{\infty}, (\|A\|_{\infty} = \max_{i} \sum_{j} |a_{ij}|) \rightarrow \begin{bmatrix} 0 & -0.2308 & 0 \\ 0 & -0.2308 & 0 \\ 0 & -0.2308 & 0 \end{bmatrix}$$

Frobenius norm 
$$\|\cdot\|_F \rightarrow \begin{bmatrix} -0.1365 & -0.1613 & 0.0522 \\ -0.0714 & -0.0844 & 0.0273 \\ -0.1065 & -0.1259 & 0.0407 \end{bmatrix}$$

$$(P) \quad \text{Minimize } \|[H, p]\|_F^2$$
  
subject to  $(A + H)x \le b + p$   
 $H \in \mathcal{R}^{m \times n}, \quad p \in \mathcal{R}^m, \quad x \in \mathbf{X}.$  (4)

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# **Fractional Quadratic Problem**

$$L(h, p, x, \lambda) = \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} h_{ij}^{2} + \frac{1}{2} \sum_{i=1}^{m} p_{i}^{2} + \sum_{i=1}^{m} \lambda_{i} \sum_{j=1}^{n} (a_{ij} + h_{ij}) x_{j} + p_{i} - b_{i}$$
(5)

From the KKT conditions we know we must have

$$\frac{\delta L(h, p, x, \lambda)}{h_{ij}} = 0 \quad \Leftrightarrow \quad h_{ij} + \lambda_i x_j = 0, \tag{6}$$

$$\frac{\delta L(h, p, x, \lambda)}{p_i} = 0 \quad \Leftrightarrow \quad p_i + \lambda_i = 0, \tag{7}$$

$$\frac{\delta L(h, p, x, \lambda)}{x_j} = 0 \quad \Leftrightarrow \quad \Sigma_{i=1}^m \lambda_i (a_{ij} + h_{ij}) = 0, \tag{8}$$

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together with

 $\lambda^{T}((A+H)x - b + p) = 0 \text{ (complementarity slackness conditions), (9)}$  $\lambda \ge \mathbf{0}. \tag{10}$ 

We can express conditions (6) to (8) by the following relations between variables

$$H = -\lambda x^T, \tag{11}$$

$$p = -\lambda, \tag{12}$$

$$\lambda^T (A+H) = \mathbf{0}. \tag{13}$$

min 
$$\lambda^T \lambda (x^T x + 1)$$
  
s.t.  $Ax - \lambda x^T x \le b + \lambda$  (14)  
 $\lambda \ge \mathbf{0}.$ 

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Through the complementarity conditions (9) we can further reduce the number of variables, since

$$\lambda_i \left( \sum_{j=1}^n a_{ij} x_j - \lambda_i \sum_{j=1}^n x_j^2 - b_i - \lambda_i \right) = 0 \Leftrightarrow$$

$$\lambda_i = 0 \text{ or } \lambda_i = \frac{\sum_{j=1}^n a_{ij} x_j - b_i}{\sum_{j=1}^n x_j^2 + 1} \quad \forall i = 1, \dots, m.$$
$$(.)^+ = \max(0, .)$$

The set of Lagrange multipliers depends on x alone

$$\lambda^* = \frac{(Ax^* - b)^+}{x^{*T}x^* + 1}.$$
(15)

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Replacing  $\lambda$  in formulation (14) by (15) we obtain

min 
$$\frac{(Ax-b)^{+T}(Ax-b)^{+}}{(x^{T}x+1)^{2}}(x^{T}x+1)$$
  
s.t. 
$$\frac{Ax-b}{x^{T}x+1} \le \frac{(Ax-b)^{+}}{x^{T}x+1}$$
$$\frac{(Ax-b)^{+}}{x^{T}x+1} \ge \mathbf{0}.$$

Thus, given that the constraints are trivially satisfied, this result proves that (4) can be formulated as the unconstrained problem

$$\min\frac{(Ax-b)^{+T}(Ax-b)^{+}}{x^{T}x+1}$$

$$\begin{split} x_1 &+2x_2 &\leq 6\\ x_1 &+x_3 &\leq -7\\ 2x_1 &+x_2 &+x_3 &\leq -5\\ x_1 &+2x_3 &= 3\\ &(x_1,x_2,x_3) \in \Omega.\\ \\ &\min\sum_{i=1}^n \sum_{j=1}^n h_{ij}^2 + \sum_{i=1}^n p_i^2\\ &(1+h_{11})x_1 &+(2+h_{12})x_2 &+(0+h_{13})x_3 &\leq 6+p_1\\ &(1+h_{21})x_1 &+(0+h_{22})x_2 &+(1+h_{23})x_3 &\leq -7+p_2\\ &(2+h_{31})x_1 &+(1+h_{32})x_2 &+(1+h_{33})x_3 &\leq -5+p_3\\ &(1+h_{41})x_1 &+(0+h_{42})x_2 &+(2+h_{34})x_3 &= 3+p_4\\ &(x_1,x_2,x_3) \in \Omega.\\ \\ &\min \widetilde{\varphi}(x) = \frac{1}{2} \frac{(x_1+2x_2-6)^{+2} + (x_1+x_3+7)^{+2} + (2x_1+x_2+x_3+5)^{+2} + (x_1+2x_3-3)^2}{1+x_1^2+x_2^2+x_3^2} \end{split}$$

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(P) 
$$\min_{x \in \mathbf{X}} \frac{\|(Ax - b)^+\|^2}{1 + \|x\|^2},$$
 (16)

Equivalent to the following CFQP, where without loss of generality we assume that  $\begin{pmatrix} = \\ \leq \end{pmatrix}$  represents m - r initial equalities, followed by r inequalities.

$$(\mathcal{P}_F): \quad \phi = \min \quad \frac{\|v\|^2}{1 + \|x\|^2} \tag{17}$$

subject to 
$$Ax - v \begin{pmatrix} = \\ \leq \end{pmatrix} b$$
 (18)

$$v_i \ge 0 \text{ for } i = m - r + 1, \dots, m$$
 (19)

$$x \in \mathcal{X}.$$
 (20)

# **Copositive Formulation**

$$\psi = \min\left\{f(\mathbf{x}) = \frac{\mathbf{x}^T C \mathbf{x} + 2\mathbf{c}^T \mathbf{x} + \gamma}{\underbrace{\mathbf{x}^T B \mathbf{x} + 2\mathbf{b}^T \mathbf{x} + \beta}_{p(x)}} : \underbrace{\mathbf{x} \ge 0, A \mathbf{x} = \mathbf{a}}_{\mathcal{T}}\right\}$$

Assumptions p(x) > 0 and  $\mathcal{T}$  is compact.

Compactness of  ${\mathcal T}$  and strict positivity of p over this set implies primal attainability.

$$\psi = \min\left\{f(\mathbf{x}) = \frac{\mathbf{x}^T C \mathbf{x} + 2\mathbf{c}^T \mathbf{x} + \gamma \mathbf{l}}{\mathbf{x}^T B \mathbf{x} + 2\mathbf{b}^T \mathbf{x} + \beta \mathbf{l}} : \mathbf{x} \ge 0, A \mathbf{x} - \mathbf{a} \mathbf{l} = 0\right\}$$
(21)  
$$\overline{A} = \begin{bmatrix} \mathbf{a}^T \mathbf{a} & -\mathbf{a}^T A \\ -A^T \mathbf{a} & A^T A \end{bmatrix}, \quad \overline{B} = \begin{bmatrix} \beta & \mathbf{b}^T \\ \mathbf{b} & B \end{bmatrix}, \quad \overline{C} = \begin{bmatrix} \gamma & \mathbf{c}^T \\ \mathbf{c} & C \end{bmatrix}.$$
$$A \mathbf{x} = \mathbf{a} \iff [-\mathbf{a}, A] \mathbf{z} = \mathbf{o} \iff \mathbf{z}^T \overline{A} \mathbf{z} = 0,$$
$$\mathbf{z} = \begin{bmatrix} \mathbf{l} \\ \mathbf{x} \end{bmatrix} \in \mathbb{R}^{n+1}$$
$$\psi = \min\left\{\frac{\mathbf{z}^T \overline{C} \mathbf{z}}{\mathbf{z}^T \overline{B} \mathbf{z}} : \mathbf{z} \in \mathbb{R}^{n+1}_+, \ \mathbf{z}_1 = 1, \ \mathbf{z}^T \overline{A} \mathbf{z} = 0\right\}.$$

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,

$$\begin{split} \psi &= \min \left\{ \frac{\mathbf{z}^T \overline{C} \mathbf{z}}{\mathbf{z}^T \overline{B} \mathbf{z}} : \mathbf{z} \in \mathbb{R}^{n+1}_+, \ \mathbf{z}_1 = 1, \ \mathbf{z}^T \overline{A} \mathbf{z} = 0 \right\} \,. \\ & Z = \mathbf{z} \mathbf{z}^T \text{ and } \mathbf{z} \in \mathbb{R}^{n+1}_+ \\ & \mathbf{z}^T \overline{A} \mathbf{z} = \overline{A} \bullet Z \\ & \overline{A} \text{ psd} \\ & Z_{11} = z_1^2 \\ \\ & \psi = \min \left\{ \frac{\overline{C} \bullet Z}{\overline{B} \bullet Z} : Z_{11} = 1 \,, \ \overline{A} \bullet Z = 0 \,, \ \operatorname{rank}(Z) = 1 \,, \ Z \in \mathcal{C}^*_{n+1} \right\} \,. \end{split}$$

$$\psi = \min\left\{\frac{\overline{C} \bullet Z}{\overline{B} \bullet Z} : Z_{11} = 1, \ \overline{A} \bullet Z = 0, \ \operatorname{rank}(Z) = 1, \ Z \in \mathcal{C}_{n+1}^*\right\}.$$

By homogeneity, for any Z feasible  $Z_{11} = 1$  can be replace the by  $Z_{11} > 0$ .

$$X = \frac{1}{\overline{B} \bullet Z} Z \in \mathcal{C}_{n+1}^*$$

X also has rank one with  $X_{11} > 0$  and satisfies  $\overline{B} \bullet X = 1$ 

 $\psi = \min\left\{\overline{C} \bullet X : \overline{B} \bullet X = 1, \, \overline{A} \bullet X = 0, \, \operatorname{rank}(X) = 1, X_{11} > 0, \, X \in \mathcal{C}_{n+1}^*\right\} \,.$ 

$$\psi = \min\left\{\overline{C} \bullet X : \overline{B} \bullet X = 1, \overline{A} \bullet X = 0, \operatorname{rank}(X) = 1, X_{11} > 0, X \in \mathcal{C}_{n+1}^*\right\}$$

It was also proved that the strict linear inequality and the (non-convex) rank-one constraint could be droped to obtain the equivalent problem

$$\min\left\{\overline{C} \bullet X : \overline{B} \bullet X = 1, \overline{A} \bullet X = 0, X \in \mathcal{C}_{n+1}^*\right\}.$$

$$\psi = \min \left\{ f(\mathbf{x}) = \frac{\mathbf{x}^T C \mathbf{x}}{\mathbf{x}^T B \mathbf{x}} : A \mathbf{x} = \mathbf{a}, \mathbf{x} \in \mathbb{R}^n_+ \right\}$$
$$= \min \left\{ \overline{C} \bullet X : \overline{B} \bullet X = 1, \overline{A} \bullet X = 0, X \in \mathcal{C}^*_{n+1} \right\}.$$

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# Duality

$$\psi = \min\left\{\overline{C} \bullet X : \overline{B} \bullet X = 1, \overline{A} \bullet X = 0, X \in \mathcal{C}_{n+1}^*\right\}.$$
(22)

By weak duality

$$\psi \ge \lambda^* = \sup\left\{\lambda : \overline{C} - \lambda \overline{B} - \mu \overline{A} \in \mathcal{C}_{n+1}\right\}.$$
(23)

Slater's condition is always violated. Indeed, if  $Z \in \text{int } C^*_{n+1}$  is feasible to (22), then  $Z - \alpha I_{n+1} \in C^*_{n+1}$  for a small  $\alpha > 0$ , and in particular this matrix is psd. But

$$\overline{A} \bullet (Z - \alpha I_{n+1}) = 0 - \alpha \operatorname{trace}(\overline{A}) < 0,$$

is a contradiction to the fact of  $\overline{A} \in \mathcal{P}_{n+1} \setminus \{O\}$ .

- it is not possible to infer strong duality (in particular, dual attainability) from standard arguments.
- the dual problem is strictly feasible, which implies attainability of the primal (this was already established before) and zero duality gap

### Lower Bounds

Checking condition  $X \in \mathcal{C}_{n+1}^*$  is (co-)NP-hard but using the inclusion  $\mathcal{C}_{n+1}^* \subseteq \mathcal{D}_{n+1} = \mathcal{P}_{n+1} \cap \mathcal{N}_{n+1}$  a lower bound for the CFQP was proposed by solving

$$\psi_{\rm cop} = \min\left\{\overline{C} \bullet X : \overline{B} \bullet X = 1, \overline{A} \bullet X = 0, X \in \mathcal{D}_{n+1}\right\}$$
(24)

Size reduction, from 
$$n^2$$
 to  $(n-m)^2$ 

A is an  $m \times n$  matrix with full row rank m < n.

 $A^TA$  is psd and  $n\times n$ 

 $\dim \ker (A^T A) = k = n - m$ 

 $\ker (A^T A) = \langle \mathbf{u}_1, \dots, \mathbf{u}_k \rangle$ 

 $\dim \ker \, \overline{A} = k+1$ 

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 $\overline{\mathbf{u}}_i = [0, \mathbf{u}_i^T]^T$  form an orthonormal system in ker  $\overline{A} \subseteq \mathbb{R}^{n+1}$ 

$$\tilde{\mathbf{u}}_0 = \begin{bmatrix} 1 \\ A^T (AA^T)^{-1} \mathbf{a} \end{bmatrix}$$
 and  $\overline{\mathbf{u}}_0 = \frac{1}{\|\tilde{\mathbf{u}}_0\|} \tilde{\mathbf{u}}_0$ .

$$\ker (\overline{A}) = \langle \overline{\mathbf{u}}_0, \dots, \overline{\mathbf{u}}_k \rangle$$

Q is a  $(k+1)\times(n+1)$  matrix, collecting the above system as rows:

$$Q^T = [\overline{\mathbf{u}}_0, \dots, \overline{\mathbf{u}}_k]$$

For any  $X \in \mathcal{D}_{n+1}$ , we have  $\overline{A} \bullet X = 0$  if and only if

$$\overline{A}X = O$$

if and only if

$$X = Q^T Y Q$$
 for some  $Y \in \mathcal{P}_{k+1}$  satisfying  $Q^T Y Q \in \mathcal{N}_{n+1}$ . (25)

Hence, using

$$\overline{C} \bullet X = (Q\overline{C}Q^T) \bullet Y$$

$$\overline{A} \bullet X = (Q\overline{A}Q^T) \bullet Y$$

$$\overline{B} \bullet X = (Q\overline{B}Q^T) \bullet Y$$

We arrive at the reduced SDP

$$\min\left\{ (Q\overline{C}Q^T) \bullet Y : (Q\overline{B}Q^T) \bullet Y = 1, \ Q^T Y Q \ge O, Y \in \mathcal{P}_{k+1} \right\},$$
(26)

working on smaller psd matrices, but retaining  $\mathcal{O}(n^2)$  linear inequalities.

## **Computational results**

### **Generate Instances**

For  $\beta = \gamma = 1$  and for selected values of n and  $m = \lfloor \frac{n}{2} \rfloor$ , we have generated instances of program (21) as follows:

1. a symmetric psd  $n \times n$  matrix B is randomly generated, along with a suitably scaled vector  $\mathbf{b} \in \operatorname{int}(\mathbb{R}^n_+)$  such that  $\overline{B}$  given by () need not be psd, and can have negative entries (but obviously  $\overline{B} \in \mathcal{D}^*_{n+1}$ ). Observe that by construction,  $\overline{B}$  is strictly  $\mathbb{R}^n_+$ -copositive and therefore, for any choice of  $\overline{A}$ , strictly  $\Gamma_{\overline{A}}$ -copositive for sure.

- 2. a (possibly indefinite) symmetric  $n \times n$  matrix C is randomly generated with entries of varying sign, along with a randomly drawn vector  $\mathbf{c} \in \mathbb{R}^n$  (again, no sign restrictions on the coordinates).
- 3. an  $m \times n$  matrix A with a strictly positive first row, but varying sign of entries elsewhere, is randomly generated;
- 4. an arbitrary vector  $\mathbf{x} \in \Delta$  is drawn at random. Then the choice  $\mathbf{a} = A\mathbf{x}$  ensures that  $\mathcal{T}$  is compact, so the model assumptions are guaranteed.
- 5. Finally, based on  $(A, \mathbf{a})$ , the matrix Q is determined and a solution Y to (26) is calculated. As stated before,  $X = Q^T Y Q$  solves (24). The objective  $\overline{C} \bullet X = (Q \overline{C} Q^T) \bullet Y$  is used as a relaxation bound.

- Instances of sizes  $n \in \{4,9,49,79\}$  were generated, resulting in SDP instances of dimensionality  $5,\,10,\,50$  and 80
- The maximum size of 80 was possible due to the size reduction achieved in (26).
- The clear impact of this reduction is depicted in the three last columns of next Figure. For two problems of size 5 (ABJ5\_0) and 10 (ABJ10\_0), SeDuMi output reports the size of the SDP problems, for the GPM approach, the direct copositive relaxation (24) and with (26).

	GPM (Gloptipoly3)	Copositive Relaxation	Copositve Relaxation with Reduction			
ABJ5_0	eqs m = 210, order n = 98,	eqs m = 15, order n = 33,	eqs m = 6, order n = 27,			
	dim = 2380, blocks = 7	dim = 53, blocks = 3	dim = 33, blocks = 3			
	nnz(A) = 2385 + 0,	nnz(A) = 55 + 0,	nnz(A) = 121 + 0,			
	nnz(ADA) = 44100,	nnz(ADA) = 225,	nnz(ADA) = 36,			
	nnz(L) = 22155	nnz(L) = 120	nnz(L) = 21			
	Detailed timing (sec)	Detailed timing (sec)	Detailed timing (sec)			
	Pre IPM Post	Pre IPM Post	Pre IPM Post			
	7.001E-03 3.920E-01 2.002E-03	5.200E-02 7.001E-02 9.958E-04	4.003E-03 3.800E-02 9.958E-04			
ABJ10_0	eqs m = 5005, order n = 718,	eqs m = 55, order n = 113,	eqs m = 15, order n = 99,			
	dim = 85638, blocks = 12	dim = 203, blocks = 3	dim = 119, blocks = 3			
	nnz(A) = 138325 + 0,	nnz(A) = 210 + 0,	nnz(A) = 1291 + 0,			
	nnz(ADA) = 25050025,	nnz(ADA) = 3025,	nnz(ADA) = 225,			
	nnz(L) = 12527515	nnz(L) = 1540	nnz(L) = 120			
	Detailed timing (sec)	Detailed timing (sec)	Detailed timing (sec)			
	Pre IPM Post	Pre IPM Post	Pre IPM Post			
	8.460E-01 4.794E+02 2.800E-02	6.100E-02 6.500E-02 1.006E-03	2.900E-02 5.301E-02 1.992E-03			

Figure 2: Sizes of SDP relaxations

Table 2 reports for each instance the information,

- Instance Instance name;
- Cop R Value of the lower bound obtained by the SDP relaxation of the copositive formulation (26);
- Time1(s) CPU time in seconds to obtain Cop R;
- GPM Value of the lower bound obtained by Gloptipoly 3;
- Time2(s) CPU time in seconds to obtain the GPM lower bound;
- St Status of Gloptipoly 3 solution for the default relaxation order;
- root B Value of the lower bound obtained at the root node by BARON;

Instance	Cop R	Time1(s)	Gap	GPM R	Time2(s)	St.	root B.
ABJ5_0	-0.7865	2.700e-02	0.4837	-0.5275	1.045e+00	1	-26.1028
ABJ5_1	-0.4923	3.400e-02	1.8293	-0.5414	1.014e+00	1	-11.8308
ABJ5_2	-0.7693	2.700e-02	0.6771	-0.5089	9.672e-01	1	-11.9631
ABJ5_3	-0.3603	2.900e-02	0.9907	-0.2207	1.310e+00	1	-3.9613
ABJ5_4	-1.2562	2.700e-02	0.5467	-0.9428	9.984e-01	1	-0.8123
ABJ5_5	+0.4643	3.000e-02	0.1552	+0.2225	1.108e+00	1	-2.2940
ABJ5_6	-0.5768	3.100e-02	0.5831	-0.3671	9.828e-01	1	-8.6291
ABJ5_7	-0.0815	3.300e-02	15.2108	-0.0657	8.892e-01	1	-5.1034
ABJ5_8	-0.5946	2.600e-02	0.4752	-0.3708	9.516e-01	1	-0.4031
ABJ5_9	-0.8705	3.100e-02	0.9123	-0.5753	6.708e-01	1	-0.4553
ABJ10_0	-0.3095	3.500e-02	0.5090	-0.1962	7.010e+02	1	-23.9325
ABJ10_1	-0.6779	3.100e-02	0.4781	-0.4882	5.737e+02	1	-0.4587
ABJ10_2	+0.4144	3.400e-02	0.0533	+0.4288	6.395e+02	1	-3.4076
ABJ10_3	-0.3105	3.500e-02	1.2843	-0.1840	6.298e+02	1	-12.3357
ABJ10_4	-0.3885	3.900e-02	0.4746	-0.2689	5.122e+02	1	-0.2635
ABJ10_5	-0.7710	4.300e-02	0.2028	-0.6198	6.619e+02	1	-55.5414
ABJ10_6	-1.2861	3.100e-02	0.5562	-0.8749	7.123e+02	1	-0.8265
ABJ10_7	-0.1154	3.900e-02	1.1720	-0.0760	6.219e+02	1	-25.4559
ABJ10_8	-0.6486	3.100e-02	0.2828	-0.4558	6.239e+02	1	-0.5056
ABJ10_9	-0.3070	4.800e-02	0.5997	-0.1794	6.183e+02	1	-0.1919

#### Table 1: Copositive Relaxation versus Gloptipoly 3 and BARON

Instance	Cop R	Time1(s)	Gap	GPM R	Time2(s)	St.	root B.
ABJ50_0	-0.7435	3.238e+00	0.3552	O of M	-		-502.4740
ABJ50_1	-0.9606	2.731e+00	0.2229	O of M	-		-0.7856
ABJ50_2	-0.7844	3.192e+00	0.2786	O of M	-		-0.6135
ABJ50_3	-0.4022	2.983e+00	0.3630	O of M	-		-1463.1800
ABJ50_4	-0.2677	3.001e+00	0.8199	O of M	-		-451.7790
ABJ50_5	-0.6484	2.981e+00	0.6369	O of M	-		-0.3962
ABJ50_6	-0.5760	3.498e+00	0.3702	O of M	-		-989.5200
ABJ50_7	-0.6486	2.993e+00	0.3201	O of M	-		-0.4914
ABJ50_8	-0.5985	3.221e+00	0.3456	O of M	-		-490.0360
ABJ50_9	-0.3730	3.244e+00	0.3215	O of M	-		-626.8870
ABJ80_0	-0.4427	5.049e+01	0.5019	O of M	-		-1394.8500
ABJ80_1	-0.5806	5.532e+01	0.2984	O of M	-		-0.4472
ABJ80_2	-0.8597	5.532e+01	0.2869	O of M	-		-0.6681
ABJ80_3	-0.4345	5.519e+01	0.3302	O of M	-		-1849.5000
ABJ80_4	-0.8625	5.101e+01	0.3214	O of M	-		-0.6528
ABJ80_5	-0.4670	5.117e+01	0.3301	O of M	-		-0.3511
ABJ80_6	-0.3473	5.539e+01	0.6090	O of M	-		-2488.4700
ABJ80_7	-0.5883	5.105e+01	0.3607	O of M	-		-1487.1000
ABJ80_8	-0.4181	5.532e+01	0.5004	O of M	-		-736.0130
ABJ80_9	-0.7023	5.099e+01	0.3568	O of M	-		-0.5177

#### Table 2: Copositive Relaxation versus Gloptipoly 3 and BARON

All the tests have been performed on a Pentium Intel(R) Core(TM)i7, with CPU E8400, 2.8GHz, 4,00 GB RAM, and 64-bit operating system Windows. A tolerance parameter  $10^{-4}$  was considered for BARON and SeDuMi.

- The lower bounds provided by solving the SDP relaxation of the Copositive formulation are very good, as the gaps show, and outperforms the initial lower bound of BARON, and of the GPM relaxation.
- For problems of size 50 and 80 Gloptipoly 3 ran out of memory (O of M), as expected given the size of the corresponding SDP problem
- The results show that the reduction proposed in (26) is crucial as the size of the problem increases.

# Conclusions?

# Think (CO) or (Completely) Positive!

Think co(mpletely)positive ! Matrix properties, examples and a clustered bibliography on copositive optimization Immanuel M. Bomze, Werner Schachinger , Gabriele Uchida J Glob Optim (2012)

# Questions?