

# Introducing PenLab

## a MATLAB code for **NLP-SDP**

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# PENNON collection

**PENNON (PENalty methods for NONlinear optimization)**

a collection of codes for NLP, SDP and BMI

– *one algorithm to rule them all* –

## READY

- PENNLP    AMPL, MATLAB, C/Fortran
- PENSDP    MATLAB/YALMIP, SDPA, C/Fortran
- PENBMI    MATLAB/YALMIP, C/Fortran

## (relatively) NEW

- PENNON (NLP + SDP)    extended AMPL, MATLAB, C/Fortran

# The problem

Optimization problems with nonlinear objective subject to nonlinear inequality and equality constraints and semidefinite bound constraints:

$$\begin{aligned} & \min_{x \in \mathbb{R}^n, Y_1 \in \mathbb{S}^{p_1}, \dots, Y_k \in \mathbb{S}^{p_k}} f(x, Y) \\ & \text{subject to} \quad g_i(x, Y) \leq 0, & i = 1, \dots, m_g \\ & \quad \quad \quad h_i(x, Y) = 0, & i = 1, \dots, m_h \quad (\text{NLP-SDP}) \\ & \quad \quad \quad \underline{\lambda}_i I \preceq Y_i \preceq \bar{\lambda}_i I, & i = 1, \dots, k. \end{aligned}$$

# The algorithm

Based on penalty/barrier functions  $\varphi_g : \mathbb{R} \rightarrow \mathbb{R}$  and  $\Phi_P : \mathbb{S}^p \rightarrow \mathbb{S}^p$ :

$$\begin{aligned} g_i(x) \leq 0 &\iff p_i \varphi_g(g_i(x)/p_i) \leq 0, \quad i = 1, \dots, m \\ Z \preceq 0 &\iff \Phi_P(Z) \preceq 0, \quad Z \in \mathbb{S}^p. \end{aligned}$$

Augmented Lagrangian of (NLP-SDP):

$$\begin{aligned} F(x, Y, u, \underline{U}, \overline{U}, p) = & f(x, Y) + \sum_{i=1}^{m_g} u_i p_i \varphi_g(g_i(x, Y)/p_i) \\ & + \sum_{i=1}^k \langle \underline{U}_i, \Phi_P(\lambda_i I - Y_i) \rangle + \sum_{i=1}^k \langle \overline{U}_i, \Phi_P(Y_i - \bar{\lambda}_i I) \rangle; \end{aligned}$$

here  $u \in \mathbb{R}^{m_g}$  and  $\underline{U}_i, \overline{U}_i$  are Lagrange multipliers.

# The algorithm

A generalized Augmented Lagrangian algorithm (based on R. Polyak '92, Ben-Tal–Zibulevsky '94, Stingl '05):

Given  $x^1, Y^1, u^1, \underline{U}^1, \overline{U}^1; p_i^1 > 0, i = 1, \dots, m_g$  and  $P > 0$ .  
For  $k = 1, 2, \dots$  repeat till a stopping criterium is reached:

- (i) Find  $x^{k+1}$  and  $Y^{k+1}$  s.t.  $\|\nabla_x F(x^{k+1}, Y^{k+1}, u^k, \underline{U}^k, \overline{U}^k, p^k)\| \leq K$
- (ii)  $u_i^{k+1} = u_i^k \varphi'_g(g_i(x^{k+1})/p_i^k), \quad i = 1, \dots, m_g$   
 $\underline{U}_i^{k+1} = D_{\mathcal{A}} \Phi_P((\underline{\lambda}_i I - Y_i); \underline{U}_i^k), \quad i = 1, \dots, k$   
 $\overline{U}_i^{k+1} = D_{\mathcal{A}} \Phi_P((Y_i - \overline{\lambda}_i I); \overline{U}_i^k), \quad i = 1, \dots, k$
- (iii)  $p_i^{k+1} < p_i^k, i = 1, \dots, m_g$   
 $P^{k+1} < P^k.$

# Interfaces

How to enter the data – the functions and their derivatives?

- Matlab interface
- AMPL interface
- c/Fortran interface

Key point: Matrix variables are treated as vectors

# What's new

PENNON being implemented in **NAG** (The Numerical Algorithms Group) library

The first routines should appear in the NAG Fortran Library, Mark 24 (Autumn 2012)

By-product:

PenLab — free, open, fully functional version of PENNON coded in MATLAB

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# PenLab

PenLab — free, open, fully functional version of PENNON coded in Matlab

- Open source, all in MATLAB (one MEX function)
- The basic algorithm is identical
- Some data handling routines not (yet?) implemented
- PenLab runs just as PENNON but is slower

Pre-programmed procedures for

- standard NLP (with AMPL input!)
- linear SDP (reading SDPA input files)
- bilinear SDP (=BMI)
- easy to add more (QP, PMI, robust QP, ...)



# PenLab

## The problem

$$\begin{aligned} & \min_{x \in \mathbb{R}^n, Y_1 \in \mathbb{S}^{p_1}, \dots, Y_k \in \mathbb{S}^{p_k}} f(x, Y) \\ & \text{subject to} \quad g_i(x, Y) \leq 0, & i = 1, \dots, m_g \\ & \quad \quad \quad h_i(x, Y) = 0, & i = 1, \dots, m_h \\ & \quad \quad \quad \mathcal{A}_i(x, Y) \succeq 0, & i = 1, \dots, m_A \\ & \quad \quad \quad \underline{\lambda}_i I \preceq Y_i \preceq \bar{\lambda}_i I, & i = 1, \dots, k \end{aligned} \quad (\text{NLP-SDP})$$

$\mathcal{A}_i(x, Y)$ ... nonlinear matrix operators

$h_i(x, Y) = 0$  input as  $0 \leq g_i(x, Y) \leq 0$  but treated as genuine equalities

# PenLab



## Solving a problem:

- prepare a structure `penm` containing basic problem data
- `>> prob = penlab(penm);` MATLAB class containing all data
- `>> solve(prob);`
- results in class `prob`

The user has to provide MATLAB functions for

- function values
- gradients
- Hessians (for nonlinear functions)

of all  $f, g, \mathcal{A}$ .

## Structure `penm` and f/g/h functions

Example:  $\min x_1 + x_2 \quad \text{s.t.} \quad x_1^2 + x_2^2 \leq 1, \quad x_1 \geq -0.5$

```
penm = [];  
penm.Nx = 2;  
penm.lbx = [-0.5 ; -Inf];  
penm.NgNLN = 1;  
penm.ubg = [1];  
penm.objfun = @(x,Y) deal(x(1) + x(2));  
penm.objgrad = @(x,Y) deal([1 ; 1]);  
penm.confun = @(x,Y) deal([x(1)^2 + x(2)^2]);  
penm.congrad = @(x,Y) deal([2*x(1) ; 2*x(2)]);  
penm.conhess = @(x,Y) deal([2 0 ; 0 2]);  
% set starting point  
penm.xinit = [2,1];
```

# Toy NLP-SDP example 1

$$\begin{aligned} \min_{x \in \mathbb{R}^2} & \frac{1}{2}(x_1^2 + x_2^2) \\ \text{subject to} & \begin{pmatrix} 1 & x_1 - 1 & 0 \\ x_1 - 1 & 1 & x_2 \\ 0 & x_2 & 1 \end{pmatrix} \succeq 0 \end{aligned}$$

D. Noll, 2007

## Toy NLP-SDP example 2

$$\min_{x \in \mathbb{R}^6} x_1 x_4 (x_1 + x_2 + x_3) + x_3$$

$$\text{subject to } x_1 x_2 x_3 x_4 - x_5 - 25 = 0$$

$$x_1^2 + x_2^2 + x_3^2 + x_4^2 - x_6 - 40 = 0$$

$$\begin{pmatrix} x_1 & x_2 & 0 & 0 \\ x_2 & x_4 & x_2 + x_3 & 0 \\ 0x_2 + x_3 & x_4 & x_3 & \\ 0 & 0 & x_3 & x_1 \end{pmatrix} \succeq 0$$

$$1 \leq x_i \leq 5, \quad i = 1, 2, 3, 4, \quad x_i \geq 0, \quad i = 5, 6$$

Yamashita, Yabe, Harada, 2007  
("augmented" Hock-Schittkowski)

## Example: nearest correlation matrix

Find a nearest correlation matrix:

$$\min_X \sum_{i,j=1}^n (X_{ij} - H_{ij})^2 \quad (1)$$

subject to

$$X_{ii} = 1, \quad i = 1, \dots, n$$

$$X \succeq 0$$

## Example: nearest correlation matrix

The condition number of the nearest correlation matrix must be bounded by  $\kappa$ .

Using the transformation of the variable  $X$ :

$$z\tilde{X} = X$$

The new problem:

$$\min_{z, \tilde{X}} \sum_{i,j=1}^n (z\tilde{X}_{ij} - H_{ij})^2 \quad (2)$$

subject to

$$z\tilde{X}_{ii} = 1, \quad i = 1, \dots, n$$

$$I \preceq \tilde{X} \preceq \kappa I$$

## Example: nearest correlation matrix

For

X =

1.0000	-0.3775	-0.2230	0.7098	-0.4272	-0.0704
-0.3775	1.0000	0.6930	-0.3155	0.5998	-0.4218
-0.2230	0.6930	1.0000	-0.1546	0.5523	-0.4914
0.7098	-0.3155	-0.1546	1.0000	-0.3857	-0.1294
-0.4272	0.5998	0.5523	-0.3857	1.0000	-0.0576
-0.0704	-0.4218	-0.4914	-0.1294	-0.0576	1.0000

the eigenvalues of the correlation matrix are

eigen =

0.2866	0.2866	0.2867	0.6717	1.6019	2.8664
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# NLP with AMPL input

Pre-programmed. All you need to do:

```
>> penm=nlp_define('datafiles/chain100.nl');  
>> prob=penlab(penm);  
>> prob.solve();
```

# Linear SDP with SDPA input

Pre-programmed. All you need to do:

```
>> sdpdata=readsdpdata('datafiles/arch0.dat-s');  
>> penm=sdp_define(sdpdata);  
>> prob=penlab(penm);  
>> prob.solve();
```

# Bilinear matrix inequalities (BMI)

Pre-programmed. All you need to do:

```
>> bmidata=define_my_problem; %matrices A, K, ...  
>> penm=bmi_define(bmidata);  
>> prob=penlab(penm);  
>> prob.solve();
```

$$\min_{x \in \mathbb{R}^n} c^T x$$

s.t.

$$A_0^i + \sum_{k=1}^n x_k A_k^i + \sum_{k=1}^n \sum_{\ell=1}^n x_k x_\ell K_{k\ell}^i \succcurlyeq 0, \quad i = 1, \dots, m$$

## Example:

### Robust quadratic programming on unit simplex with constrained uncertainty set

#### Nominal QP

$$\min_{x \in \mathbb{R}^n} [x^T A x - b^T x] \quad \text{s.t.} \quad \sum x \leq 1, x \geq 0$$

Assume  $A$  uncertain:  $A \in \mathcal{U} := \{A_0 + \varepsilon U, \sigma(U) \leq 1\}$

#### Robust QP

$$\min_{x \in \mathbb{R}^n} \max_{A \in \mathcal{U}} [x^T A x - b^T x] \quad \text{s.t.} \quad \sum x \leq 1, x \geq 0$$

equivalent to

$$\min_{x \in \mathbb{R}^n} [x^T (A_0 + \varepsilon I) x - b^T x] \quad \text{s.t.} \quad \sum x \leq 1, x \geq 0$$

## Example: Robust QP

**Optimal solution:**  $x^*$ ,  $A^* = A_0 + \varepsilon U^*$  (non-unique)

**Constraint:**  $A^*$  should share some properties with  $A_0$

**For instance:**  $(A_0)_{ii} = A^*_{ii} = 1$ , i.e.,  $U^*_{ii} = 0$  for all  $i$

$\implies$  then the above equivalence no longer holds

**Remedy:** for a given  $x^*$  find a feasible solution  $\hat{A}$  to the maximization problem. This is a linear SDP:

$$\max_{U \in \mathbb{S}^m} [x^{*T}(A_0 + \varepsilon U)x^* - b^T x^*]$$

s.t.

$$-I \preceq U \preceq I$$

$$U_{ii} = 0, \quad i = 1, \dots, m$$

## Example: Robust QP

**Alternatively:** find feasible  $\hat{A}$  nearest to  $A^* \rightarrow$  **nonlinear SDP**

Finally, we need to solve the original QP with the feasible worst-case  $\hat{A}$  to get a feasible robust solution  $x_{rob}$ :

$$\min_{x \in \mathbb{R}^n} [x^T \hat{A} x - b^T x] \quad \text{s.t.} \quad \sum x \leq 1, \quad x \geq 0$$

**The whole procedure**

- solve QP with  $A = A_0$  (**nominal**)
- solve QP with  $A = A_0 + \varepsilon I$  (**robust**)
- solve (non-)linear SDP to get  $\hat{A}$
- solve QP with  $\hat{A}$  (**robust feasible**)

# Availability

PENNON: Free time-limited academic version of the code available

PENLAB: Free open MATLAB version available in Autumn 2012 from NAG

# What's missing?

SOCP (Second-Order Conic Programming) - nonlinear,  
integrated in PENLAB (and PENNON)

Postdoctoral research position in Birmingham  
(sponsored by NAG)

- development of NL-SOCP algorithm (compatible with PENNON algorithm)
- implementation in PENNON
- 24 months
- start: THIS AUTUMN
- if interested, contact me



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