

We will finish discussing the Burer, Monteiro and Y. Zhang method.

Burer Monteiro and Y. Zhang's nonlinear transformation method:

$$\begin{aligned}
 (P) \quad & \max \quad C \bullet X \\
 & \text{diag}(X) \geq d \\
 & \mathcal{A}X = b \\
 & X \succeq 0, \\
 \\
 (D) \quad & \max \quad d^T z + b^T y \\
 & \text{Diag}(z) + \mathcal{A}^*y - S = C \\
 & z \leq 0 \\
 & S \succeq 0.
 \end{aligned}$$

Assume that both (P) and (D) have strictly feasible solutions and that the  $A_i$ 's are linear independent.

For every  $y$ , for every  $z$  large enough,  $\text{Diag}(z) + \mathcal{A}^*y - C$  is positive definite. So  $S \succ 0$  and it has a Cholesky factorization.

Burer, Monteiro, and Zhang (BMZ) turn this around: for every  $y$  and diagonal of the Cholesky factor, they obtain  $z$  and the rest of the factor.

**Theorem 1** a) For every  $y \in \mathbb{R}^m$  and  $w \in \mathbb{R}_{++}^n$ , there is a unique  $z = z(w, y) \in \mathbb{R}^n$  and strictly lower triangular  $\hat{L} = \hat{L}(w, y) \in \mathbb{R}^{n \times n}$  such that  $\text{Diag}(z) + \mathcal{A}^*y - C = (\text{Diag}(w) + \hat{L})(\text{Diag}(w) + \hat{L})^T$ .

b) The functions  $z(w, y)$  and  $\hat{L}(w, y)$  are infinite differentiable on  $\mathbb{R}_{++}^n \times \mathbb{R}^m$ .

c) There is a bijection between  $(w, y) \in \mathbb{R}_{++}^n \times \mathbb{R}^m$  and  $(y, z, S) \in \{\mathbb{R}^m \times \mathbb{R}^n \times M_{++}^n : \text{Diag}(z) + \mathcal{A}^*y - S = C\}$ , given by  $z = z(w, y)$ ,  $S = LL^T$ , where  $L := L(w, y) := \text{Diag}(w(z, y)) + \hat{L}(w, y)$ .

(Note that the sign conditions on  $z$  are not present here.)

Sketch of the proof of (a) (Constructive):

Consider  $n = 3$ , and let  $T := \mathcal{A}^*y - C$ . We want

$$\text{Diag}(z) + T = (\text{Diag}(w) + \hat{L})(\text{Diag}(w) + \hat{L})^T = \begin{pmatrix} w_1 & 0 & 0 \\ l_{21} & w_2 & 0 \\ l_{31} & l_{32} & w_3 \end{pmatrix} \begin{pmatrix} w_1 & 0 & 0 \\ l_{21} & w_2 & 0 \\ l_{31} & l_{32} & w_3 \end{pmatrix}^T.$$

So,

$$\begin{aligned}
 z_1 + t_{11} &= w_1^2 \rightarrow z_1 \\
 t_{21} &= (\text{Diag}(z) + T)_{21} = l_{21}w_1 \rightarrow l_{21} \\
 t_{31} &= (\text{Diag}(z) + T)_{31} = l_{31}w_1 \rightarrow l_{31} \\
 z_2 + t_{22} &= l_{21}^2 + w_2^2 \rightarrow z_2 \\
 t_{32} &= l_{31}l_{21} + l_{32}w_2 \rightarrow l_{32} \dots
 \end{aligned}$$

This proves part (a) of the theorem.  $\square$

Problem:  $z(w, y)$  and  $\hat{L}(w, y)$  do not extend smoothly to the boundary of  $\mathbb{R}_{++}^n \times \mathbb{R}^m$ , and the bijection similarly cannot be extended. Nevertheless, by the bijection,

$$\inf_{y,z,S} \begin{array}{l} d^T z + b^T y \\ \text{Diag}(z) + \mathcal{A}^* y - S \\ z \\ S \end{array} \begin{array}{l} = C \\ < 0 \\ > 0, \end{array}$$

is equivalent to

$$\inf_{w,y} \begin{array}{l} d^T z(w, y) + b^T y \\ z(w, y) \\ w \end{array} \begin{array}{l} < 0 \\ > 0. \end{array}$$

Note that, by our assumptions, both these problems have feasible solutions, and the first approximates  $(D)$ .

Idea: ‘‘Solve’’

$$(\bar{D}) \quad \inf_{w,y} \begin{array}{l} d^T z + b^T y \\ z(w, y) \\ w \end{array} \begin{array}{l} \leq 0 \\ \geq 0 \end{array}$$

This is a nonconvex NLP in  $n + m$  variables.

Suppose we solve  $(\bar{D})$  by a log barrier method, using subproblems of the form

$$(B\bar{D}_\mu) \quad \min_{w,y} \quad d^T z(w, y) + b^T y - \mu \sum \ln(-z_j(w, y)) - 2\mu \sum \ln w_j$$

for  $\mu > 0$ .

Note that, if  $S(w, y) = L(w, y)L(w, y)^T$  then this is

$$\min \quad d^T z(w, y) + b^T y - \mu \sum \ln(-z_j(w, y)) - \mu \ln \det S(w, y)$$

since

$$\begin{aligned} \ln \det S(w, y) &= \ln \det(\text{Diag}(w) + \hat{L})(\text{Diag}(w) + \hat{L})^T \\ &= 2 \ln \det(\text{Diag}(w) + \hat{L}) \\ &= 2 \sum \ln w_j. \end{aligned}$$

Moreover, by the bijection, this is equivalent to

$$(BD_\mu) \quad \min_{y,z,S} \begin{array}{l} d^T z + b^T y - \mu \sum(-z_j) - \mu \ln \det S \\ \text{Diag}(z) + \mathcal{A}^* y - S \\ z \\ S \end{array} \begin{array}{l} = C \\ < 0 \\ > 0. \end{array}$$

BMZ prove

**Theorem 2** *For any  $\mu > 0$ , there is a unique minimizer, which is also the unique stationary point, for  $(B\bar{D}_\mu)$ . Moreover, this corresponds by our bijection to the unique minimizer of  $(BD_\mu)$ .*

Hence, BMZ apply a unconstrained minimization algorithm (they use limited memory BFGS) to  $(B\bar{D}\mu)$  to get an approximate stationary point, then update  $\mu$  to  $\sigma\mu$ ,  $0 < \sigma < 1$  fixed, and continue. They prove global convergence.

In computing derivatives of  $z$  and the Lagrangian for  $(\bar{D})$ , and in the analysis, a key quantity turns out to be a primal estimate  $X$ .

**Theorem 3** *For any  $v \in \mathbb{R}^n$  and any lower triangular  $L \in \mathbb{R}^{n \times n}$  with positive diagonal, there is a unique  $X \in \mathbb{M}^n$  with  $\text{diag}(X) = v$  and  $XL$  upper triangular.*

Sketch of the proof (for  $n = 3$ ). Compute  $X$  from bottom to top and right to left.

$$\begin{aligned} x_{33} &= v_3 \\ 0 &= (XL)_{32} = x_{33}l_{32} + x_{32}l_{22} \rightarrow x_{32} \\ 0 &= (XL)_{31} = x_{33}l_{31} + x_{32}l_{21} + x_{31}l_{11} \rightarrow x_{31} \\ x_{22} &= v_2 \\ 0 &= (XL)_{21} = x_{21}l_{11} + x_{22}l_{21} + x_{23}l_{31} \rightarrow x_{21} \\ &\text{etc.} \end{aligned}$$

(Note that, in the last equation, we know  $x_{23}$  since  $X$  is symmetric.)  $\square$

Note:  $XL$  upper triangular implies  $L^T XL$  is upper triangular and symmetric so diagonal; say it's equal to  $\Lambda$ .

$$L^T XL = \Lambda \Rightarrow X = L^{-T} \Lambda L^{-1}.$$

If  $\Lambda = \mu I$ ,

$$X = \mu L^{-T} L^{-1} = \mu S^{-1},$$

as on the central path.

For further information, see the original paper.

Semidefinite programming solvers can be found at NEOS at <http://www.neos-server.org/neos/solvers/index.html>.

Computational results comparing interior-point codes with a code for the spectral bundle method, a code for Burer and Monteiro's low-rank method, and a code for the Burer-Monteiro-Zhang method can be found at

<http://plato.asu.edu/dimacs/paper93.html>.