Strongly polynomial algorithm for box-constrained quadratic programs with H_0 -matrix

Shaoning Han

Department of Industrial & Systems Engineering University of Southern California

shaoning@usc.edu

March, 2022

Collaborator



Jong-Shi Pang

Shaoning Han (USC)

Box-constrained QP with H₀-matrix

Liu et al. (2021) investigate the following MIQP

$$\min_{x,z} a^{\mathsf{T}} z + c^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} Q x$$

s.t. $\mathbb{R}^n \ni x \perp z \in \{0,1\}^n$,

where matrix Q is sparse positive definite and $x \perp z$ represents $x_i z_i = 0 \forall i$.

Liu et al. (2021) investigate the following MIQP

$$\min_{x,z} a^{\mathsf{T}} z + c^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} Q x$$

s.t. $\mathbb{R}^n \ni x \perp z \in \{0,1\}^n$,

where matrix Q is sparse positive definite and $x \perp z$ represents $x_i z_i = 0 \forall i$. Solution Strategy

• Decompose $x^{\mathsf{T}}Qx = \sum_{j} x^{\mathsf{T}} M^{j}x + x^{\mathsf{T}} Rx$, where each M^{j} is tridiagonal

Liu et al. (2021) investigate the following MIQP

$$\min_{x,z} a^{\mathsf{T}} z + c^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} Q x$$

s.t. $\mathbb{R}^n \ni x \perp z \in \{0,1\}^n$,

where matrix Q is sparse positive definite and $x \perp z$ represents $x_i z_i = 0 \forall i$. Solution Strategy

- Decompose $x^{\mathsf{T}}Qx = \sum_{j} x^{\mathsf{T}} M^{j}x + x^{\mathsf{T}} Rx$, where each M^{j} is tridiagonal
- At each iteration, solve unconstrained convex QPs

$$\min_{x} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x$$

in strongly linear time $\mathcal{O}(n)$.

Liu et al. (2021) investigate the following MIQP

$$\min_{x,z} a^{\mathsf{T}} z + c^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} Q x$$

s.t. $\mathbb{R}^n \ni x \perp z \in \{0,1\}^n$,

where matrix Q is sparse positive definite and $x \perp z$ represents $x_i z_i = 0 \forall i$. Solution Strategy

- Decompose $x^{\mathsf{T}}Qx = \sum_{j} x^{\mathsf{T}} M^{j}x + x^{\mathsf{T}} Rx$, where each M^{j} is tridiagonal
- At each iteration, solve unconstrained convex QPs

$$\min_{x} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x$$

in strongly linear time $\mathcal{O}(n)$.

Question: What QPs are strongly polynomially solvable? Constraints?

Consider a convex quadratic program

$$\min_{\ell \le x \le u} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x, \qquad (\mathsf{QP})$$

where $M \in \mathbb{S}_{+}^{n}$ is symmetric and positive semidefinite (PSD).

Consider a convex quadratic program

$$\min_{\ell \le x \le u} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x, \qquad (\mathsf{QP})$$

where $M \in \mathbb{S}_{+}^{n}$ is symmetric and positive semidefinite (PSD).

• We allow $\ell_i = -\infty$ and $u_i = +\infty$

Consider a convex quadratic program

$$\min_{\ell \le x \le u} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x, \qquad (\mathsf{QP})$$

where $M \in \mathbb{S}_{+}^{n}$ is symmetric and positive semidefinite (PSD).

- We allow $\ell_i = -\infty$ and $u_i = +\infty$
- Polynomial solvable (in input size)

Consider a convex quadratic program

$$\min_{\ell \le x \le u} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x, \qquad (\mathsf{QP})$$

where $M \in \mathbb{S}_{+}^{n}$ is symmetric and positive semidefinite (PSD).

- We allow $\ell_i = -\infty$ and $u_i = +\infty$
- Polynomial solvable (in input size)
- If M > 0, the QP is strongly polynomially solvable (in dimension n)

Consider a convex quadratic program

$$\min_{\ell \le x \le u} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x, \qquad (\mathsf{QP})$$

where $M \in \mathbb{S}_{+}^{n}$ is symmetric and positive semidefinite (PSD).

- We allow $\ell_i = -\infty$ and $u_i = +\infty$
- Polynomial solvable (in input size)
- If M > 0, the QP is strongly polynomially solvable (in dimension n)

Goal: Solve (QP) in strongly polynomial time under the assumption that M is an H_0 -matrix.

Comparison matrix

$$M = \begin{bmatrix} m_{11} & m_{12} & m_{13} & \dots \\ m_{12} & m_{22} & m_{23} & \dots \\ m_{13} & m_{23} & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix}$$

Comparison matrix

$$M = \begin{bmatrix} m_{11} & m_{12} & m_{13} & \dots \\ m_{12} & m_{22} & m_{23} & \dots \\ m_{13} & m_{23} & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix} \Rightarrow \bar{M} = \begin{bmatrix} m_{11} & -|m_{12}| & -|m_{13}| & \dots \\ -|m_{12}| & m_{22} & -|m_{23}| & \dots \\ -|m_{13}| & -|m_{23}| & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix}$$

1

Comparison matrix

$$M = \begin{bmatrix} m_{11} & m_{12} & m_{13} & \dots \\ m_{12} & m_{22} & m_{23} & \dots \\ m_{13} & m_{23} & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix} \Rightarrow \bar{M} = \begin{bmatrix} m_{11} & -|m_{12}| & -|m_{13}| & \dots \\ -|m_{12}| & m_{22} & -|m_{23}| & \dots \\ -|m_{13}| & -|m_{23}| & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix}$$

 H_0 -matrix¹: A matrix M is called an H_0 -matrix if $\overline{M} \ge 0$.

¹There are at least 50 equivalent conditions under which M is an H-matrix!

Shaoning Han (USC)

Box-constrained QP with H₀-matrix

Comparison matrix

$$M = \begin{bmatrix} m_{11} & m_{12} & m_{13} & \dots \\ m_{12} & m_{22} & m_{23} & \dots \\ m_{13} & m_{23} & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix} \Rightarrow \bar{M} = \begin{bmatrix} m_{11} & -|m_{12}| & -|m_{13}| & \dots \\ -|m_{12}| & m_{22} & -|m_{23}| & \dots \\ -|m_{13}| & -|m_{23}| & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix}$$

 H_0 -matrix¹: A matrix M is called an H_0 -matrix if $\overline{M} \ge 0$.

• *M* is an H_0 -matrix $\Rightarrow M \ge 0$.

¹There are at least 50 equivalent conditions under which M is an H-matrix!

Comparison matrix

$$M = \begin{bmatrix} m_{11} & m_{12} & m_{13} & \dots \\ m_{12} & m_{22} & m_{23} & \dots \\ m_{13} & m_{23} & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix} \Rightarrow \bar{M} = \begin{bmatrix} m_{11} & -|m_{12}| & -|m_{13}| & \dots \\ -|m_{12}| & m_{22} & -|m_{23}| & \dots \\ -|m_{13}| & -|m_{23}| & m_{33} & \dots \\ \vdots & \vdots & \vdots & m_{nn} \end{bmatrix}$$

 H_0 -matrix¹: A matrix M is called an H_0 -matrix if $\overline{M} \ge 0$.

- M is an H_0 -matrix $\Rightarrow M \ge 0$.
- $M \ge 0$ is tridiagonal $\Rightarrow M$ is an H_0 -matrix.

¹There are at least 50 equivalent conditions under which M is an H-matrix!

Shaoning Han (USC)

Notation. Given a matrix $M \ge 0$ and $\alpha, \beta \subseteq [n] := \{1, 2, ..., n\}$

- submatrix $M_{\alpha\beta} \coloneqq (m_{ij})_{i \in \alpha, j \in \beta}$
- the Schur complement of $M_{\alpha\alpha} > 0$: $(M/M_{\alpha\alpha}) := M_{\bar{\alpha}\bar{\alpha}} M_{\bar{\alpha}\alpha}M_{\alpha\alpha}^{-1}M_{\alpha\bar{\alpha}}$, where $\bar{\alpha} = [n] \setminus \alpha$.

Notation. Given a matrix $M \ge 0$ and $\alpha, \beta \subseteq [n] := \{1, 2, ..., n\}$

- submatrix $M_{\alpha\beta} \coloneqq (m_{ij})_{i \in \alpha, j \in \beta}$
- the Schur complement of $M_{\alpha\alpha} > 0$: $(M/M_{\alpha\alpha}) := M_{\bar{\alpha}\bar{\alpha}} M_{\bar{\alpha}\alpha}M_{\alpha\alpha}^{-1}M_{\alpha\bar{\alpha}}$, where $\bar{\alpha} = [n] \setminus \alpha$.

Proposition (Operations preserving H_0 -property)

Suppose M and N are two H_0 -matrices. The following matrices are H_0 -matrices.

- Principle submatrix: $M_{\alpha\alpha}$ of M, $\alpha \subseteq [n]$
- Schur complement: $(M/M_{\alpha\alpha})$
- Nonnegative combination: $\lambda_1 M + \lambda_2 N$ where $\lambda_1, \lambda_2 \ge 0$

Irreducibility

• *M* is reducible
$$\stackrel{\text{def}}{\longleftrightarrow} M = \begin{bmatrix} M_{\alpha\alpha} & 0\\ 0 & M_{\beta\beta} \end{bmatrix}$$
 (up to permutation), $\alpha, \beta \in [n]$

• *M* is *irreducible* $\stackrel{\text{def}}{\longleftrightarrow}$ *M* is not reducible

Irreducibility

• *M* is reducible
$$\stackrel{\text{def}}{\longleftrightarrow} M = \begin{bmatrix} M_{\alpha\alpha} & 0\\ 0 & M_{\beta\beta} \end{bmatrix}$$
 (up to permutation), $\alpha, \beta \in [n]$

- *M* is *irreducible* $\stackrel{\text{def}}{\iff}$ *M* is not reducible
- Recognizing all irreducible blocks of M can be accomplished in $\mathcal{O}(n^2)$ complexity

Irreducibility

• *M* is reducible
$$\stackrel{\text{def}}{\longleftrightarrow} M = \begin{bmatrix} M_{\alpha\alpha} & 0\\ 0 & M_{\beta\beta} \end{bmatrix}$$
 (up to permutation), $\alpha, \beta \in [n]$

- *M* is *irreducible* $\stackrel{\text{def}}{\iff}$ *M* is not reducible
- Recognizing all irreducible blocks of M can be accomplished in $\mathcal{O}(n^2)$ complexity

Proposition

If M is an irreducible H_0 -matrix, then $\operatorname{Rank}(M) \ge n - 1$.

Irreducibility

• *M* is reducible
$$\stackrel{\text{def}}{\longleftrightarrow} M = \begin{bmatrix} M_{\alpha\alpha} & 0\\ 0 & M_{\beta\beta} \end{bmatrix}$$
 (up to permutation), $\alpha, \beta \in [n]$

- *M* is *irreducible* $\stackrel{\text{def}}{\longleftrightarrow}$ *M* is not reducible
- Recognizing all irreducible blocks of M can be accomplished in $\mathcal{O}(n^2)$ complexity

Proposition

If M is an irreducible H_0 -matrix, then $Rank(M) \ge n - 1$.

Key observation: if M is reducible,

$$\min_{\ell \le x \le u} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x = \min_{\ell \le x_{\alpha} \le u_{\alpha}} q^{\mathsf{T}}_{\alpha} x_{\alpha} + \frac{1}{2} x^{\mathsf{T}}_{\alpha} M_{\alpha \alpha} x_{\alpha} + \min_{\ell \le x_{\beta} \le u_{\beta}} q^{\mathsf{T}}_{\beta} x_{\beta} + \frac{1}{2} x^{\mathsf{T}}_{\beta} M_{\beta \beta} x_{\beta}$$

is separable.

Irreducibility

• *M* is reducible
$$\stackrel{\text{def}}{\longleftrightarrow} M = \begin{bmatrix} M_{\alpha\alpha} & 0\\ 0 & M_{\beta\beta} \end{bmatrix}$$
 (up to permutation), $\alpha, \beta \in [n]$

- *M* is *irreducible* $\stackrel{\text{def}}{\iff}$ *M* is not reducible
- Recognizing all irreducible blocks of M can be accomplished in $\mathcal{O}(n^2)$ complexity

Proposition

If M is an irreducible H_0 -matrix, then $\operatorname{Rank}(M) \ge n - 1$.

Key observation: if M is reducible,

$$\min_{\ell \le x \le u} q^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x = \min_{\ell \le x_{\alpha} \le u_{\alpha}} q^{\mathsf{T}}_{\alpha} x_{\alpha} + \frac{1}{2} x^{\mathsf{T}}_{\alpha} M_{\alpha \alpha} x_{\alpha} + \min_{\ell \le x_{\beta} \le u_{\beta}} q^{\mathsf{T}}_{\beta} x_{\beta} + \frac{1}{2} x^{\mathsf{T}}_{\beta} M_{\beta \beta} x_{\beta}$$

is separable. \Rightarrow assume *M* is irreducible.

WLOG, assume *M* is an irreducible H_0 -matrix, $\ell = 0$ and $u \in \mathbb{R}^n$. Instead of directly solving

$$\min_{0\leq x\leq u} q^{\mathsf{T}}x + \frac{1}{2}x^{\mathsf{T}}Mx,$$

WLOG, assume *M* is an irreducible H_0 -matrix, $\ell = 0$ and $u \in \mathbb{R}^n$. Instead of directly solving

$$\min_{0\leq x\leq u} q^{\mathsf{T}}x + \frac{1}{2}x^{\mathsf{T}}Mx,$$

PPPA traces the solution path of the parametric problem

$$\min_{0\leq x\leq u} (q+\tau p)^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x,$$

where $p \ge 0$ and $\exists \tau_0 > 0$ s.t. $q + \tau_0 p \ge 0$.

WLOG, assume *M* is an irreducible H_0 -matrix, $\ell = 0$ and $u \in \mathbb{R}^n$. Instead of directly solving

$$\min_{0\leq x\leq u} q^{\mathsf{T}}x + \frac{1}{2}x^{\mathsf{T}}Mx,$$

PPPA traces the solution path of the parametric problem

$$\min_{0\leq x\leq u} (q+\tau p)^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x,$$

where $p \ge 0$ and $\exists \tau_0 > 0$ s.t. $q + \tau_0 p \ge 0$. Denote

$$\alpha = \left\{i: 0 < x_i < u_i\right\}, \quad \beta = \left\{i: x_i = 0\right\}, \quad \gamma = \left\{i: x_i = u_i\right\}$$

WLOG, assume *M* is an irreducible H_0 -matrix, $\ell = 0$ and $u \in \mathbb{R}^n$. Instead of directly solving

$$\min_{0\leq x\leq u} q^{\mathsf{T}}x + \frac{1}{2}x^{\mathsf{T}}Mx,$$

PPPA traces the solution path of the parametric problem

$$\min_{0\leq x\leq u} (q+\tau p)^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x,$$

where $p \ge 0$ and $\exists \tau_0 > 0$ s.t. $q + \tau_0 p \ge 0$. Denote

$$\alpha = \left\{i: 0 < x_i < u_i\right\}, \quad \beta = \left\{i: x_i = 0\right\}, \quad \gamma = \left\{i: x_i = u_i\right\}$$

Algorithm

• Initialization.
$$\alpha = \gamma = \emptyset, \beta = [n]$$
 and $\tau = \tau_0 \implies x^* = 0$

WLOG, assume *M* is an irreducible H_0 -matrix, $\ell = 0$ and $u \in \mathbb{R}^n$. Instead of directly solving

$$\min_{0\leq x\leq u} q^{\mathsf{T}}x + \frac{1}{2}x^{\mathsf{T}}Mx,$$

PPPA traces the solution path of the parametric problem

$$\min_{0\leq x\leq u} (q+\tau p)^{\mathsf{T}} x + \frac{1}{2} x^{\mathsf{T}} M x,$$

where $p \ge 0$ and $\exists \tau_0 > 0$ s.t. $q + \tau_0 p \ge 0$. Denote

$$\alpha = \left\{i: 0 < x_i < u_i\right\}, \quad \beta = \left\{i: x_i = 0\right\}, \quad \gamma = \left\{i: x_i = u_i\right\}$$

Algorithm

- Initialization. $\alpha = \gamma = \emptyset, \beta = [n]$ and $\tau = \tau_0$
- General iteration. Decrease τ until τ = 0. At each break point, implement diagonal or 2 × 2 pivots and update index sets α, β, γ τ = 0 ⇒ x* is optimal for the original QP

 $\Rightarrow x^* = 0$

KKT/LCP

$$0 \le w = q + \tau p + Mx + \lambda \perp x \ge 0$$
$$0 \le s = u - x \perp \lambda \ge 0$$

 $\begin{array}{l} \mathsf{KKT}/\mathsf{LCP} & 0 \leq w = q + \tau p + Mx + \lambda \perp x \geq 0 \\ 0 \leq s = u - x \perp \lambda \geq 0 \end{array}$ $\begin{array}{l} \mathsf{Rearranging:} \ \alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}. \end{array}$ $\begin{array}{l} 0 \leq x_\alpha = -\bar{q}_\alpha - \tau \bar{p}_\alpha + \Box w_\alpha + \Box x_\beta + \Box s_\gamma + \Box \lambda_\alpha \quad \bot w_\alpha \geq 0 \\ 0 \leq w_\beta = -\bar{q}_\beta - \tau \bar{p}_\beta + \Box w_\alpha + (M/M_{\alpha\alpha})_{\beta\beta}x_\beta + \Box s_\gamma + \Box \lambda_\alpha + \lambda_\beta \perp x_\beta \geq 0 \\ 0 \leq \lambda_\gamma = \Box - \tau \bar{p}_\gamma + \Box w_\alpha + \Box x_\beta + \Box s_\gamma + \Box \lambda_\alpha + w_\gamma \perp s_\gamma \geq 0 \\ 0 \leq s_\alpha = -\Phi + \tau \bar{p}_\alpha + \Box w_\alpha + \Box x_\beta + \Box s_\gamma + \Box \lambda_\alpha \quad \bot w_\alpha \geq 0 \end{array}$

$$0 \leq \mathbf{s}_{\beta} = u_{\beta} \qquad - \qquad \mathbf{x}_{\beta} \qquad \pm \lambda_{\beta} \geq 0$$
$$0 \leq \mathbf{x}_{\gamma} = u_{\gamma} \qquad - \mathbf{s}_{\gamma} \qquad \pm w_{\gamma} \geq 0$$

Basic variables

 $0 \leq w = a + \tau p + Mx + \lambda \perp x \geq 0$ KKT/LCP $0 \leq s = \mu - x + \lambda \geq 0$ **Rearranging**: $\alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}.$ $0 \le x_{\alpha} = -\bar{q}_{\alpha} - \tau \bar{p}_{\alpha} + \Box w_{\alpha} + \Box x_{\beta} + \Box s_{\gamma} + \Box \lambda_{\alpha} \qquad \bot w_{\alpha} \ge 0$ $0 \le w_{\beta} = \bar{q}_{\beta} - \tau \bar{p}_{\beta} + \Box w_{\alpha} + (M/M_{\alpha\alpha})_{\beta\beta} x_{\beta} + \Box x_{\gamma} + \Box \lambda_{\alpha} + \lambda_{\beta} \perp x_{\beta} \ge 0$ $0 \le \lambda_{\gamma} = \Box - \tau \bar{p}_{\gamma} + \Box w_{\alpha} + \Box x_{\beta} + \Box s_{\gamma} + \Box \lambda_{\alpha} + w_{\gamma} \perp s_{\gamma} \ge 0$ $\Box x_{\beta} + \Box s_{\gamma} + \Box \lambda_{\alpha} \qquad \bot w_{\alpha} \ge 0$ $0 \leq s_{\alpha} = \oplus + \tau \bar{p}_{\alpha} + \Box w_{\alpha} + \Box w_{\alpha}$ $\begin{array}{ccc} x_{\beta} & & \bot & \lambda_{\beta} \geq 0 \\ & - & s_{\gamma} & & \bot & w_{\gamma} \geq 0 \end{array}$ $0 \leq s_{\beta} = u_{\beta}$ $0 \leq x_{\gamma} = u_{\gamma}$

Non-basic variables

• H_0 -property $\Rightarrow \bar{p}_{\alpha} \ge 0, \bar{p}_{\gamma} \ge 0, \oplus \ge 0.$

KKT/LCP $0 \le w = q + \tau p + Mx + \lambda \perp x \ge 0$ $0 \le s = u - x \perp \lambda \ge 0$ Rearranging: $\alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}.$

• H_0 -property $\Rightarrow \bar{p}_{\alpha} \ge 0, \bar{p}_{\gamma} \ge 0, \oplus \ge 0.$

• Ratio test
$$\tau_{\text{new}} := \max\left\{\max_{i \in \alpha} \left\{-\frac{u_i + \bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, \max_{i \in \beta} \left\{-\frac{\bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, 0\right\}$$

KKT/LCP $0 \le w = q + \tau p + Mx + \lambda \perp x \ge 0$ $0 \le s = u - x \perp \lambda \ge 0$ Rearranging: $\alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}.$

• H_0 -property $\Rightarrow \bar{p}_{\alpha} \ge 0, \bar{p}_{\gamma} \ge 0, \oplus \ge 0.$

• Ratio test $\tau_{\text{new}} := \max\left\{\max_{i \in \alpha} \left\{-\frac{u_i + \bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, \max_{i \in \beta} \left\{-\frac{\bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, 0\right\}$ • $\bar{i} \in \alpha \to \alpha_{\text{new}} = \alpha \setminus \{\bar{i}\}, \gamma_{\text{new}} = \gamma \cup \{\bar{i}\}$

KKT/LCP $0 \le w = q + \tau p + Mx + \lambda \perp x \ge 0$
 $0 \le s = u - x \perp \lambda \ge 0$ Rearranging: $\alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}.$

• H_0 -property $\Rightarrow \bar{p}_{\alpha} \ge 0, \bar{p}_{\gamma} \ge 0, \oplus \ge 0.$

• Ratio test
$$\tau_{\text{new}} := \max\left\{\max_{i \in \alpha} \left\{-\frac{u_i + \bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, \max_{i \in \beta} \left\{-\frac{\bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, 0\right\}$$

• $\bar{i} \in \alpha \to \alpha_{\text{new}} = \alpha \setminus \{\bar{i}\}, \gamma_{\text{new}} = \gamma \cup \{\bar{i}\}$
• $\bar{i} \in \beta \to \left\{(M/M_{\alpha\alpha})_{\bar{i}\bar{i}} \neq 0 \to \alpha_{\text{new}} = \alpha \cup \{\bar{i}\}, \beta_{\text{new}} = \beta \setminus \{\bar{i}\}\right\}$

Shaoning Han (USC)

KKT/LCP
$$0 \le w = q + \tau p + Mx + \lambda \perp x \ge 0$$
 $0 \le s = u - x \perp \lambda \ge 0$

 $\text{Rearranging: } \alpha = \{i: 0 < x_i < u_i\}, \quad \beta = \{i: x_i = 0\}, \quad \gamma = \{i: x_i = u_i\}.$

• H_0 -property $\Rightarrow \bar{p}_{\alpha} \ge 0, \bar{p}_{\gamma} \ge 0, \oplus \ge 0.$

• Ratio test
$$\tau_{\text{new}} \coloneqq \max\left\{\max_{i \in \alpha} \left\{-\frac{u_i + \bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, \max_{i \in \beta} \left\{-\frac{\bar{q}_i}{\bar{p}_i} : \bar{p}_i > 0\right\}, 0\right\}$$

• $\bar{i} \in \alpha \to \alpha_{\text{new}} = \alpha \setminus \{\bar{i}\}, \gamma_{\text{new}} = \gamma \cup \{\bar{i}\}$
• $\bar{i} \in \beta \to \begin{cases} (M/M_{\alpha\alpha})_{\bar{i}\bar{i}} \neq 0 \to \alpha_{\text{new}} = \alpha \cup \{\bar{i}\}, \beta_{\text{new}} = \beta \setminus \{\bar{i}\} \\ (M/M_{\alpha\alpha})_{\bar{i}\bar{i}} = 0 \to 2 \times 2 \text{ pivot} \end{cases}$

Shaoning Han (USC)

Box-constrained QP with H₀-matrix

Note
$$\alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}$$

Type of pivots
(1) $\alpha_{new} = \alpha \setminus \{\overline{i}\}, \quad \gamma_{new} = \gamma \cup \{\overline{i}\}$
(2) $\alpha_{new} = \alpha \cup \{\overline{i}\}, \quad \beta_{new} = \beta \setminus \{\overline{i}\}$
(3) $\beta_{new} = \beta \setminus \{\overline{i}\}, \quad \gamma_{new} = \gamma \cup \{\overline{i}\}$
(4) $\beta_{new} = \beta \setminus \{\overline{i}\}, \quad \alpha_{new} = \alpha \cup \{\overline{i}\} \setminus \{\overline{j}\}, \quad \gamma_{new} = \gamma \cup \{\overline{j}\}$
(5) $\beta_{new} = \beta \setminus \{\overline{i}\} \cup \{\overline{j}\}, \quad \alpha_{new} = \alpha \cup \{\overline{i}\} \setminus \{\overline{j}\}$

Note $\alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}$ Type of pivots

(1)
$$\alpha_{new} = \alpha \setminus \{\overline{i}\}, \ \gamma_{new} = \gamma \cup \{\overline{i}\}$$

(2) $\alpha_{new} = \alpha \cup \{\overline{i}\}, \ \beta_{new} = \beta \setminus \{\overline{i}\}$
(3) $\beta_{new} = \beta \setminus \{\overline{i}\}, \ \gamma_{new} = \gamma \cup \{\overline{i}\}$
(4) $\beta_{new} = \beta \setminus \{\overline{i}\}, \ \alpha_{new} = \alpha \cup \{\overline{i}\} \setminus \{\overline{j}\}, \ \gamma_{new} = \gamma \cup \{\overline{j}\}$
(5) $\beta_{new} = \beta \setminus \{\overline{i}\} \cup \{\overline{j}\}, \ \alpha_{new} = \alpha \cup \{\overline{i}\} \setminus \{\overline{j}\}$



Note
$$\alpha = \{i : 0 < x_i < u_i\}, \quad \beta = \{i : x_i = 0\}, \quad \gamma = \{i : x_i = u_i\}$$

Type of pivots

(1)
$$\alpha_{new} = \alpha \setminus \{i\}, \ \gamma_{new} = \gamma \cup \{i\}$$

(2) $\alpha_{new} = \alpha \cup \{\bar{i}\}, \ \beta_{new} = \beta \setminus \{\bar{i}\}$
(3) $\beta_{new} = \beta \setminus \{\bar{i}\}, \ \gamma_{new} = \gamma \cup \{\bar{i}\}$
(4) $\beta_{new} = \beta \setminus \{\bar{i}\}, \ \alpha_{new} = \alpha \cup \{\bar{i}\} \setminus \{\bar{j}\}, \ \gamma_{new} = \gamma \cup \{\bar{j}\}$
(5) $\beta_{new} = \beta \setminus \{\bar{i}\} \cup \{\bar{j}\}, \ \alpha_{new} = \alpha \cup \{\bar{i}\} \setminus \{\bar{j}\}$



Theorem (Pang and Han (2021))

The streamlined PPPA terminates in at most 2n + 2 pivots. Consequently, the overall complexity of the PPPA is of order $O(n^3)$.

Shaoning Han (USC)

Box-constrained QP with Ho-matrix

March, 2022 10 / 13



Proof.

Shaoning Han (USC)

Box-constrained QP with H₀-matrix

March, 2022 11 / 13



Proof.

(a) No element can escape from γ



Box-constrained QP with H₀-matrix



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β

Box-constrained QP with H₀-matrix



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β
- (c) There is only one backward arc due to (5)



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β
- (c) There is only one backward arc due to (5)

Note that 2×2 pivot (5) is triggered only if

 $\exists \overline{i} \in \beta, \ (M/M_{\alpha\alpha})_{\overline{i}i} = 0 \Rightarrow M_{\alpha \cup \{i\}, \alpha \cup \{i\}} \text{ is singular}$



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β
- (c) There is only one backward arc due to (5)

Note that 2×2 pivot (5) is triggered only if

$$\exists \overline{i} \in \beta, \ (M/M_{\alpha\alpha})_{\overline{i}\overline{i}} = 0 \Rightarrow M_{\alpha\cup\{i\},\alpha\cup\{i\}} \text{ is singular}$$

$$\Rightarrow \alpha_{\mathsf{new}} = [n] \setminus \{\overline{j}\}, \ \beta_{\mathsf{new}} = \{\overline{j}\}, \ \gamma_{\mathsf{new}} = \emptyset \qquad (\mathsf{Rank}(M) = n - 1)$$



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β
- (c) There is only one backward arc due to (5)

Note that 2×2 pivot (5) is triggered only if

$$\exists \overline{i} \in \beta, \ (M/M_{\alpha\alpha})_{\overline{i}\overline{i}} = 0 \Rightarrow M_{\alpha\cup\{i\},\alpha\cup\{i\}} \text{ is singular}$$

$$\Rightarrow \alpha_{\mathsf{new}} = [n] \setminus \{\overline{j}\}, \ \beta_{\mathsf{new}} = \{\overline{j}\}, \ \gamma_{\mathsf{new}} = \emptyset \qquad (\mathsf{Rank}(M) = n - 1)$$

$$\Rightarrow \mathsf{next pivot must be (1)}$$



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β
- (c) There is only one backward arc due to (5)

Note that 2×2 pivot (5) is triggered only if

$$\exists \overline{i} \in \beta, \ (M/M_{\alpha\alpha})_{\overline{i}\overline{i}} = 0 \Rightarrow M_{\alpha\cup\{i\},\alpha\cup\{i\}} \text{ is singular}$$

$$\Rightarrow \alpha_{\mathsf{new}} = [n] \setminus \{\overline{j}\}, \ \beta_{\mathsf{new}} = \{\overline{j}\}, \ \gamma_{\mathsf{new}} = \emptyset \qquad (\mathsf{Rank}(M) = n - 1)$$

$$\Rightarrow \mathsf{next pivot must be} \ (1) \Rightarrow \gamma_{\mathsf{newnew}} \neq \emptyset$$



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β
- (c) There is only one backward arc due to (5)

Note that 2×2 pivot (5) is triggered only if

$$\exists \overline{i} \in \beta, \ (M/M_{\alpha\alpha})_{\overline{i}\overline{i}} = 0 \Rightarrow M_{\alpha\cup\{i\},\alpha\cup\{i\}} \text{ is singular}$$

$$\Rightarrow \alpha_{\mathsf{new}} = [n] \setminus \{\overline{j}\}, \ \beta_{\mathsf{new}} = \{\overline{j}\}, \ \gamma_{\mathsf{new}} = \emptyset \qquad (\mathsf{Rank}(M) = n - 1)$$

$$\Rightarrow \mathsf{next pivot must be} \ (1) \Rightarrow \gamma_{\mathsf{newnew}} \neq \emptyset \Rightarrow \mathsf{No more} \ 2 \times 2 \mathsf{ pivots!}$$

Box-constrained QP with H_0 -matrix



Proof.

- (a) No element can escape from γ
- (b) Except (1), all pivots lead to one element departing from β
- (c) There is only one backward arc due to (5)

Note that 2×2 pivot (5) is triggered only if

$$\exists \overline{i} \in \beta, \ (M/M_{\alpha\alpha})_{\overline{i}\overline{i}} = 0 \Rightarrow M_{\alpha\cup\{i\},\alpha\cup\{i\}} \text{ is singular} \Rightarrow \alpha_{\text{new}} = [n] \setminus \{\overline{j}\}, \ \beta_{\text{new}} = \{\overline{j}\}, \ \gamma_{\text{new}} = \emptyset \qquad (\text{Rank}(M) = n - 1) \Rightarrow \text{next pivot must be } (1) \Rightarrow \gamma_{\text{newnew}} \neq \emptyset \Rightarrow \text{No more } 2 \times 2 \text{ pivots!} \Rightarrow \text{Acyclic Graph}$$

Shaoning Han (USC)

Box-constrained QP with H_0 -matrix

Question: Existence of p such that $q + \tau_0 p \ge 0$? How to find it?

Question: Existence of p such that $q + \tau_0 p \ge 0$? How to find it?

• If
$$M = \overline{M}$$
, i.e. $M_{ij} \le 0 \ \forall i \ne j$, solve
$$\begin{cases} Mp = 0 \\ p_n = 1 \end{cases}$$
 or $Mp = \mathbf{1}$

Question: Existence of p such that $q + \tau_0 p \ge 0$? How to find it?

• If
$$M = \overline{M}$$
, i.e. $M_{ij} \le 0 \ \forall i \ne j$, solve
$$\begin{cases} Mp = 0 \\ p_n = 1 \end{cases}$$
 or $Mp = \mathbf{1}$

Tridiagonal case

• Cholesky factorization $\Rightarrow \mathcal{O}(n^2)$

Question: Existence of p such that $q + \tau_0 p \ge 0$? How to find it?

• If
$$M = \overline{M}$$
, i.e. $M_{ij} \le 0 \ \forall i \ne j$, solve
$$\begin{cases} Mp = 0 \\ p_n = 1 \end{cases}$$
 or $Mp = \mathbf{1}$

Tridiagonal case

• Cholesky factorization $\Rightarrow \mathcal{O}(n^2)$

Extension?

• k-weakly quasi-diagonally dominant matrices

Take home message

Take home message

- *H*₀-matrices have many remarkable properties
- Box-constrained convex quadratic programs with *H*₀-matrices are strongly polynomially solvable

Take home message

- *H*₀-matrices have many remarkable properties
- Box-constrained convex quadratic programs with *H*₀-matrices are strongly polynomially solvable

Our paper is available at: https://arxiv.org/abs/2112.03886

Thank You!

- Liu, P., Fattahi, S., Gomez, A., and Kucukyavuz, S. (2021). A graph-based decomposition method for convex quadratic optimization with indicators. www. optimization-online. org/DB_HTML/2021/10/8645. html.
- Pang, J.-S. and Han, S. (2021). Some strongly polynomially solvable convex quadratic programs with bounded variables. https://arxiv.org/abs/2112.03886.