

# Exactness conditions for SDP relaxation of bipartite-structured and sign-indefinite QCQPs

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# QCQP: Quadratically Constrained Quadratic Programming

Let  $Q^0, \dots, Q^m$  be  $n \times n$  symmetric matrices,  $\mathbf{b} \in \mathbb{R}^m$ .

$$\begin{aligned} v^* &:= \min_{\mathbf{x} \in \mathbb{R}^n} \mathbf{x}^T Q^0 \mathbf{x} \\ \text{s.t. } & \mathbf{x}^T Q^p \mathbf{x} \leq b_p, \quad p \in [m] := \{1, \dots, m\}, \end{aligned} \tag{\mathcal{P}}$$

## Applications

MAX-CUT, sensor location problems, optimal flow problems,...

- $(\mathcal{P})$  is a homogeneous form (no linear terms).
- **Calculation of  $v^*$  is NP-hard.**
- Semidefinite programming relaxation is often used.

# Semidefinite Programming (SDP) Relaxation

$$\begin{aligned} v^* &= \min \{ \mathbf{x}^T Q^0 \mathbf{x} \mid \mathbf{x}^T Q^p \mathbf{x} \leq b_p \quad \forall p \in [m] \} \\ &= \min \left\{ Q^0 \bullet X \mid \begin{array}{l} X = \mathbf{x}\mathbf{x}^T \\ Q^p \bullet X \leq b_p \quad \forall p \in [m] \end{array} \right\} \\ &\geq \min \left\{ Q^0 \bullet X \mid \begin{array}{l} X \succeq \mathbf{x}\mathbf{x}^T \\ Q^p \bullet X \leq b_p \quad \forall p \in [m] \end{array} \right\} =: v_{\text{SDP}}^* \quad (\mathcal{P}_R) \end{aligned}$$

where

- $Q^p \bullet X := \sum_{i,j} Q_{ij}^p X_{ij}$ ,
- $X \succeq O \iff X$  is positive semidefinite.

**Pros:**  $v_{\text{SDP}}^*$  can be calculated **in polynomial time**.

**Cons:** In general,  $v^* \neq v_{\text{SDP}}^*$ .

# Exactness of SDP Relaxation

$$v^* \geq \min \left\{ Q^0 \bullet X \mid \begin{array}{l} X \succeq O \\ Q^p \bullet X \leq b_p \quad \forall p \in [m] \end{array} \right\} = v_{\text{SDP}}^*$$

= holds

$\iff$  SDP relaxation is **exact**

## Interested in

What conditions of QCQPs guarantee the exact SDP relaxation?

$$(v^* = v_{\text{SDP}}^*)$$

- $\implies$
- Classify QCQPs according to tractability
  - Identify the gap between a QCQP and its SDP relaxation

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= holds

$\iff$  SDP relaxation is **exact**

$\iff$

an optimal solution  $X^*$   
of **rank-1** exists

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- "Full-rank minus one" solutions of dual SDP relaxation
- Idea for diagonal matrices  $Q^0, \dots, Q^m$
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# Primal/Dual Problems of SDP Relaxation

$$v^* = \min_{\mathbf{x} \in \mathbb{R}^n} \{ \mathbf{x}^T Q^0 \mathbf{x} \mid \mathbf{x}^T Q^p \mathbf{x} \leq b_p, p \in [m] \} \quad (\mathcal{P})$$



Primal

$$\begin{aligned} v_{\text{SDP}}^* &= \min_X Q^0 \bullet X \\ \text{s.t.} \quad & Q^p \bullet X \leq b_p, p \in [m] \quad (\mathcal{P}_R) \\ & X \succeq O \end{aligned}$$

Dual

$$\begin{aligned} \max_{\mathbf{y} \in \mathbb{R}^m} \quad & -\mathbf{b}^T \mathbf{y} \\ \text{s.t.} \quad & \mathbf{y} \geq \mathbf{0}, \quad (\mathcal{D}_R) \\ & S(\mathbf{y}) \succeq O \end{aligned}$$

where

$$S(\mathbf{y}) := Q^0 + \sum_{p=1}^m y_p Q^p \quad \text{for } \mathbf{y} \in \mathbb{R}^m.$$

# Dual Solution of rank- $(n - 1)$ is Important for Exactness

Primal

$$\begin{aligned} v_{\text{SDP}}^* &= \min_X Q^0 \bullet X \\ \text{s.t.} \quad & Q^p \bullet X \leq b_p, \quad p \in [m] \quad (\mathcal{P}_R) \\ & X \succeq O \end{aligned}$$

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Exact if

Rank-1 solution  $X^*$



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Exact if

Rank-1 solution  $X^*$

$\iff$

Rank- $(n - 1)$  solution  $S(\mathbf{y}^*)$

Proof.

Let  $X^*$  be an optimal solution of  $(\mathcal{P}_R)$  satisfying  $X^* S(\mathbf{y}^*) = O$ .

From Sylvester's rank inequality,

$$\begin{aligned} \text{rank}(X^*) &\leq n - \text{rank}\{S(\mathbf{y}^*)\} + \text{rank}\{X^* S(\mathbf{y}^*)\} \\ &= n - \underbrace{\text{rank}\{S(\mathbf{y}^*)\}}_{\geq n-1} \leq 1. \quad \square \end{aligned}$$

- Extended Trust-region subproblems  
Jeyakumar[2014], Hsia and Sheu[2013], Locatelli[2016]
- Diagonal QCQPs    Burer and Ye[2020]
- Exactness by faces of convex lagrangian multipliers  
Wang and Kılınç-Karzan[2021]
- Rank-one generated cones  
Argue, Kılınç-Karzan and Wang[2020]

## Idea for Diagonal Matrices $Q^0, \dots, Q^m$

Assume:  $Q^0, \dots, Q^m$  are diagonal matrices.

$$S(\mathbf{y}^*) = \begin{bmatrix} S_{11} & & & \\ & S_{22} & & \\ & & \ddots & \\ & & & S_{nn} \end{bmatrix} \in \mathbb{R}^{n \times n}.$$

It holds that  $\text{rank}\{S(\mathbf{y}^*)\} \geq n - 1$  if  
at least  $(n - 1)$  of  $S_{11}, \dots, S_{nn}$  are nonzero.

# Exactness Condition for Diagonal QCQPs

Non-homogeneous version of QCQP:

$$\begin{aligned} v^* &:= \min_{\mathbf{x} \in \mathbb{R}^n} && \mathbf{x}^T Q^0 \mathbf{x} + 2(\mathbf{q}^0)^T \mathbf{x} \\ &&& \text{s.t. } \mathbf{x}^T Q^p \mathbf{x} + 2(\mathbf{q}^p)^T \mathbf{x} \leq b_p, \quad p \in [m], \end{aligned}$$

Define  $S(\mathbf{y}) = Q^0 + \sum y_p Q^p$ ,  $s(\mathbf{y}) = q_0 + \sum y_p q_p$ .

## Theorem

[Burer and Ye, 2020]

Suppose  $Q^0, Q^1, \dots, Q^m$  are diagonal matrices.

If the following system is infeasible for all  $k \in \{1, \dots, n\}$ :

$$\mathbf{y} \geq 0, \quad S(\mathbf{y}) \succeq 0, \quad S(\mathbf{y})_{kk} = 0, \quad s(\mathbf{y})_k = 0,$$

then  $v^* = v_{\text{SDP}}^*$ .

## Problem:

- Diagonal property is too strong.  
(c.f., simultaneous diagonalization, adding auxiliary variables)
- Range of applicable problems is still small.

## Objective of our research

To expand the range of applicable problems by

- dropping the diagonal property
- employing the **sparsity structure of QCQPs** instead

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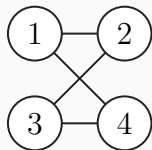
# Aggregated Sparsity Pattern of QCQP

Aggregated Sparsity Pattern of QCQP:  $G(\mathcal{V}, \mathcal{E})$

$$\mathcal{V} := [n],$$

$$\mathcal{E} := \{(i, j) \in \mathcal{V}^2 \mid i \neq j, Q_{ij}^p \neq 0 \text{ for some } p \in \{0, \dots, m\}\}.$$

ex.  $\min \{ \mathbf{x}^T Q^0 \mathbf{x} \mid \mathbf{x}^T Q^1 \mathbf{x} \leq 10 \}$



$$Q^0 = \begin{bmatrix} 0 & -2 & 0 & 2 \\ -2 & 0 & -1 & 0 \\ 0 & -1 & 5 & 1 \\ 2 & 0 & 1 & -4 \end{bmatrix}, \quad Q^1 = \begin{bmatrix} -1 & 1 & 0 & 0 \\ 1 & 4 & -1 & 0 \\ 0 & -1 & 6 & 1 \\ 0 & 0 & 1 & -2 \end{bmatrix}.$$

## Matrix $S(\mathbf{y})$ under Sparsity Structure $G$

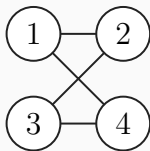
$S(\mathbf{y})$  has the same sparsity structure as that of QCQP.

### Observation

$$S(\mathbf{y})_{ij} = Q_{ij}^0 + y_1 Q_{ij}^1 + \cdots + y_m Q_{ij}^m = 0 \quad \forall \mathbf{y} \in \mathbb{R}^m \quad \forall (i, j) \notin \mathcal{E}$$

ex.

$$S(\mathbf{y}) = \begin{bmatrix} -y_1 & -2 + y_1 & 0 & 2 \\ -2 + y_1 & +4y_1 & -1 - y_1 & 0 \\ 0 & -1 - y_1 & 5 + 6y_1 & 1 + y_1 \\ 2 & 0 & 1 + y_1 & -4 - 2y_1 \end{bmatrix}$$

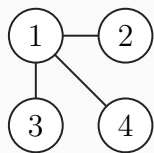




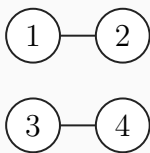
# Forest and Bipartite Graph

Let  $G(\mathcal{V}, \mathcal{E})$  be a nonempty graph.

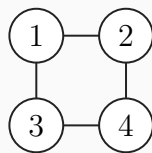
| $G$              | Cycle      |             | #Components |
|------------------|------------|-------------|-------------|
|                  | Odd length | Even length |             |
| <b>Tree</b>      |            |             | 1           |
| <b>Forest</b>    |            |             | $\geq 1$    |
| <b>Bipartite</b> |            | allowed     | $\geq 1$    |



Tree



Forest



Bipartite

## Idea for $S(\mathbf{y})$ with Structured Sparsity

$$v^* = v_{\text{SDP}}^*$$

$\iff (\mathcal{P}_R)$  has an optimal  $X^*$  satisfying  $\text{rank}(X^*) \leq 1$

$\iff (\mathcal{D}_R)$  has an optimal  $\mathbf{y}^*$  satisfying  $\text{rank}\{S(\mathbf{y}^*)\} \geq n - 1$

$\iff \text{rank}\{S(\mathbf{y})\} \geq n - 1 \quad \forall \mathbf{y} \geq \mathbf{0}$  satisfying  $S(\mathbf{y}) \succeq O$

$\iff \left\{ \begin{array}{l} G: \text{connected bipartite,} \\ S(\mathbf{y}) \succeq O, S(\mathbf{y})_{ij} > 0 \quad \forall (i, j) \in \mathcal{E} \end{array} \right. \quad [\text{Grone et al., 1992}]$

If  $\mathbf{y} \geq \mathbf{0}, S(\mathbf{y}) \succeq O, S(\mathbf{y})_{ij} \leq 0$  has no solutions,  
we can obtain  $S(\mathbf{y})_{ij} > 0 \quad \forall (i, j) \in \mathcal{E}$ .

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we can obtain  $S(\mathbf{y})_{ij} > 0 \quad \forall (i, j) \in \mathcal{E}$ .

## Exactness Condition for QCQPs with Bipartite Structures

If  $G$  is a bipartite and the system

$$\mathbf{y} \geq 0, S(\mathbf{y}) \succeq O, [S(\mathbf{y})]_{k\ell} \leq 0, \quad (1)$$

has no solutions for all  $(k, \ell) \in \mathcal{E}$ , then  $v^* = v_{\text{SDP}}^*$ .

- Checking  $|\mathcal{E}|$  feasibility systems is required.
- (1) is a tractable problem.

# Comparison of Exactness Conditions

|                           | Graph $G$ | Systems to check                                 |
|---------------------------|-----------|--------------------------------------------------|
| Burer & Ye <sup>1</sup>   | no edges  | $S_{=}$ for all $(k, \ell)$ such that $k = \ell$ |
| Azuma et al. <sup>2</sup> | forest    | $S_{=}$ for all $(k, \ell) \in \mathcal{E}$      |
| Proposed method           | bipartite | $S_{\leq}$ for all $(k, \ell) \in \mathcal{E}$   |

a LP or a SDP: tractable problem

where systems are:

$$\text{find } \mathbf{y} \geq 0 \text{ such that } S(\mathbf{y}) \succeq O, [S(\mathbf{y})]_{k\ell} \diamond 0. \quad (S_{\diamond})$$

<sup>1</sup>Samuel Burer and Yinyu Ye. "Exact semidefinite formulations for a class of (random and non-random) nonconvex quadratic programs". In: *Mathematical Programming* 181.1 (2020), pp. 1–17.

<sup>2</sup>Godai Azuma et al. "Exact SDP Relaxations of Quadratically Constrained Quadratic Programs with Forest Structures". In: *Journal of Global Optimization* 82.2 (2022), pp. 243–262.

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## Definition of Sign-definite QCQP

- QCQPs with no sparsity
- For all  $(i, j)$ , the set  $T_{ij} := \{Q_{ij}^0, \dots, Q_{ij}^m\}$  is sign-definite

all nonnegative or all nonpositive

## Theorem 2<sup>3</sup>

[Sojoudi and Lavaei, 2014]

$$\prod_{(i,j) \in \mathcal{C}} \sigma_{ij} = (-1)^{|\mathcal{C}|} \quad \text{for all cycles } \mathcal{C} \text{ in } G \quad (2)$$

where  $\sigma_{ij}$  is called edge sign:

$$\sigma_{ij} = \begin{cases} +1 & (T_{ij} \text{ has all nonnegative}), \\ -1 & (T_{ij} \text{ has all nonpositive}). \end{cases}$$

<sup>3</sup>Somayeh Sojoudi and Javad Lavaei. "Exactness of Semidefinite Relaxations for Nonlinear Optimization Problems with Underlying Graph Structure". In: *SIAM Journal on Optimization* 24.4 (2014), pp. 1746–1778.



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**even-length** cycle  $\iff$  **even** number of negative  $\sigma_{ij}$ s

014]

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Corollary from our exactness condition.

## Nonnegative Off-diagonal

$v^* = v_{\text{SDP}}^*$  holds if  $G(\mathcal{V}, \mathcal{E})$  is bipartite, and all the off-diagonal elements of  $Q^0, \dots, Q^m$  are nonnegative, i.e.,

$$\sigma_{ij} = +1 \text{ for all } (i, j) \in \mathcal{E}$$

Moreover, based on the transformation, we have proved:

## Comparison

Our proposed condition is weaker than the condition (2).

Transform from general QCQPs to sparse QCQPs.

1. Objective function and constraints have the form:

$$\mathbf{x}^T \begin{bmatrix} Q_{11}^p & Q_{12}^p & Q_{13}^p & Q_{14}^p \\ Q_{21}^p & Q_{22}^p & Q_{23}^p & Q_{24}^p \\ Q_{31}^p & Q_{32}^p & Q_{33}^p & Q_{34}^p \\ Q_{41}^p & Q_{42}^p & Q_{43}^p & Q_{44}^p \end{bmatrix} \mathbf{x}, \quad \forall p,$$

where  $n = 4$ ,  $Q^p$ : symmetric matrices.

2. Assume remove edges (1, 3) and (2, 4)  
because of  $Q_{13}^p < 0$ ,  $Q_{24}^p < 0$ .

## Essence of Proof (2)

3. New variable  $z := -x$  is introduced.

4. It can be written as

$$\begin{bmatrix} x \\ z \end{bmatrix}^T \left[ \begin{array}{cccc|cccc} Q_{11}^p & Q_{12}^p & 0 & Q_{14}^p & 0 & 0 & -\frac{1}{2}Q_{13}^p & 0 \\ Q_{21}^p & Q_{22}^p & Q_{23}^p & 0 & 0 & 0 & 0 & 0 \\ 0 & Q_{32}^p & Q_{33}^p & Q_{34}^p & -\frac{1}{2}Q_{31}^p & 0 & 0 & 0 \\ Q_{41}^p & 0 & Q_{43}^p & Q_{44}^p & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & -\frac{1}{2}Q_{13}^p & 0 & & & & \\ 0 & 0 & 0 & 0 & & & & \\ -\frac{1}{2}Q_{31}^p & 0 & 0 & 0 & & & & \\ 0 & 0 & 0 & 0 & & & & \end{array} \right] \begin{bmatrix} x \\ z \end{bmatrix}, \forall p.$$

5. Off-diagonal elements are **all nonnegative** with some zero elements (bipartite).

The obtained problem satisfies our simple corollary.

## Summary

- QCQPs whose  $G$  is bipartite were analyzed.
- New sufficient condition of  $v^* = v_{\text{SDP}}^*$  was proposed.
- It was compared with three existing results.

## Future works

- Approximated problems of QCQPs with exact SDP relaxation
- Analysis of QCQPs transformed from general problems

More information is available at [arXiv:2204.09509](https://arxiv.org/abs/2204.09509),

“Exact SDP relaxations for quadratic programs with bipartite graph structures.”

Thank you for your attention!

## Backup Slides

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## Assumption

- (i) Both  $(\mathcal{P}_R)$  and  $(\mathcal{D}_R)$  have optimal solutions, and
- (ii) At least one of the following two conditions holds:
  - (a) the feasible region of  $(\mathcal{P}_R)$  is bounded, or
  - (b) the set of optimal solutions for  $(\mathcal{D}_R)$  is bounded.

- **strong duality** holds: (Kim and Kojima<sup>4</sup>)

$\exists(X^*, \mathbf{y}^*)$ : solutions of  $(\mathcal{P}_R)$  and  $(\mathcal{D}_R)$  such that

$$X^* S(\mathbf{y}^*) = O.$$

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<sup>4</sup>Sunyoung Kim and Masakazu Kojima. *Strong duality of a conic optimization problem with a single hyperplane and two cone constraints*. arXiv:2111.03251v2. 2021.



# Cycle Basis

$\mathcal{C} := \{C_1, \dots, C_\kappa\}$  : set of (simple) cycles

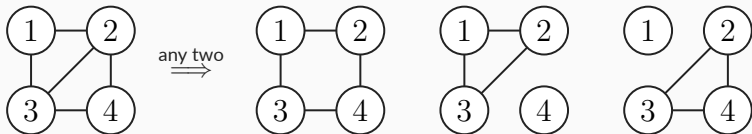
$A \Delta B$  : symmetric difference of  $A$  and  $B$

$$A \Delta B := (A \setminus B) \cup (B \setminus A)$$

$\mathcal{C}$  is called a **cycle basis** of  $G$

$\Leftrightarrow$   $\left\{ \begin{array}{l} \circ \text{ allows any cycle in } G \text{ to be expressed by } \Delta \text{ of its elements} \\ \circ \text{ be a minimum set} \end{array} \right.$

Ex.



# Estimation of Rank of Sparse Matrices

Let  $M$  be an  $n \times n$  symmetric matrix,  
 $G(\mathcal{V}, \mathcal{E})$  be a graph.

For tree

[Johnson et al., 2003, Corollary 3.9]

$$\left. \begin{array}{l} G \text{ is tree} \\ M \succeq O \\ M_{ij} \neq 0 \quad \forall (i, j) \in \mathcal{E}_M \end{array} \right\} \implies \text{rank } M \geq n - 1$$

For bipartite

[Grone et al., 1992, Proposition 1]

$$\left. \begin{array}{l} G \text{ is connected and bipartite} \\ M \succeq O, M\mathbf{1} > 0 \\ M_{ij} > 0 \quad \forall (i, j) \in \mathcal{E}_M \end{array} \right\} \implies \text{rank } M \geq n - 1$$

where  $\mathbf{1}$  is the one vector  $[1 \ \dots \ 1]^T$ .

## Example 1<sup>5</sup>

$$\begin{aligned} v^* = \min \quad & x^2 + y^2 \\ \text{s.t.} \quad & y^2 \geq 1, \quad x^2 - xy \geq 1, \quad x^2 + xy \geq 1 \end{aligned}$$

From last two inequality,

- $$\left. \begin{aligned} xy > 0 &\implies xy > -xy \\ xy < 0 &\implies -xy > xy \end{aligned} \right\} \implies x^2 \geq |x||y| + 1$$
- $$x^2 \geq 1.$$

$$\therefore x^2 + y^2 \geq (|x||y| + 1) + 1 \geq 3$$

<sup>5</sup>Luo-Lecture14.

## Instance for SDP relaxation (SDP side)

$$\begin{aligned}
 v^* &= \min \{x^2 + y^2 \mid y^2 \geq 1, x^2 - xy \geq 1, x^2 + xy \geq 1\} \\
 &= \min \left\{ \mathbf{x}^T I \mathbf{x} \mid \begin{array}{l} \mathbf{x}^T \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \mathbf{x} \geq 1, \\ \mathbf{x}^T \begin{bmatrix} 1 & -1/2 \\ -1/2 & 0 \end{bmatrix} \mathbf{x} \geq 1, \mathbf{x}^T \begin{bmatrix} 1 & 1/2 \\ 1/2 & 0 \end{bmatrix} \mathbf{x} \geq 1 \end{array} \right\} \\
 &\geq \min \left\{ I \bullet X \mid \begin{array}{l} \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \bullet X \geq 1, X \succeq O \\ \begin{bmatrix} 1 & -1/2 \\ -1/2 & 0 \end{bmatrix} \bullet X \geq 1, \begin{bmatrix} 1 & 1/2 \\ 1/2 & 0 \end{bmatrix} \bullet X \geq 1 \end{array} \right\} \\
 &= \min \{X_{11} + X_{22} \mid X_{22} \geq 1, X_{11} - X_{12} \geq 1, X_{11} + X_{12} \geq 1, X \succeq O\}
 \end{aligned}$$

$$X = I \text{ is feasible} \implies v_{\text{SDP}}^* \leq 2 < 3 \leq v^*$$

Used in various problems:

- MAX-CUT, MAX-CLIQUE
- sensor (facility) location problem, pooling problem
- optimal flow problem, polynomial optimization
- (robust / sparse) principal component analysis, phase retrieval

### Theorem 3.7'

Suppose **Assumption 3.8 holds** &  $G$  is a forest and connected graph.

Then,  $v^* = v_{\text{SDP}}^*$  if for all  $(k, \ell) \in \mathcal{E}$ , the following system has no solutions:

$$\mathbf{y} \geq 0, S(\mathbf{y}) \succeq O, [S(\mathbf{y})]_{k\ell} = 0, \quad (??)$$

Ex.  $n = 2, \quad m = 1,$

$$\min. \quad \mathbf{x}^T \begin{bmatrix} -3 & -1 \\ -1 & -2 \end{bmatrix} \mathbf{x} \quad \text{s.t.} \quad \mathbf{x}^T \begin{bmatrix} 3 & 4 \\ 4 & 6 \end{bmatrix} \mathbf{x} \leq 1.$$

- $\mathcal{E} = \{(1, 2), (2, 1)\}$
- Systems – only for  $(k, \ell) = (1, 2)$

$$y_1 \geq 0, \quad \begin{bmatrix} -3 & -1 \\ -1 & -2 \end{bmatrix} + y_1 \begin{bmatrix} 3 & 4 \\ 4 & 6 \end{bmatrix} \succeq O, \quad -1 + 4y_1 \leq 0$$

- $S(y) \succeq O \iff y_1 \geq 3 + \frac{3\sqrt{6}}{2} \simeq 6.67$

second inequality  $\implies -1 + 4y_1 > 0$

$$\implies v^* = v_{\text{SDP}}^*$$

No solutions

## Example 2

$$\begin{aligned} \min \quad & \mathbf{x}^T Q^0 \mathbf{x} \\ \text{s.t.} \quad & \mathbf{x}^T Q^1 \mathbf{x} \leq 10, \quad \mathbf{x}^T Q^2 \mathbf{x} \leq 10, \quad \mathbf{x}^T Q^3 \mathbf{x} \leq 5 \end{aligned}$$

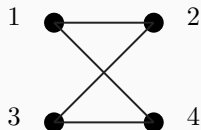
where

$$Q^0 = \begin{bmatrix} 0 & -2 & 0 & 2 \\ -2 & 0 & -1 & 0 \\ 0 & -1 & 5 & 1 \\ 2 & 0 & 1 & -4 \end{bmatrix}, \quad Q^1 = \begin{bmatrix} 5 & 2 & 0 & 1 \\ 2 & -1 & 3 & 0 \\ 0 & 3 & 3 & -1 \\ 1 & 0 & -1 & 4 \end{bmatrix},$$
$$Q^2 = \begin{bmatrix} -1 & 1 & 0 & 0 \\ 1 & 4 & -1 & 0 \\ 0 & -1 & 6 & 1 \\ 0 & 0 & 1 & -2 \end{bmatrix}, \quad Q^3 = \begin{bmatrix} 4 & -1 & 0 & 0 \\ -1 & -2 & 1 & 0 \\ 0 & 1 & -2 & 4 \\ 0 & 0 & 4 & 2 \end{bmatrix}.$$



## Sparsity of Example 2

$$Q^0 = \begin{bmatrix} 0 & -2 & 0 & 2 \\ -2 & 0 & -1 & 0 \\ 0 & -1 & 5 & 1 \\ 2 & 0 & 1 & -4 \end{bmatrix}, \quad Q^1 = \begin{bmatrix} 5 & 2 & 0 & 1 \\ 2 & -1 & 3 & 0 \\ 0 & 3 & 3 & -1 \\ 1 & 0 & -1 & 4 \end{bmatrix},$$
$$Q^2 = \begin{bmatrix} -1 & 1 & 0 & 0 \\ 1 & 4 & -1 & 0 \\ 0 & -1 & 6 & 1 \\ 0 & 0 & 1 & -2 \end{bmatrix}, \quad Q^3 = \begin{bmatrix} 4 & -1 & 0 & 0 \\ -1 & -2 & 1 & 0 \\ 0 & 1 & -2 & 4 \\ 0 & 0 & 4 & 2 \end{bmatrix}.$$



$$\mathcal{E} = \left\{ \begin{array}{l} (1, 2), (2, 1), (1, 4), (4, 1), \\ (2, 3), (3, 2), (3, 4), (4, 3) \end{array} \right\}.$$

## Systems of Example 2

Consider the problem for  $(k, \ell) \in \mathcal{E}$ :

$$\begin{aligned} \mu^* &= \min S(\mathbf{y})_{k\ell} \\ \text{s.t. } &\mathbf{y} \geq \mathbf{0}, S(\mathbf{y}) \succeq O. \end{aligned} \tag{3}$$

|             |        |        |        |        |
|-------------|--------|--------|--------|--------|
| $(k, \ell)$ | (1, 2) | (2, 3) | (1, 4) | (3, 4) |
| $\mu^*$     | 18.58  | 12.84  | 8.897  | 0.3215 |

All positives  $\implies$  the following systems have no solutions:

$$\mathbf{y} \geq \mathbf{0}, S(\mathbf{y}) \succeq O, S(\mathbf{y})_{k\ell} \leq 0. \tag{1}$$

Let  $P \neq O \in \mathbb{S}^n$  and  $\varepsilon > 0$

$$v^* = \min \{ \mathbf{x}^T Q^0 \mathbf{x} \mid \mathbf{x}^T Q^p \mathbf{x} \leq b_p \quad \forall p \in [m] \} \quad (\mathcal{P})$$

↓

$$v_\varepsilon^* = \min \{ \mathbf{x}^T (Q^0 + \varepsilon P) \mathbf{x} \mid \mathbf{x}^T Q^p \mathbf{x} \leq b_p \quad \forall p \in [m] \} \quad (\mathcal{P}^\varepsilon)$$

- $(\mathcal{P}^\varepsilon)$  converges to  $(\mathcal{P})$  as  $\varepsilon \downarrow 0$ .
- If  $P \preceq O$ , then  $v_\varepsilon^* \leq v^*$ .

Let  $P \neq O \in \mathbb{S}^n$  and  $\varepsilon > 0$

$$v^* = \min \{ \mathbf{x}^T Q^0 \mathbf{x} \mid \mathbf{x}^T Q^p \mathbf{x} \leq b_p \quad \forall p \in [m] \} \quad (\mathcal{P})$$

↓

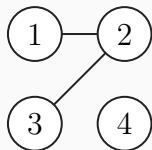
$$v_\varepsilon^* = \min \{ \mathbf{x}^T (Q^0 + \varepsilon P) \mathbf{x} \mid \mathbf{x}^T Q^p \mathbf{x} \leq b_p \quad \forall p \in [m] \} \quad (\mathcal{P}^\varepsilon)$$

Preferred edges can be added to  $G$

- $(\mathcal{P}^\varepsilon)$  converges to  $(\mathcal{P})$  as  $\varepsilon \downarrow 0$ .
- If  $P \preceq O$ , then  $v_\varepsilon^* \leq v^*$ .

## Instance of Adding Edges

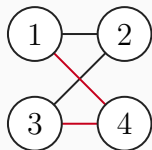
$$\min \{ \mathbf{x}^T (Q^0 + Q^1) \mathbf{x} \mid \mathbf{x}^T Q^1 \mathbf{x} \leq 10 \}$$



$$Q^0 = \begin{bmatrix} 0 & -2 & 0 & 0 \\ -2 & 0 & -1 & 0 \\ 0 & -1 & 5 & 0 \\ 0 & 0 & 0 & -4 \end{bmatrix}, \quad Q^1 = \begin{bmatrix} 5 & 2 & 0 & 0 \\ 2 & -1 & 3 & 0 \\ 0 & 3 & 3 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix},$$

## Instance of Adding Edges

$$\min \{ \mathbf{x}^T (Q^0 + \epsilon P) \mathbf{x} \mid \mathbf{x}^T Q^1 \mathbf{x} \leq 10 \}$$



$$Q^0 = \begin{bmatrix} 0 & -2 & 0 & 0 \\ -2 & 0 & -1 & 0 \\ 0 & -1 & 5 & 0 \\ 0 & 0 & 0 & -4 \end{bmatrix}, \quad Q^1 = \begin{bmatrix} 5 & 2 & 0 & 0 \\ 2 & -1 & 3 & 0 \\ 0 & 3 & 3 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix}, \quad P = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix}.$$

$\{\varepsilon_t\}_{t=1}^{\infty} \subseteq \mathbb{R}_+$  : monotonically decreasing and  $\lim_{t \rightarrow \infty} \varepsilon_t = 0$

$P \neq O$  :  $n \times n$  negative semidefinite matrix

## Lemma 4.1, Lemma 4.4, and Lemma 4.5

Suppose Assumption 3.6 holds, or  
Assumption 3.8 and an additional one hold.

SDP relaxation of  $(\mathcal{P}^\varepsilon)$  is exact  
for all  $\varepsilon = \varepsilon_1, \varepsilon_2, \dots$   $\implies v^* = v_{\text{SDP}}^*$ .

# Result for Disconnected Sparsity Structures

Let  $G(\mathcal{V}, \mathcal{E})$  be the aggregated sparsity pattern graph of  $(P)$ .

## Theorem 4.2

Suppose Assumption 3.6 holds &  $G$  is a forest and connected.

Then,  $v^* = v_{\text{SDP}}^*$  if, for all  $(k, \ell) \in \mathcal{E}$ , the following system has no solutions:

$$\mathbf{y} \geq 0, S(\mathbf{y}) \succeq O, [S(\mathbf{y})]_{k\ell} = 0, \quad (??)$$

## Theorem 4.6

Suppose Assumption 4.3 holds &  $G$  is a bipartite and connected.

Then,  $v^* = v_{\text{SDP}}^*$  if, for all  $(k, \ell) \in \mathcal{E}$ , the following system has no solutions:

$$\mathbf{y} \geq 0, S(\mathbf{y}) \succeq O, [S(\mathbf{y})]_{k\ell} \leq 0, \quad (1)$$



# Result for Disconnected Sparsity Structures

Let  $G(\mathcal{V}, \mathcal{E})$  be the aggregated sparsity pattern graph of  $(\mathcal{P})$ .

## Theorem 4.2

Suppose Assumption 3.6 holds &  $G$  is a forest.

Then,  $v^* = v_{\text{SDP}}^*$  if, for all  $(k, \ell) \in \mathcal{E}$ , the following system has no solutions:

$$\mathbf{y} \geq 0, S(\mathbf{y}) \succeq O, [S(\mathbf{y})]_{k\ell} = 0, \quad (??)$$

## Theorem 4.6

Suppose Assumption 4.3 holds &  $G$  is a bipartite.

Then,  $v^* = v_{\text{SDP}}^*$  if, for all  $(k, \ell) \in \mathcal{E}$ , the following system has no solutions:

$$\mathbf{y} \geq 0, S(\mathbf{y}) \succeq O, [S(\mathbf{y})]_{k\ell} \leq 0, \quad (1)$$

## Proof of Theorem 4.6.

1. Let  $\mathcal{F}$  be the set of additional edges.
2. Define  $P \preceq O$  as

$$P_{ij} = \begin{cases} -\deg(i) & \text{if } i = j, \\ 1 & \text{if } (i, j) \in \mathcal{F} \text{ or } (j, i) \in \mathcal{F}, \\ 0 & \text{otherwise,} \end{cases}$$

3.  $(\mathcal{P}^\varepsilon)$  satisfies assumptions of Theorem 3.10.  
 $\implies$  **SDP relaxation of  $(\mathcal{P}^\varepsilon)$  is exact.**
4. Using Lemma 4.4 (4.5), we conclude  $v^* = v_{\text{SDP}}^*$ . □

- Trust-region subproblems (TRS: QCQP with one constraint)  
Yakubovich[1971]
- Extended TRS (TRS + linear constraints)  
Jeyakumar[2014], Hsia and Sheu[2013], Locatelli[2016]
- QCQPs with sign-definiteness  
Kim and Kojima[2003], Sojoudi and Lavaei[2014]
- Exactness by faces of convex lagrangian multipliers  
Wang and Kılınç-Karzan[2021]
- Rank-one generated cones  
Argue, Kılınç-Karzan and Wang[2020]

### Proposition

If a given  $(\mathcal{P})$  satisfies the condition (2), proposed condition can detect the exactness of its SDP relaxation.

### Idea:

We develop conversion method of QCQPs such that

- The obtained QCQP has bipartite sparsity.
- The obtained QCQP satisfies proposed condition:  
 $\forall (k, \ell) \in \mathcal{E}$ , the system (1) has no solutions.