# Sufficient Conditions for Exact SDP Reformulations of QCQPs 

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## (1) Introduction: SDP Relaxations of QCQP

(2) Symmetries in quadratic forms
(3) A dual object
(4) Conclusion

# (1) Introduction: SDP Relaxations of QCQP 

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## Quadratically Constrained Quadratic Programs (QCQP)

- $q_{0}, q_{1}, \ldots, q_{m}: \mathbb{R}^{n} \rightarrow \mathbb{R}$ be (possibly nonconvex!) quadratic functions

$$
q_{i}(x)=x^{\top} A_{i} x+2 b_{i}^{\top} x+c_{i}
$$

- Want to find

$$
\text { Opt }:=\inf _{x \in \mathbb{R}^{n}}\left\{\begin{array}{l|l}
q_{0}(x) & \begin{array}{l}
q_{1}(x) \leq 0 \\
\vdots \\
q_{m}(x) \leq 0
\end{array}
\end{array}\right\}
$$

## The QCQP Epigraph

$$
\begin{aligned}
\mathrm{Opt} & =\inf _{x \in \mathbb{R}^{n}}\left\{q_{0}(x) \mid q_{i}(x) \leq 0, \forall i \in[m]\right\} \\
& =\inf _{x, t}\left\{t \left\lvert\, \begin{array}{l}
q_{0}(x) \leq t \\
q_{i}(x) \leq 0, \forall i \in[m]
\end{array}\right.\right\}=: \inf _{x, t}\{t \mid(x, t) \in \mathcal{E}\} \\
& =\inf _{x, t}\{t \mid(x, t) \in \operatorname{conv}(\mathcal{E})\}
\end{aligned}
$$



## The standard SDP relaxation of QCQP

## Standard (Shor) SDP relaxation

$$
\begin{aligned}
\text { Opt } & =\inf _{x, X}\left\{\begin{array}{l|l}
\left\langle A_{0}, X\right\rangle+2 b_{0}^{\top} x+c_{0} & \begin{array}{l}
\left\langle A_{1}, X\right\rangle+2 b_{1}^{\top} x+c_{1} \leq 0 \\
\vdots \\
\left\langle A_{m}, X\right\rangle+2 b_{m}^{\top} x+c_{1} \leq 0 \\
X=x x^{\top}
\end{array}
\end{array}\right\} \\
& \geq \inf _{x, X}\left\{\begin{array}{l|l}
\left\langle A_{0}, X\right\rangle+2 b_{0}^{\top} x+c_{0} & \begin{array}{l}
\left\langle A_{1}, X\right\rangle+2 b_{1}^{\top} x+c_{1} \leq 0 \\
\vdots \\
\left\langle A_{m}, X\right\rangle+2 b_{m}^{\top} x+c_{1} \leq 0 \\
X \succeq x x^{\top}
\end{array}
\end{array}\right\} \\
& =: \operatorname{Opt}_{\text {SDP }}
\end{aligned}
$$

## SDP epigraph

$$
\begin{aligned}
& \mathrm{Opt}_{\mathrm{SDP}}=\inf _{x, X}\left\{\begin{array}{l|l}
\left\langle A_{0}, X\right\rangle+2 b_{0}^{\top} x+c_{0} & \begin{array}{l}
\left\langle A_{1}, X\right\rangle+2 b_{1}^{\top} x+c_{1} \leq 0 \\
\vdots \\
\left\langle A_{m}, X\right\rangle+2 b_{m}^{\top} x+c_{1} \leq 0 \\
X \succeq x x^{\top}
\end{array}
\end{array}\right\} \\
& =\inf _{x, X, t}\left\{t \left\lvert\, \begin{array}{l}
\left\langle A_{0}, X\right\rangle+2 b_{0}^{\top} x+c_{0} \leq t \\
\left\langle A_{i}, X\right\rangle+2 b_{i}^{\top} x+c_{i} \leq 0, \forall i \in[m] \\
X \succeq x x^{\top}
\end{array}\right.\right\}
\end{aligned}
$$

- Let $\mathcal{E}_{\text {SDP }}$ be the projection of the epigraph onto $(x, t)$ variables


## The story so far

- QCQP is NP hard, but we can solve SDP relaxation instead
- What are sufficient conditions for
- SDP tightness: $\mathrm{Opt}=\mathrm{Opt}_{\text {SDP }}$ ?
- Convex hull result: $\operatorname{conv}(\mathcal{E})=\mathcal{E}_{\text {SDP }}$ ?


## Related work

- SDP reformulations for QCQPs with a single constraint [Fradkov and Yakubovich, 1979], [W, Kilınç-Karzan, 2019]
- SDP reformulations for variants of TRS [Sturm and Zhang, 2003], [Burer, 2015], [Yang, Anstreicher, and Burer, 2018]
- SDP reformulations for Diagonal QCQPs [Burer and Ye, 2018]
- Quadratic Matrix Programming [Beck, 2007], [Beck, Drori, and Teboulle, 2012]


## Outline

- Analyze a parameter $k$ which captures "amount of symmetry" in a given QCQP
- Under additional "polyhedrality" assumption, $k \geq \operatorname{aff} \operatorname{dim}\left(\left\{b_{i}\right\}\right)+1 \Longrightarrow$ SDP tightness and convex hull result


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## Quadratic eigenvalue multiplicity

## Definition

Let $1 \leq k \leq n$ be the largest integer such that for each $i=0, \ldots, m$, the matrix $A_{i} \in \mathbb{S}^{n}$ has the following block form

$$
A_{i}=\mathcal{A}_{i} \otimes I_{k}=\left(\begin{array}{llll}
\mathcal{A}_{i} & & & \\
& \mathcal{A}_{i} & & \\
& & \ddots & \\
& & & \mathcal{A}_{i}
\end{array}\right)
$$

where $\mathcal{A}_{i} \in \mathbb{S}^{n / k}$

## Quadratic eigenvalue multiplicity

- $A_{i}=\mathcal{A}_{i} \otimes I_{k}$
- Suppose $n=4$

$$
\left.\left.\begin{array}{c}
x_{1}^{2}+x_{2}^{2}+x_{3}^{2}+x_{4}^{2} \\
\left(x_{1}-x_{2}\right)^{2}+\left(x_{3}-x_{4}\right)^{2}
\end{array} \right\rvert\, \begin{array}{cccc} 
& 1 & & \\
& & 1 & \\
& & & 1
\end{array}\right) \left\lvert\, \begin{aligned}
& k=4 \\
& \left(\begin{array}{ccccc}
1 & -1 & & \\
-1 & 1 & & \\
& & 1 & -1 \\
& & -1 & 1
\end{array}\right)
\end{aligned}\right.
$$

## Our first result

## Theorem

Suppose primal feasibility and dual strict feasibility. If $\Gamma$ is polyhedral and

$$
k \geq \operatorname{aff} \operatorname{dim}(\{b(\gamma) \mid \gamma \in \mathcal{F}\})+1
$$

for every semidefinite face $\mathcal{F}$ of $\Gamma$ of affine dimension at most $m-1$, then

$$
\begin{gathered}
\operatorname{conv}(\mathcal{E})=\mathcal{E}_{\mathrm{SDP}} \quad \text { and } \quad \text { Opt }=\mathrm{Opt}_{\mathrm{SDP}} . \\
\Gamma:=\left\{\gamma \in \mathbb{R}^{m} \mid \gamma \geq 0, A_{0}+\sum_{i=1}^{m} \gamma_{i} A_{i} \succeq 0\right\}
\end{gathered}
$$

## Our first result

## Corollary

Suppose primal feasibility and dual strict feasibility. If $\left\{A_{i}\right\}_{i=0}^{m}$ are diagonal and

$$
k \geq \min \left(m, 1+\left|\left\{b_{i} \neq 0\right\}_{i=1}^{m}\right|\right),
$$

then

$$
\operatorname{conv}(\mathcal{E})=\mathcal{E}_{\mathrm{SDP}} \quad \text { and } \quad \mathrm{Opt}=\mathrm{Opt} \mathrm{SDP} .
$$

- When $m=1$
- When $b_{1}=b_{2}=\cdots=b_{m}=0$, the condition is trivially satisfied
- $A_{i}=\alpha_{i} I_{n}$ for all $i=0, \ldots, m$ and $n \geq m$


## Example: Swiss cheese

- $A_{i}=\alpha_{i} I_{n}$ for all $i=0, \ldots, m$ and $n \geq m$
- Minimizing distance to a piece of Swiss cheese

$$
\inf _{x \in \mathbb{R}^{n}}\left\{\begin{array}{l|l}
\|x\|^{2} & \begin{array}{l}
\text { inside ball constraints } \\
\text { outside ball constraints } \\
\text { linear constraints }
\end{array}
\end{array}\right\}
$$

- If nonempty and $n \geq m$, then the standard SDP relaxation is tight for this QCQP


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## Aggregation

- For $\gamma \in \mathbb{R}^{m}$ such that $\gamma \geq 0$, define

$$
q(\gamma, x):=q_{0}(x)+\sum_{i=1}^{m} \gamma_{i} q_{i}(x) \quad A(\gamma):=A_{0}+\sum_{i=1}^{m} \gamma_{i} A_{i}
$$

- Define

$$
\Gamma:=\left\{\gamma \in \mathbb{R}^{m}: \gamma \geq 0, A(\gamma) \succeq 0\right\}
$$




## What does $\Gamma$ look like?



## Rewriting the SDP in terms of $\Gamma$

- $\Gamma$ plays a crucial role in the analysis!


## Theorem

Suppose primal feasibility and dual strict feasibility, then

$$
\begin{aligned}
\mathrm{Opt}_{\mathrm{SDP}} & =\min _{x \in \mathbb{R}^{n}} \sup _{\gamma \in \Gamma} q(\gamma, x) \\
\mathcal{E}_{\mathrm{SDP}} & =\left\{(x, t): \sup _{\gamma \in \Gamma} q(\gamma, x) \leq t\right\}
\end{aligned}
$$

- If $\Gamma$ is polyhedral, then $\mathcal{E}_{\text {SDP }}$ is defined by finitely many convex quadratics $\Longrightarrow$ SOC-representable


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## Conclusion

- Analyzed
- "amount of symmetry" $k$
- the geometry of a dual object $\Gamma$
- Assuming primal feasibility and dual strict feasibility

|  | Polyhedral $\Gamma$ | General $\Gamma$ |
| :---: | :---: | :---: |
| SDP tightness | aff $\operatorname{dim}(\{b(\gamma) \mid \gamma \in \mathcal{F}\})+1$ | $m+1$ |
| Convex hull result | aff $\operatorname{dim}(\{b(\gamma) \mid \gamma \in \mathcal{F}\})+1$ | $m+2$ |

- Results extend to equalities!
- A general framework for proving sufficient conditions
- Future directions
- Are the assumptions on $k$ sharp?
- Can techniques say anything about when SDP is approximately tight?

Thank you. Questions?

Slides and preprint available (hopefully) soon cs.cmu.edu/~alw1

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