

# Inclusion constants for matrix convex sets relevant to quantum incompatibility

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## Convex Combinations

Given a set  $C \subset \mathbb{R}^g$  and a finite collection of tuples  $\{x^\ell\} \subset C$  where  $x^\ell = (x_1^\ell, x_2^\ell, \dots, x_g^\ell)$  and coefficients  $\alpha_\ell \geq 0$  a **convex combination** is a sum of the form

$$\sum_{\ell=1}^k \alpha_\ell x^\ell \in \mathbb{R}^g \quad \text{such that} \quad \sum_{\ell=1}^k \alpha_\ell = 1$$

The **convex hull** of a set  $C$  is the set of all convex combinations of  $C$ . Say  $C$  is **convex** if it is closed under convex combinations.

A point  $x \in C$  is an **extreme point** of  $C$  if it cannot be expressed as a nontrivial convex combination of elements of  $C$ .

## Convex sets have many nice properties

### Theorem [Carathéodory (also see Krein-Milman)]

*Let  $C \subset \mathbb{R}^g$  be a closed bounded convex set. Then  $C$  is the convex hull of its extreme points.*

*Furthermore, every element of  $C$  can be expressed as a convex combination of at most  $g + 1$  extreme points of  $C$ .*

## Linear matrix inequalities give convex sets

A (monic) linear pencil is a matrix valued function  $L_{\mathcal{A}}$  of the form

$$L_{\mathcal{A}}(x) := \mathbf{I}_d - \sum_{j=1}^g \mathbf{A}_j x_j = I_d - \Lambda_{\mathcal{A}}(x),$$

where  $\mathcal{A} = (\mathbf{A}_1, \dots, \mathbf{A}_g)$  with each  $\mathbf{A}_j$  symmetric  $d \times d$  and  $x = (x_1, \dots, x_g) \in \mathbb{R}^g$

A Linear Matrix Inequality (LMI) is one of the form:

$$L_{\mathcal{A}}(x) \succeq 0, \quad i.e., \quad L_{\mathcal{A}}(x) \text{ is positive semidefinite.}$$

The set of solutions  $x$  above is a convex set called a **spectrahedron**. Spectrahedra are the feasibility domains of convex optimization problems called semidefinite programs (SDP).

## Spectrahedron example

Take  $\mathbf{A}_1 = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$  and  $\mathbf{A}_2 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$ . Then

$$L_{\mathcal{A}}(x) = \mathbf{I}_2 - \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} x_1 - \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} x_2 = \begin{pmatrix} 1 - x_1 & -x_2 \\ -x_2 & 1 + x_1 \end{pmatrix}$$

Observe  $L_{\mathcal{A}}(x) \succeq 0$  IFF  $\det(L_{\mathcal{A}}(x)) = 1 - x_1^2 - x_2^2 \geq 0$ . So  $L_{\mathcal{A}}(x)$  defines circle in  $\mathbb{R}^2$ .

## Dimension free sets

Let  $SM_n(\mathbb{R})^g$  denote  $g$ -tuples of real symmetric  $n \times n$  matrices. I.e. if  $\mathcal{X} \in SM_n(\mathbb{R})^g$  then

$$\mathcal{X} = (\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_g)$$

where each  $\mathbf{X}_i$  is a symmetric  $n \times n$  matrix.

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where each  $\mathbf{X}_i$  is a symmetric  $n \times n$  matrix.

Define  $SM(\mathbb{R})^g = \cup_{n=1}^{\infty} SM_n(\mathbb{R})^g$ . A subset of  $SM(\mathbb{R})^g$  is a **dimension free set**.

Our goal: Study solution sets of linear matrix inequalities over  $SM(\mathbb{R})^g$ .

## Free Linear matrix inequalities

A **free (monic) linear pencil** is a matrix valued function  $L_{\mathcal{A}}$  of the form

$$L_{\mathcal{A}}(\mathcal{X}) := \mathbf{I}_{dn} - \sum_{j=1}^g \mathbf{A}_j \otimes \mathbf{X}_j = \mathbf{I}_{dn} - \Lambda_{\mathcal{A}}(\mathcal{X}),$$

where  $\mathcal{A} \in SM_d(\mathbb{R})^g$  and  $\mathcal{X} \in SM_n(\mathbb{R})^g$ . Here  $\otimes$  denotes the Kronecker Product. E.g.

$$\begin{pmatrix} 2 & 3 \\ 3 & 4 \end{pmatrix} \otimes \begin{pmatrix} 4 & 5 \\ 5 & 2 \end{pmatrix} = \begin{pmatrix} 2 \begin{pmatrix} 4 & 5 \\ 5 & 2 \end{pmatrix} & 3 \begin{pmatrix} 4 & 5 \\ 5 & 2 \end{pmatrix} \\ 3 \begin{pmatrix} 4 & 5 \\ 5 & 2 \end{pmatrix} & 4 \begin{pmatrix} 4 & 5 \\ 5 & 2 \end{pmatrix} \end{pmatrix}$$

A **Free Linear Matrix Inequality (LMI)** is one of the form:

$$L_{\mathcal{A}}(\mathcal{X}) \succeq 0.$$



## Free spectrahedra

For each fixed  $n$  the solution set

$$\mathcal{D}_{\mathcal{A}}(n) = \{\mathcal{X} \in SM_n(\mathbb{R})^g : L_{\mathcal{A}}(\mathcal{X}) = \mathbf{I}_{dn} - \sum_{j=1}^g \mathbf{A}_j \otimes \mathbf{X}_j \succeq 0\}$$

is called a **free spectrahedron at level  $n$** .

The set  $\mathcal{D}_{\mathcal{A}} = \cup_n \mathcal{D}_{\mathcal{A}}(n) \subset \cup_n SM_n(\mathbb{R})^g$  is called a **free spectrahedron**.

If  $\mathcal{A}$  a tuple of simultaneously diagonalizable matrices, then  $\mathcal{D}_{\mathcal{A}}$  is called free polyhedron.

## Matrix Convex Combinations

Given a finite collection of tuples  $\{\mathcal{X}^\ell\} \subset SM(\mathbb{R})^g$  where  $\mathcal{X}^\ell = (\mathbf{X}_1^\ell, \dots, \mathbf{X}_g^\ell) \in SM_{n_\ell}(\mathbb{R})^g$ , a **matrix convex combination** is a sum of the form

$$\sum_{\ell=1}^k \mathbf{V}_\ell^T \mathcal{X}^\ell \mathbf{V}_\ell \in SM_n(\mathbb{R})^g \quad \text{such that} \quad \sum_{\ell=1}^k \mathbf{V}_\ell^T \mathbf{V}_\ell = \mathbf{I}_n$$

Here the  $\mathbf{V}_\ell$  are  $n_\ell \times n$  matrices which serve as convex coefficients, and

$$\mathbf{V}_\ell^T \mathcal{X}^\ell \mathbf{V}_\ell = (\mathbf{V}_\ell^T \mathbf{X}_1^\ell \mathbf{V}_\ell, \dots, \mathbf{V}_\ell^T \mathbf{X}_g^\ell \mathbf{V}_\ell).$$

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$$\mathbf{V}_\ell^T \mathcal{X}^\ell \mathbf{V}_\ell = (\mathbf{V}_\ell^T \mathbf{X}_1^\ell \mathbf{V}_\ell, \dots, \mathbf{V}_\ell^T \mathbf{X}_g^\ell \mathbf{V}_\ell).$$

For  $K \subset SM(\mathbb{R})^g$  let  $\text{co}^{\text{mat}}(K)$  denote the set of matrix convex combinations of  $K$ . Say  $K$  is **matrix convex** if it is closed under matrix convex combinations, i.e., if  $K = \text{co}^{\text{mat}}(K)$ .

Say  $K$  is **bounded** if there exists a  $M \geq 0$  such that  $M\mathbf{I} - \sum_{i=1}^g \mathbf{X}_i^2 \succeq 0$  for all  $\mathcal{X} = (\mathbf{X}_1, \dots, \mathbf{X}_g) \in K$ .

## Matrix convex combinations allow for convex combinations of tuples of different sizes

For example, if  $\mathcal{X}^1 \in SM_{n_1}(\mathbb{R})^g$  and  $\mathcal{X}^2 \in SM_{n_2}(\mathbb{R})^g$  and

$$\mathbf{V}_1^T = (\mathbf{I}_{n_1} \quad \mathbf{0}_{n_1 \times n_2}) \quad \text{and} \quad \mathbf{V}_2^T = (\mathbf{0}_{n_2 \times n_1} \quad \mathbf{I}_{n_2}),$$

then

$$\mathbf{V}_1^T \mathcal{X}^1 \mathbf{V}_1 + \mathbf{V}_2^T \mathcal{X}^2 \mathbf{V}_2 = \mathcal{X}^1 \oplus \mathcal{X}^2 = \begin{pmatrix} \mathcal{X}^1 & 0 \\ 0 & \mathcal{X}^2 \end{pmatrix} \quad \text{and} \quad \mathbf{V}_1^T \mathbf{V}_1 + \mathbf{V}_2^T \mathbf{V}_2 = \mathbf{I}_{n_1+n_2}.$$

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On the other hand, if  $\mathcal{X} \in SM_n(\mathbb{R})^g$ , and  $\mathbf{V} \in \mathbb{R}^{n \times m}$  and  $\mathbf{V}^T \mathbf{V} = \mathbf{I}_m$ , then

$$\mathbf{V}^T \mathcal{X} \mathbf{V} \in SM_m(\mathbb{R})^g$$

is a matrix convex combination of  $\mathcal{X}$ .

## Matrix convex combinations vs dilations

Given a finite collection of tuples  $\{\mathcal{X}^\ell\}_{\ell=1}^k \subset SM(\mathbb{R})^g$  and matrices  $\mathbf{V}_\ell \in M_{n_\ell \times n}(\mathbb{R})$  such that  $\mathbf{V}_\ell^T \mathbf{V}_\ell = \mathbf{I}_n$ , define

$$\mathcal{X} = \oplus_{\ell=1}^k \mathcal{X}^\ell \quad \text{and} \quad \mathbf{V}^T = (\mathbf{V}_1^T \ \dots \ \mathbf{V}_k^T).$$

Then

$$\sum_{\ell=1}^k \mathbf{V}_\ell^T \mathcal{X}^\ell \mathbf{V}_\ell = \mathbf{V}^T \mathcal{X} \mathbf{V} \quad \text{and} \quad \mathbf{V}^T \mathbf{V} = \mathbf{I}.$$

## Sets defined by Free LMI are matrix convex

Free spectrahedra are matrix convex.

### Theorem [Helton-McCullough 12]

*Let  $p$  be a noncommutative polynomial and let  $\mathcal{D}_p$  be the component containing 0 of  $\{\mathcal{X} \in SM(\mathbb{R})^g \mid p(\mathcal{X}) \succeq 0\}$ . If  $\mathcal{D}_p$  is matrix convex, then  $\mathcal{D}_p$  is a free spectrahedron.*

Question: What is the right notion of extreme point for matrix convex sets (and in particular for free spectrahedra)?

## Extreme points of matrix convex sets

Say  $\mathcal{X}$  is a **matrix extreme point** of  $K \subset SM(\mathbb{R})^g$  if  $\mathcal{X}$  cannot be expressed as a nontrivial matrix convex combination of elements of  $K$  *which have size less than or equal to  $\mathcal{X}$* .

Say  $\mathcal{X}$  is a **free (absolute) extreme point** of  $K \subset SM(\mathbb{R})^g$  if  $\mathcal{X}$  cannot be expressed as a nontrivial matrix convex combination of **any** elements of  $K$ .



## Matrix extreme vs free extreme

Let  $K \subset SM(\mathbb{R})^g$  be a (level-wise) closed bounded matrix convex set

### Matrix extreme points

1. Always span  $K$  through matrix convex combinations. (Webster-Winkler 99)
2. Not necessarily a minimal spanning set.
3. Carathéodory bound:  $\mathcal{X} \in K(n)$  can be expressed as a sum of at most  $n^2(g+1)$  matrix extreme points of  $K$ . (Hartz-Lupini 21)

### Free extreme points

1. Can fail to exist. (E 18, Passer 22)
2. Necessarily a minimal spanning set if they span.
3. Carathéodory bound: If  $K$  is a free spectrahedron, then  $\mathcal{X} \in K(n)$  can be expressed as matrix convex combo of free extreme points of  $K$  with **sum of sizes** at most  $n(g+1)$ . (E-Helton 19)

# Containment of Matrix Convex Sets

## Free spectrahedral containment

Let  $\mathcal{A} \in SM_{d_1}(\mathbb{R})^g$  and  $\mathcal{B} \in SM_{d_2}(\mathbb{R})^g$ . Determining the spectrahedral containment  $\mathcal{D}_{\mathcal{A}}(1) \subset \mathcal{D}_{\mathcal{B}}(1)$  is NP-hard in general . (Ben-Tal, Nemirovski)

## Free spectrahedral containment

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Determining the optimal constant  $\gamma$  such that  $\mathcal{D}_{\mathcal{A}} \subset \gamma \mathcal{D}_{\mathcal{B}}$  is a **semidefinite program**. (Helton, Klep, McCullough).

HKM show that  $\mathcal{D}_{\mathcal{A}} \subset \gamma \mathcal{D}_{\mathcal{B}} = \mathcal{D}_{\mathcal{B}/\gamma}$  if and only if the map  $\tau$  defined by

$$\tau(\mathbf{I}_{d_1}) = \gamma \mathbf{I}_{d_2} \quad \text{and} \quad \tau(\mathbf{A}_j) = \mathbf{B}_j \quad \text{for } j = 1, \dots, g.$$

is **completely positive**, which happens if and only if  $\tau$  is  $d_2$ -positive.

## Containment of general matrix convex sets and free polar duals

Let  $K$  be a compact matrix convex set. Given  $\mathcal{X} \in SM(\mathbb{R})^g$ , how can one check if  $\mathcal{X} \in K$ ?

## Containment of general matrix convex sets and free polar duals

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The free polar dual  $K^\circ$  of  $K$  is

$$K^\circ := \{\mathcal{Y} \in SM(\mathbb{R})^g : L_{\mathcal{Z}}(\mathcal{Y}) \succeq 0 \text{ for all } \mathcal{Z} \in K\} = \cap_{\mathcal{Z} \in K} \mathcal{D}_{\mathcal{Z}}$$

A quick check now shows

$$\mathcal{X} \in K \quad \Longleftrightarrow \quad K^\circ \subseteq \{\mathcal{X}\}^\circ = \mathcal{D}_{\mathcal{X}}$$

Thus, if  $K^\circ$  is a free spectrahedron, then the containment can be checked via an SDP.

## Minimal and maximal matrix Convex sets

Let  $C \subset \mathbb{R}^g$  be convex set and assume that  $0 \in C$ . The minimal matrix convex set generated by  $C$ , denoted  $\mathcal{W}^{\min}(C)$  is the matrix convex hull of  $C$ .

The maximal matrix convex  $\mathcal{W}^{\max}(C)$  is the set of  $\mathcal{X} \in SM(\mathbb{R})^g$  which satisfy all of the affine linear relations satisfied by  $C$ .

In particular, if  $C$  is a polyhedron containing 0, then  $\mathcal{W}^{\max}(C)$  is a free spectrahedron.

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Fact: If  $K$  is a matrix convex set with  $K(1) = C$ , then  $\mathcal{W}^{\min}(C) \subset K \subset \mathcal{W}^{\max}(C)$

Question: how can one determine the optimal  $\gamma \geq 1$  such that

$$\mathcal{W}^{\max}(C) \subset \gamma \mathcal{W}^{\min}(C)$$



## Duality of minimal and maximal matrix convex sets

For a compact convex set  $C \subset \mathbb{R}^g$ , let  $C'$  denote its classical dual. That is

$$C' = \{x \in \mathbb{R}^g : \langle x, y \rangle \leq 1 \text{ for all } y \in C\}.$$

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Davidson, Dor-on, Shalit, Solel show that, minimal and maximal matrix convex sets are dual to each other in that

$$(\mathcal{W}^{\min}(C))^{\circ} = \mathcal{W}^{\max}(C')$$

Furthermore if  $0 \in C$ , then

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Furthermore if  $0 \in C$ , then

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Thus, the free polar dual of a minimal matrix convex set generated by a polyhedron is in fact a free spectrahedron.

# Incompatibility of Quantum measurements

## Free spectrahedra vs. incompatibility of quantum measurements

Key feature of quantum mechanics is existence of incompatible observables, e.g., position and momentum, which are not jointly measurable.

Idea: Quantify incompatibility of measurements (interpreted as POVMs) by determining the probability that adding noise makes measurements jointly measurable.

## Free spectrahedra vs. incompatibility of quantum measurements

Key feature of quantum mechanics is existence of incompatible observables, e.g., position and momentum, which are not jointly measurable.

Idea: Quantify incompatibility of measurements (interpreted as POVMs) by determining the probability that adding noise makes measurements jointly measurable.

(Bluhm, Nechita) This is equivalent to determining the smallest constant  $\gamma$  such that

$$\mathcal{D}_{\mathcal{A}}(n) \subset \gamma \mathcal{W}^{\min}(\mathcal{D}_{\mathcal{A}}(1))$$

where  $\mathcal{D}_{\mathcal{A}}$  is a Cartesian product of free polyhedron of interest determined by the quantum system and where  $n$  is the dimension of the POVM. (E.g,  $n = 2$  is qubits).

## Incompatibility vs Matrix extreme points

Since  $\mathcal{D}_{\mathcal{A}}(n)$  is contained in the matrix convex hull of the matrix extreme points of  $\mathcal{D}_{\mathcal{A}}$  of size at most  $n$ , one has

$$\mathcal{D}_{\mathcal{A}}(n) \subset \gamma\mathcal{W}^{\min}(\mathcal{D}_{\mathcal{A}}(1))$$

if and only if

$$\mathcal{X} \subset \gamma\mathcal{W}^{\min}(\mathcal{D}_{\mathcal{A}}(1))$$

for all matrix extreme points  $\mathcal{X} \in \mathcal{D}_{\mathcal{A}}$  of size at most  $n$ .

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for all matrix extreme points  $\mathcal{X} \in \mathcal{D}_{\mathcal{A}}$  of size at most  $n$ .

This is in turn equivalent to

$$\mathcal{D}_{\mathcal{A}'} \subset \gamma\mathcal{D}_{\mathcal{X}}$$

for all matrix extreme points  $\mathcal{X} \in \mathcal{D}_{\mathcal{A}}$  of size at most  $n$ , where  $\mathcal{D}_{\mathcal{A}'}$  is a free polyhedron whose first level is the classical dual of  $\mathcal{D}_{\mathcal{A}}(1)$ .



## Matrix Extreme points vs Cartesian products

### Proposition [Bluhm-E-Klep-Magron-Nechita]

*Let  $\mathcal{D}_{\mathcal{A}}$  and  $\mathcal{D}_{\mathcal{B}}$  be bounded free spectrahedra. If  $\mathcal{X}$  and  $\mathcal{Y}$  are matrix extreme points of  $\mathcal{D}_{\mathcal{A}}$  and  $\mathcal{D}_{\mathcal{B}}$ , then  $(\mathcal{X}, \mathcal{Y})$  is a matrix extreme points of  $\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}}$ . However, matrix extreme points of  $\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}}$  need not be pairs of matrix extreme points of  $\mathcal{D}_{\mathcal{A}}$  and  $\mathcal{D}_{\mathcal{B}}$ .*

*If  $\mathcal{D}_{\mathcal{A}}$  is assumed to be a free simplex and  $\mathcal{D}_{\mathcal{B}}$  is the free interval, then  $(\mathcal{X}, \mathcal{Y})$  is a real matrix extreme point of  $(\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(2)$  if and only if (up to minor details)  $\mathcal{X}$  and  $\mathcal{Y}$  are matrix extreme points of  $\mathcal{D}_{\mathcal{A}}$  and  $\mathcal{D}_{\mathcal{B}}$ , respectively.*

Here  $\mathcal{D}_{\mathcal{A}}$  is a free simplex if  $\mathcal{A} \in SM_{g+1}(\mathbb{R})^g$  is a tuple of diagonal matrices and  $\mathcal{D}_{\mathcal{A}}$  is bounded.

In the classical setting, pairs of extreme points are extreme points in a Cartesian product.

## The Cartesian product of a free simplex and a line

### Theorem [Bluhm-E-Klep-Magron-Nechita]

For  $\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}}$  the Cartesian product of a “(real) standard free simplex in  $k$  variables” and the “(real) free interval”, the smallest constant  $\gamma_k$  such that

$$(\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(2) \subset \gamma_k \mathcal{W}^{\min}((\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(1))$$

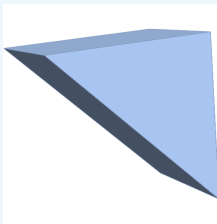
is given by

$$\gamma_k = \frac{2k}{k-1+\sqrt{k+1}}$$

We conjecture also that  $\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}} \subset \gamma_k \mathcal{W}^{\min}((\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(1))$ .

## Extreme points of a two variable free simplex and a line

When the simplex has two variables,  $\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}}$  at level one is the following spectrahedron,



which has extreme points

$E = \{(1, 1, 1), (1, -2, 1), (-2, 1, 1), (1, 1, -1), (1, -2, -1), (-2, 1, -1)\}$ . Let  $\mathcal{E} \in SM_6(\mathbb{R})^3$  be the diagonal tuple given by taking a direct sum of elements of  $E$ .

Fact:  $\mathcal{D}_{\mathcal{E}}(1)$  is the classical dual of  $(\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(1)$ . Thus the optimization in question is equivalent to finding  $\gamma$  s.t.

$$\min_{\gamma \in \mathbb{R}} \quad \text{s.t.} \quad \mathcal{D}_{\mathcal{E}} \subset \gamma \mathcal{D}_{\mathcal{X}}$$

for all matrix extreme points  $\mathcal{X}$  of  $(\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(2)$ .

## A feasibility SDP to find $\gamma$

Let  $E = \{(1, 1, 1), (1, -2, 1), (-2, 1, 1), (1, 1, -1), (1, -2, -1), (-2, 1, -1)\}$ . Let  $\mathcal{E} \in SM_6(\mathbb{R})^3$  be the diagonal tuple given by taking a direct sum of elements of  $E$  and let  $\mathcal{X} \in (\mathcal{D}_A \times \mathcal{D}_B)(2)$ . Then  $\mathcal{D}_{\mathcal{E}} \subset \gamma \mathcal{D}_{\mathcal{X}}$  if and only if the HKM SDP

$$C \in SM_2(\mathbb{R})^6$$

$$\oplus_{i=1}^6 C_i \succeq 0,$$

$$C_1 - 2C_2 + C_3 + C_4 - 2C_5 + C_6 = X_1,$$

$$C_1 + C_2 - 2C_3 + C_4 + C_5 - 2C_6 = X_2,$$

$$C_1 + C_2 + C_3 - C_4 - C_5 - C_6 = X_3,$$

$$C_1 + C_2 + C_3 + C_4 + C_5 + C_6 = \gamma I,$$

is feasible.

## A feasibility SDP to find $\gamma$

### Theorem [Bluhm-E-Klep-Magron-Nechita]

For  $\mathcal{D}_{\mathcal{A}}$  the Cartesian product of a standard free simplex in two variables and interval and  $\gamma \in \mathbb{R}$ , we have  $(\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(2) \subset \gamma(\text{co}^{\text{mat}}(\mathcal{D}_{\mathcal{A}}(1)))$  if and only if

$$\mathcal{D}_{\mathcal{E}} \subset \mathcal{D}_{\mathcal{X}(\theta)} \quad \text{for all } \theta \in [0, \pi/2]$$

where

$$\mathcal{X}(\theta) = \left( \begin{pmatrix} 1 & 0 \\ 0 & -2 \end{pmatrix}, \begin{pmatrix} -2 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) \end{pmatrix} \right)$$

Moreover, if  $\gamma_2 = \frac{4}{1+\sqrt{3}}$ , then  $\mathcal{D}_{\mathcal{E}} \subset \gamma_2 \mathcal{D}_{\mathcal{X}(\theta)}$  for all  $\theta \in [0, \pi/2]$ .

## Proof of the theorem for $k = 2$

Using our classification of the matrix extreme points of  $(\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(2)$ , we find that up to unitary equivalence, all matrix extreme points of  $(\mathcal{D}_{\mathcal{A}} \times \mathcal{D}_{\mathcal{B}})(2)$  have one of the forms

$$\mathcal{X}(\theta) = \left( \begin{pmatrix} 1 & 0 \\ 0 & -2 \end{pmatrix}, \begin{pmatrix} -2 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) \end{pmatrix} \right)$$

$$\mathcal{Y}(\theta) = \left( \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} -2 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) \end{pmatrix} \right)$$

$$\mathcal{Z}(\theta) = \left( \begin{pmatrix} 1 & 0 \\ 0 & -2 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) \end{pmatrix} \right)$$

where  $\theta \in [0, \pi]$ .

## Proof of the theorem for $k = 2$

By examining the HKM SDP in question, we can show that solutions for extreme points of the form  $\mathcal{X}(\theta)$  give solutions to the remaining forms.

E.g., one can show that  $(C_1, C_2, C_3, C_4, C_5, C_6)$  is a solution for  $\mathcal{X}(\theta)$  if and only if  $(C_2, C_1, C_3, C_5, C_4, C_6)$  is a solution for  $\mathcal{Y}(\theta)$ .

Arguing similarly allows one to restrict to  $\theta \in [0, \pi/2]$ .

From here, we construct an exact feasible point of the HKM SDP.

## Proof of the theorem for $k \geq 3$

Classifying extreme points of  $(\mathcal{D}_\mathcal{A} \times \mathcal{D}_\mathcal{B})(2)$  and examining the form of the HKM SDP allows a dimension reduction from a  $k$ -variable simplex to a scaled 2-variable simplex.



## Proof of the theorem for $k \geq 3$

Classifying extreme points of  $(\mathcal{D}_A \times \mathcal{D}_B)(2)$  and examining the form of the HKM SDP allows a dimension reduction from a  $k$ -variable simplex to a scaled 2-variable simplex.

This leads to the HKM feasibility SDP

$$C \in SM_2(\mathbb{R})^6$$

$$\oplus_{i=1}^6 C_i \succeq 0,$$

$$C_1 - kC_2 + C_3 + C_4 - kC_5 + C_6 = \begin{pmatrix} 1 & 0 \\ 0 & -k \end{pmatrix},$$

$$C_1 + C_2 - kC_3 + C_4 + C_5 - kC_6 = \begin{pmatrix} -k & 0 \\ 0 & 1 \end{pmatrix},$$

$$C_1 + C_2 + C_3 - C_4 - C_5 - C_6 = \begin{pmatrix} \cos(\theta) & \sin(\theta) \\ \sin(\theta) & -\cos(\theta) \end{pmatrix},$$

$$C_1 + C_2 + C_3 + C_4 + C_5 + C_6 = \gamma_k I,$$

### A feasible point for $k \geq 3$

The following point is feasible. Set  $\alpha(k) := \frac{1}{2k+4\sqrt{k+1}+2}$  and set

$$C_1(\theta) = \alpha(k) \begin{pmatrix} k-1-2\cos(\theta) & (k-1)\sin(\theta) \\ (k-1)\sin(\theta) & k-1+2\cos(\theta) \end{pmatrix}$$

$$C_2(\theta) = \alpha(k) \begin{pmatrix} 1+\cos(\theta) & (\sqrt{k+1}+1)\sin(\theta) \\ (\sqrt{k+1}+1)\sin(\theta) & (k+2\sqrt{k+1}+2)(1-\cos(\theta)) \end{pmatrix}$$

$$C_3(\theta) = \alpha(k) \begin{pmatrix} (k+2\sqrt{k+1}+2)(1+\cos(\theta)) & (\sqrt{k+1}+1)\sin(\theta) \\ (\sqrt{k+1}+1)\sin(\theta) & 1-\cos(\theta) \end{pmatrix}$$

$$C_4(\theta) = \alpha(k) \begin{pmatrix} k-1+2\cos(\theta) & -(k-1)\sin(\theta) \\ -(k-1)\sin(\theta) & k-1-2\cos(\theta) \end{pmatrix}$$

$$C_5(\theta) = \alpha(k) \begin{pmatrix} 1-\cos(\theta) & -(\sqrt{k+1}+1)\sin(\theta) \\ -(\sqrt{k+1}+1)\sin(\theta) & (k+2\sqrt{k+1}+2)(1+\cos(\theta)) \end{pmatrix}$$

$$C_6(\theta) = \alpha(k) \begin{pmatrix} (k+2\sqrt{k+1}+2)(1-\cos(\theta)) & -(\sqrt{k+1}+1)\sin(\theta) \\ -(\sqrt{k+1}+1)\sin(\theta) & 1+\cos(\theta) \end{pmatrix}$$

## Checking the point is feasible

To check the point is feasible, one need only put it into the HKM SDP and verify the constraints hold, then verify each  $C_j(\theta)$  is positive semidefinite by showing its trace and determinant are nonnegative (which is sufficient since they are  $2 \times 2$ ).

This solution does not extend to the  $k = 2$  variable case. The issue is that

$$\det(C_1(\theta)) = \det(C_4(\theta)) = \alpha(k)^2(k-3)(k+1)\cos(\theta)^2$$

which is negative when  $k = 2$ .

The  $k = 2$  feasible point we constructed

Set

$$C_1 = \left( \frac{1}{\sqrt{3}} - \frac{1}{2} \right) \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \quad \text{and} \quad C_2 = \alpha \begin{pmatrix} 1 & \beta \\ \beta & \beta^2 \end{pmatrix}$$

where  $\alpha$  and  $\beta$  defined on the next slide. Then  $(C_1, C_2)$  is a feasible point of the HKM SDP

$$\begin{aligned} C_1 \oplus C_2 &\succeq 0, \\ -2C_1 - 2C_2 + X_3(\theta) + \gamma I &\succeq 0, \\ -3C_1 + X_1 + X_2 + \gamma I &\succeq 0, \\ -3C_2 - X_1 + \gamma I &\succeq 0, \\ C_1 + C_2 - X_2/3 - X_3(\theta)/2 - \gamma I/6 &\succeq 0, \end{aligned}$$

The constraints in the HKM SDP allow us to solve for the remaining variables unknowns in terms of  $C_1, C_2$ , so this formulation is equivalent

## The choice of $\alpha$ and $\beta$

In the previous slide

$$\alpha = \frac{2}{6 + 4\sqrt{3} + \sqrt{3}\beta^2},$$

and

$$\beta_+ := \frac{\zeta_1 + \zeta_2}{\zeta_3} \quad \text{or} \quad \beta_- := \frac{\zeta_1 - \zeta_2}{\zeta_3}$$

with

$$\zeta_1 = 12(2 + \sqrt{3})\sin(\theta) - 4\sqrt{3}$$

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$$\zeta_2 = \sqrt{6}\sqrt{8\eta_1\sin(\theta) + 6\eta_1\sin(2\theta) + 6\eta_2\cos(\theta) + 6(2 + \sqrt{3})\cos(2\theta) + 181\sqrt{3} + 318}$$

$$\zeta_3 = -6\sin(\theta) + 12(2 + \sqrt{3})\cos(\theta) + 14\sqrt{3} + 21$$

and

$$\eta_1 = 12 + 7\sqrt{3} \quad \text{and} \quad \eta_2 = 54 + 31\sqrt{3}.$$

For context as to how much messier this is than the  $k \geq 3$  case...

A big challenge ends up being showing that  $C_1 + C_2 - X_2/3 - X_3(\theta)/2 - \gamma I/6 \succeq 0$ . One can do this by looking at the trace and determinant. We couldn't show that this is positive if one fixes a choice  $\beta_+$  of  $\beta_-$ .

We showed that if  $h(\theta)$  defined below is positive for  $\theta \in [0, \pi/2]$ , then for each  $\theta$ , either choosing  $\beta_+$  or  $\beta_-$  will work.

$$\begin{aligned} h(\theta) = & 3 (1659159 + 957244\sqrt{3}) \sin(\theta) + 24 (108048 + 62413\sqrt{3}) \sin(2\theta) \\ & - 18 (84547 + 48802\sqrt{3}) \sin(3\theta) - 36 (48096 + 27769\sqrt{3}) \sin(4\theta) \\ & - 81 (5307 + 3064\sqrt{3}) \sin(5\theta) + 48 (11401 + 6598\sqrt{3}) \cos(\theta) \\ & + 54 (5341 + 3100\sqrt{3}) \cos(2\theta) - 36 (7538 + 4359\sqrt{3}) \cos(3\theta) \\ & - 108 (3469 + 2003\sqrt{3}) \cos(4\theta) - 324 (362 + 209\sqrt{3}) \cos(5\theta) \\ & + 62 (3963 + 2266\sqrt{3}) . \end{aligned}$$