Ungleichungen und ähnlich verwirrende Konzepte

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University of Cologne

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- Grothendieck-Tsirelson Theorem
 - Motivation: The Grothendieck-Tsirelson Theorem
 - Grothendieck's Inequality
 - Tsirelson's Theorem
 - Gorthendieck-Tsirelson Theorem

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Theorem (Grothendieck-Tsirelson)

There exists an absolute constant $K \ge 1$ such that, for any positive integers m, n, the following three equivalent conditions hold:

(1) We have the inclusion

$$QC_{m,n} \subset KLC_{m,n}. \tag{1}$$

(2) For any $M \in \mathbb{R}^{m \times n}$ and for any ρ, X_i, Y_j verifying the conditions of Definition 4.2.1 we have

$$\sum_{i,j} M_{ij} \operatorname{Tr} \rho(X_i \otimes Y_j) \le K \max_{\xi \in \{-1,1\}^m, \eta \in \{-1,1\}^n} \sum_{i,j} M_{ij} \xi_i \eta_j \qquad (2)$$

$$\Leftrightarrow$$

$$\operatorname{\mathsf{Tr}} M A^{ op} \leq \max_{\xi \in \{-1,1\}^m, \eta \in \{-1,1\}^n} \operatorname{\mathsf{Tr}} M (\xi \eta^{ op})^{ op}.$$
 (3)

(3) For any $M \in \mathbb{R}^{m \times n}$ and for any (real) Hilbert space vectors x_i, y_j with $|x_i| \le 1$, $|y_j| \le 1$ we have

$$\sum_{i,j} M_{i,j} \langle x_i, y_j \rangle \le K \max_{\xi \in \{-1,1\}^m, \eta \in \{-1,1\}^n} \operatorname{Tr} \xi^\top M \eta. \tag{4}$$

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Let $x, y \in \mathbb{R}^d$ be unit vectors. Let $r \in \mathbb{R}^d$ be a random unit vector chosen from O(d)-invariant probability distribution on the unit sphere. Then

- i, $\mathbb{P}[\operatorname{sign}(\langle x, r \rangle) \neq \operatorname{sign}(\langle y, r \rangle)] = \frac{\operatorname{arccos}(\langle x, y \rangle)}{\pi}$
- ii, $\mathbb{E}[\operatorname{sign}(\langle x, r \rangle) \operatorname{sign}(\langle y, r \rangle)] = \frac{2}{\pi} \arcsin(\langle x, y \rangle)$.

Proof.

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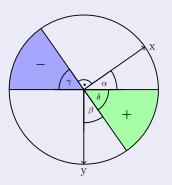
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 - project r orthogonally on span $\{x,y\}$ which gives us a vector s with $\langle x,r\rangle=\langle x,s\rangle$ and $\langle y,r\rangle=\langle y,s\rangle$

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- if x and y are linearly independent, then
 - project r orthogonally on span $\{x,y\}$ which gives us a vector s with $\langle x,r\rangle=\langle x,s\rangle$ and $\langle y,r\rangle=\langle y,s\rangle$
 - the normalized vector $n := s/\|s\|$ is uniformly distributed on the intersection of the unit sphere and span $\{x,y\}$ by the O(d)-invariance of the probability distribution

Calculation of the probability that the signs of the scalar products $\langle x, n \rangle$ and $\langle y, n \rangle$ are unlike:



$$\mathbb{P}[\mathsf{sign}(\langle x, \textit{n} \rangle) \neq \mathsf{sign}(\langle y, \textit{n} \rangle)] = 2\frac{\frac{\pi}{2} + \alpha}{2\pi} = \frac{\mathsf{arccos}(\langle x, y \rangle)}{\pi}$$

We conclude with the proof of the second part of Lemma 1:

$$\begin{split} \mathbb{E}[\operatorname{sign}(\langle x, r \rangle) \operatorname{sign}(\langle y, r \rangle)] &= 1 \cdot \mathbb{P}[\operatorname{sign}(\langle x, r \rangle) = \operatorname{sign}(\langle y, r \rangle)] - 1 \cdot \mathbb{P}[\operatorname{sign}(\langle x, r \rangle) \neq \operatorname{sign}(\langle y, r \rangle)] \\ &= 1 - 2\mathbb{P}[\operatorname{sign}(\langle x, r \rangle) \neq \operatorname{sign}(\langle y, r \rangle)] \\ &= 1 - 2\frac{\operatorname{arccos}(\langle x, y \rangle)}{\pi} \\ &= \frac{2}{\pi} \operatorname{arcsin}(\langle x, y \rangle), \end{split}$$

because
$$\arcsin(t) + \arccos(t) = \pi/2$$
.

Lemma (Krivine's trick)

Let $x_1,\ldots,x_m,y_1,\ldots,y_n\in S^{m+n-1}$ be given. Furthermore, let $r\in\mathbb{R}^d$ be a random unit vector chosen form the O(d)-invariant probability distribution on the unit sphere. Then there are $x_1',\ldots,x_m',y_1',\ldots,y_n'\in S^{m+n-1}$ so that

$$\mathbb{E}[\operatorname{sign}(\langle x_i', r \rangle) \operatorname{sign}(\langle y_j', r \rangle)] = \beta \langle x_i, y_j \rangle, \tag{5}$$

with
$$\beta = \frac{2}{\pi} \ln(1 + \sqrt{2})$$
.

Definition (The k-th tensor product)

The k-th tensor product of \mathbb{R}^n with orthonormal basis e_1, \ldots, e_n is denoted by $(\mathbb{R}^n)^{\otimes k}$ and it is a Euclidean vector space of dimension n^k with othonormal basis $e_{i_k} \otimes \cdots \otimes e_{i_k}$, $i_j \in \{1, \ldots, n\}$. In particular

$$\langle e_{i_1} \otimes \cdots \otimes e_{i_k}, e_{j_1} \otimes \cdots \otimes e_{j_k} \rangle = \prod_{l=1}^{\kappa} \langle e_{i_l}, e_{j_l} \rangle$$

$$= \begin{cases} 1 & , \text{ if } i_l = j_l \text{ for all } l = 1, \dots, n, \\ 0 & , \text{ otherwise,} \end{cases}$$
 (6)

and for $v \in \mathbb{R}^n$ with $v = v_1 e_1 + \dots + v_n e_n$ we define $v^{\otimes k} \in (\mathbb{R}^n)^{\otimes k}$ by

$$v^{\otimes k} := (v_1 e_1 + \dots + v_n e_n) \otimes \dots \otimes (v_1 e_1 + \dots + v_n e_n)$$

$$= \sum_{i_1, \dots, i_k} v_{i_1} \cdots v_{i_k} e_{i_1} \otimes \dots \otimes e_{i_k}.$$
(7)

Thus, for $v, w \in \mathbb{R}^n$

$$\langle v^{\otimes k}, w^{\otimes k} \rangle = \langle v, w \rangle^k.$$
 (8)

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- idea: To find β, x'_i, y'_i invert E:

$$E^{-1}(t) = \sin(\pi/2 \cdot t) = \sum_{k=0}^{\infty} \underbrace{\frac{(-1)^{2k+1}}{(2k+1)!} \left(\frac{\pi}{2}\right)^{2k+1}}_{=:g_{2k+1}} t^{2k+1}$$

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• define the infinite-dimensional Hilbert space

$$H = \bigoplus_{n=0}^{\infty} (\mathbb{R}^{m+n})^{\otimes 2k+1}.$$
 (9)



• define $\tilde{x}_i, \tilde{y}_i \in H$, $i = 1, \dots, m, j = 1, \dots, n$ componentwise:

$$(\tilde{x}_i)_k = \operatorname{sign}(g_{2k+1}) \sqrt{|g_{2k+1}|\beta^{2k+1}} x_i^{\otimes 2k+1}$$
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$$(\tilde{y}_j)_k = \sqrt{|g_{2k+1}|\beta^{2k+1}} y_j^{\otimes 2k+1}$$
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then

$$\begin{split} \langle \tilde{x}_i, \tilde{y}_j \rangle &= \sum_{k=0}^{\infty} g_{2k+1} \beta^{2k+1} \langle x_i^{\otimes 2k+1}, y_j^{\otimes 2k+1} \rangle \\ &= \sum_{k=0}^{\infty} g_{2k+1} \beta^{2k+1} \langle x_i, y_j \rangle^{2k+1} \\ &= E^{-1} (\beta \langle x_i, y_i \rangle). \end{split}$$

• hence, β is defined by the condition that the vectors $\tilde{x}_i, \ldots, \tilde{x}_m, \tilde{y}_1, \ldots, \tilde{y}_n$ are unit vectors:

$$\begin{split} 1 &= \langle \tilde{x}_i, \tilde{x}_i \rangle = \langle \tilde{y}_j, \tilde{y}_j \rangle = \sum_{k=0}^{\infty} \frac{1}{(2k+1)!} \left(\frac{\pi}{2}\right)^{2k+1} \beta^{2k+1} = \sinh(\frac{\pi}{2}\beta) \\ \Leftrightarrow \qquad \beta &= \frac{2}{\pi} \operatorname{arcsinh}(1) = \frac{2}{\pi} \ln(1+\sqrt(2)) \end{split}$$

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- problem: $\tilde{x}_1, \dots, \tilde{x}_m, \tilde{y}_1, \dots, \tilde{y}_n$ are infinite-dimensional
- ullet solution: the positive definite and symmetric Gram matrix G

$$G = \begin{pmatrix} \langle \tilde{\mathbf{x}}_{1}, \tilde{\mathbf{x}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{x}}_{1}, \tilde{\mathbf{x}}_{m} \rangle & \langle \tilde{\mathbf{x}}_{1}, \tilde{\mathbf{y}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{x}}_{1}, \tilde{\mathbf{y}}_{n} \rangle \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \langle \tilde{\mathbf{x}}_{m}, \tilde{\mathbf{x}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{x}}_{m}, \tilde{\mathbf{x}}_{m} \rangle & \langle \tilde{\mathbf{x}}_{m}, \tilde{\mathbf{y}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{x}}_{m}, \tilde{\mathbf{y}}_{n} \rangle \\ \langle \tilde{\mathbf{y}}_{1}, \tilde{\mathbf{x}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{y}}_{1}, \tilde{\mathbf{x}}_{m} \rangle & \langle \tilde{\mathbf{y}}_{1}, \tilde{\mathbf{y}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{y}}_{1}, \tilde{\mathbf{y}}_{n} \rangle \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \langle \tilde{\mathbf{y}}_{n}, \tilde{\mathbf{x}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{y}}_{n}, \tilde{\mathbf{x}}_{m} \rangle & \langle \tilde{\mathbf{y}}_{n}, \tilde{\mathbf{y}}_{1} \rangle & \cdots & \langle \tilde{\mathbf{y}}_{n}, \tilde{\mathbf{y}}_{n} \rangle \end{pmatrix}$$

$$(12)$$

• due to the properties of G we can decompose G via a real orthogonal matrix Q with columns that are the eigenvectors of G and a real diagonal matrix Λ having the eigenvalues of G on the diagonal, thus

$$G = Q\Lambda Q^{\top} = \underbrace{(Q\Lambda^{1/2})^{\top}(Q\Lambda^{1/2})}_{=:A}$$
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• the columns of A are the vectors $x_1',\ldots,x_m',y_1',\ldots,y_n'\in S^{m+n-1}$ we are looking for

Definition

For $M \in \mathbb{R}^{m \times n}$ define the quadratic program

$$||M||_{\infty \to 1} = \max \left\{ \sum_{i=1}^{m} \sum_{j=1}^{n} M_{ij} \xi_{i} \eta_{j} : \xi_{i}^{2} = 1, i = 1, \dots, m, \eta_{j}^{2} = 1, j = 1, \dots, n \right\}$$

$$= \max \left\{ \operatorname{Tr} M \eta \xi^{\top} : \xi \in \{-1, 1\}^{m}, \eta \in \{-1, 1\}^{n} \right\}. \tag{14}$$

Definition

The SDP relaxation of $||M||_{\infty \to 1}$ is given via:

$$\mathsf{sdp}_{\infty \to 1}(M) = \max \sum_{i=1}^{m} \sum_{j=1}^{n} M_{ij} \langle x_i, y_j \rangle$$

$$x_i, y_j \in \mathbb{R}^{m+n}$$

$$\|x_i\| = 1, i = 1, \dots, m$$

$$\|y_j\| = 1, j = 1, \dots, n$$

Theorem (Grothendieck's inequality)

There exists a constant K such that for all $M \in \mathbb{R}^{m \times n}$:

$$||M||_{\infty \to 1} \le \operatorname{sdp}_{\infty \to 1}(M) \le K||M||_{\infty \to 1}. \tag{15}$$

Proof.

Use the following approximation algorithm with randomized rounding:

Algorithm 1: Approximation algorithm with randomized rounding for $||M||_{\infty \to 1}$

- 1. Solve $\operatorname{sdp}_{\infty \to 1}(M)$. Let $x_1, \ldots, x_m, y_1, \ldots, y_n \in S^{m+n-1}$ be the optimal unit vectors
- 2. Apply Krivine's trick (Lemma 2) and use vectors x_i, y_i to create new unit vectors $x'_1, ..., x'_m, y'_1, ..., y'_n \in S^{m+n-1}$.
- 3. Choose $r \in S^{m+n-1}$ randomly
- 4. Round: $u_i = \text{sign}(\langle x_i', r \rangle)$ $v_i = \operatorname{sign}(\langle y_i', r \rangle)$

Expected quality of the outcome:

$$||M||_{\infty \to 1} \ge \mathbb{E} \left[\sum_{i=1}^{m} \sum_{j=1}^{n} M_{ij} u_{i} v_{j} \right]$$

$$= \sum_{i=1}^{m} \sum_{j=1}^{n} M_{ij} \mathbb{E}[\operatorname{sign}(\langle x'_{i}, r \rangle) \operatorname{sign}(\langle y'_{j}, r \rangle)]$$

$$= \sum_{i=1}^{m} \sum_{j=1}^{n} M_{ij} \beta \langle x_{i}, y_{j} \rangle$$

$$= \beta \operatorname{sdp}_{\infty \to 1}(M),$$

where the last equality follows by Krivine's trick with $\beta=\frac{2\ln(1+\sqrt{2})}{\pi}$, thus $K<\beta^{-1}$.

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Theorem (Tsirelson)

(Hard direction) For all positive integers n, r and any $x_1, \ldots, x_n, y_1, \ldots, y_n \in S^r$, there exists a positive integer d := d(r), a state $|\psi\rangle \in \mathbb{C}^d \otimes \mathbb{C}^d$ and $\{-1,1\}$ -observables $F_1, \ldots, F_n, G_1, \ldots, G_n \in O(\mathbb{C}^d)$, such that for every $i,j \in \{1,\ldots,n\}$, we have

$$\langle \psi | F_i \otimes G_j | \psi \rangle = \langle x_i, y_j \rangle.$$
 (16)

Moreover, $d \leq 2^{\lceil r/2 \rceil}$.

(Easy direction) Conversely, for all positive integers n,d, state $|\psi\rangle \in \mathbb{C}^d \otimes \mathbb{C}^d$ and $\{-1,1\}$ -observables $F_1,\ldots,F_n,G_1,\ldots,G_n \in O(\mathbb{C}^d)$, there exist a positive integer r:=r(d) and $x_1,\ldots,x_n,y_1,\ldots,y_n \in S^r$ such that for every $i,j\in\{1,\ldots,n\}$, we have

$$\langle x_i, y_j \rangle = \langle \psi | F_i \otimes G_j | \psi \rangle.$$
 (17)

Moreover, $r < 2d^2$.



Since

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Theorem (Grothendieck-Tsirelson)

There exists an absolute constant $K \ge 1$ such that, for any positive integers m, n, the following three equivalent conditions hold:

(1) We have the inclusion

$$QC_{m,n} \subset KLC_{m,n}. \tag{18}$$

(2) For any $M \in \mathbb{R}^{m \times n}$ and for any ρ, X_i, Y_j verifying the conditions of Definition 4.2.1 we have

$$\sum_{i,j} M_{ij} \operatorname{Tr} \rho(X_i \otimes Y_j) \le K \max_{\xi \in \{-1,1\}^m, \eta \in \{-1,1\}^n} \sum_{i,j} M_{ij} \xi_i \eta_j$$
 (19)

$$\Leftrightarrow$$

$$\operatorname{\mathsf{Tr}} M A^{ op} \leq \max_{\xi \in \{-1,1\}^m, \eta \in \{-1,1\}^n} \operatorname{\mathsf{Tr}} M (\xi \eta^{ op})^{ op}.$$
 (20)

(3) For any $M \in \mathbb{R}^{m \times n}$ and for any (real) Hilbert space vectors x_i, y_j with $|x_i| \le 1$, $|y_j| \le 1$ we have

$$\sum_{i:i} M_{i,j} \langle x_i, y_j \rangle \le K \max_{\xi \in \{-1,1\}^m, \eta \in \{-1,1\}^n} \operatorname{Tr} \xi^\top M \eta. \tag{21}$$

Proof.

Since (21) is a direct consequence of Grothendieck's inequality the only thing left to prove is the equivalence between (1)-(3). The equivalence of (3) and (2) (the Tsirelson's bound) is a consequence of either the proof of Lemma ?? or Tsirelsons Theorem (Theorem 1).

