



A statistical interpretation of Grothendieck's inequality: towards an approximation of the real Grothendieck constant

Frank Oertel

Philosophy, Logic & Scientific Method
Centre for Philosophy of Natural and Social Sciences (CPNSS)
London School of Economics & Political Science, UK
<http://www.frank-oertel-math.de>

Geometrical Aspects of Banach Spaces

*School of Mathematics
University of Birmingham, UK*

25-29 June 2018



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- 5 Grothendieck's identity
- 6 Towards a computation of $K_G^{\mathbb{R}}$



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An important information for readers

The current version is a shortened (“web-publishable” 😊) version of my presentation in Birmingham.



An important information for readers

The current version is a shortened (“web-publishable” 😊) version of my presentation in Birmingham. If you are interested in a copy of my original slides, presented in Birmingham, could you please send an email to me in advance? I am happy to forward these to you, of course. Many thanks!



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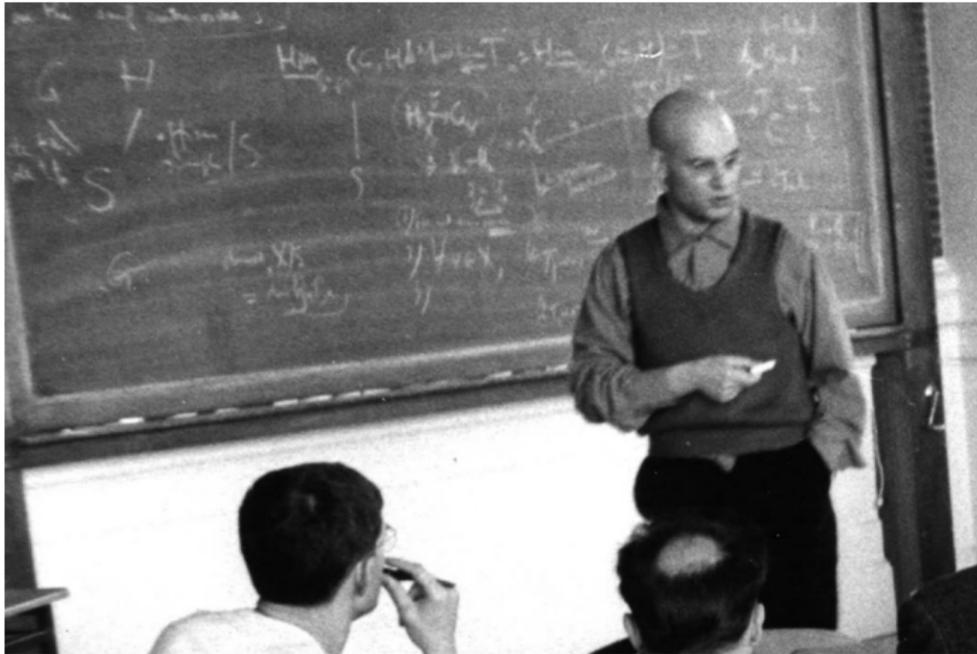


A portrait of A. Grothendieck





A. Grothendieck lecturing at IHES (1958-1970)





Excerpt from A. Grothendieck's handwritten lecture notes I

Exposé de la théorie

① Théorie de la H

Notation: Soit M un module sur R . On considère M comme un R - R -bimodule. On pose $M^* = \text{Hom}_R(M, R)$. On a $M^{**} \cong M$ si M est de type fini et projectif. On a $(M \otimes N)^* \cong M^* \otimes N^*$ si M et N sont de type fini.

Propriétés: Soit M, N des R -modules. On a $(M \oplus N)^* \cong M^* \oplus N^*$. On a $(M \otimes N)^* \cong M^* \otimes N^*$ si M et N sont de type fini.

② Exposé de la théorie

Notation: Soit L un R -module. On considère L comme un R - R -bimodule. On pose $L^* = \text{Hom}_R(L, R)$. On a $L^{**} \cong L$ si L est de type fini et projectif. On a $(L \otimes M)^* \cong L^* \otimes M^*$ si L et M sont de type fini.

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Excerpt from A. Grothendieck's handwritten lecture notes III

(1) soit M un \mathbb{Z} -module de torsion $\neq 0$, $L = L(M, \mathbb{Z})$, $F = L(M, \mathbb{Z})$
 soit $u \in L(M, \mathbb{Z})$, $y \in L(M, \mathbb{Z})$
 $(1) \quad Nu = M(u-1)$
 et $y \in L(M, \mathbb{Z})$
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 $(3) \quad Nu = L_y(T(u))$
 $(4) \quad Nu = L_y(T(u))$
 Soit $L^*(M, \mathbb{Z})$ le \mathbb{Z} -module de torsion $\neq 0$ de $L(M, \mathbb{Z})$
 soit $u \in L^*(M, \mathbb{Z})$, $y \in L(M, \mathbb{Z})$
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Grothendieck's inequality in matrix form I

Theorem (Lindenstrauss-Pelczyński (1968))

Let $\mathbb{F} \in \{\mathbb{R}, \mathbb{C}\}$ and $m, n \in \mathbb{N}$. Then there exists a *universal constant* $K > 0$ - *not depending on m and n* - such that *for all matrices* $A = (a_{ij}) \in \mathbb{M}(m \times n; \mathbb{F})$, *for all \mathbb{F} -Hilbert spaces H , for all unit vectors $u_1, \dots, u_m, v_1, \dots, v_n \in S_H$ the following inequality is satisfied:*

$$\left| \sum_{i=1}^m \sum_{j=1}^n a_{ij} \langle u_i, v_j \rangle_H \right| \leq K \max \left\{ \left| \sum_{i=1}^m \sum_{j=1}^n a_{ij} p_i q_j \right| : p_i, q_j \in \{-1, 1\} \right\}.$$



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The smallest possible value of the corresponding constant K is denoted by $K_G^{\mathbb{F}}$. It is called **Grothendieck's constant**.



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The smallest possible value of the corresponding constant K is denoted by $K_G^{\mathbb{F}}$. It is called **Grothendieck's constant**. **Computing the exact numerical value of this constant is an open problem (unsolved since 1953)!**



Grothendieck's inequality in matrix form II

Theorem (R. E. Rietz (1974), H. Niemi (1983))

Let $\mathbb{F} \in \{\mathbb{R}, \mathbb{C}\}$ and H be an arbitrary Hilbert space over \mathbb{F} . Let $n \in \mathbb{N}$. Let $K_{GH}^{\mathbb{F}}$ denote the Grothendieck constant, derived from Grothendieck's inequality "restricted" to the set of all **positive semidefinite $n \times n$ -matrices over \mathbb{F}** . Then



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From now on are going to consider the real case (i. e., $\mathbb{F} = \mathbb{R}$) only. Nevertheless, we allow an unrestricted use of all matrices $A \in \mathbb{M}(m \times n; \mathbb{R})$ for any $m, n \in \mathbb{N}$ in GT.



Grothendieck's inequality in matrix form III

Until present the following encapsulation of $K_G^{\mathbb{R}}$ holds, *primarily thanks to R. E. Rietz (1974), J. L. Krivine (1977), and recently, due to an impressive work of M. Braverman, K. Makarychev, Y. Makarychev, and A. Naor (2011):*



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$$1,676 < K_G^{\mathbb{R}} < \frac{\pi}{2 \ln(1 + \sqrt{2})} \approx 1,782.$$



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Screening these numbers we might be tempted to guess the following



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Conjecture

$$Is K_G^{\mathbb{R}} = \sqrt{\pi}$$



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$$Is K_G^{\mathbb{R}} = \sqrt{\pi} = \Gamma\left(\frac{1}{2}\right)$$



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Screening these numbers we might be tempted to guess the following

Conjecture

Is $K_G^{\mathbb{R}} = \sqrt{\pi} = \Gamma(\frac{1}{2}) \approx 1,772$?



Grothendieck's inequality rewritten I

By transforming Grothendieck's inequality into an equivalent inequality between traces of matrix products (respectively Hilbert-Schmidt inner products) we are lead to a surprising interpretation which reveals deep links to combinatorial (binary) optimisation, semidefinite programming (SDP) and multivariate statistics, **built on suitable non-linear mappings between correlation matrices.**



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We will sketch this approach which might lead to a constructive improvement of Krivine's upper bound $\frac{\pi}{2 \ln(1+\sqrt{2})}$. At least it also can be reproduced in this approach.



Grothendieck's inequality rewritten II

Let $m, n \in \mathbb{N}$, $A \in \mathbb{M}(m \times n; \mathbb{R})$, $u := (u_1, \dots, u_m)^\top \in S_H^m$ and $v := (v_1, \dots, v_n)^\top \in S_H^n$ be given, where $S_H := \{w \in H : \|w\| = 1\}$ denotes the unit sphere in H .



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Firstly, note that

$$\sum_{i=1}^m \sum_{j=1}^n a_{ij} \langle u_i, v_j \rangle_H =$$



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is precisely the Hilbert-Schmidt inner product (or the Frobenius inner product) of the matrices $A \in \mathbb{M}(m \times n; \mathbb{R})$ and $\Gamma_H(u, v) \in \mathbb{M}(m \times n; \mathbb{R})$, where



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$$\Gamma_H(u, v) := \begin{pmatrix} \langle u_1, v_1 \rangle_H & \langle u_1, v_2 \rangle_H & \cdots & \langle u_1, v_n \rangle_H \\ \langle u_2, v_1 \rangle_H & \langle u_2, v_2 \rangle_H & \cdots & \langle u_2, v_n \rangle_H \\ \vdots & \vdots & \vdots & \vdots \\ \langle u_m, v_1 \rangle_H & \langle u_m, v_2 \rangle_H & \cdots & \langle u_m, v_n \rangle_H \end{pmatrix}.$$



Grothendieck's inequality rewritten III

Let $m, n \in \mathbb{N}$, $A \in \mathbb{M}(m \times n; \mathbb{R})$, $p := (p_1, \dots, p_m)^\top \in (\mathbb{S}^0)^m$ and $q := (q_1, \dots, q_n)^\top \in (\mathbb{S}^0)^n$ be given, where $\mathbb{S}^0 := \{-1, 1\}$ denotes the unit “sphere” in $\mathbb{R} = \mathbb{R}^{0+1}$.

Similarly as before, we obtain

$$\sum_{i=1}^m \sum_{j=1}^n a_{ij} p_i q_j = \text{tr}(A^\top \Gamma_{\mathbb{R}}(p, q)) = \langle A, \Gamma_{\mathbb{R}}(p, q) \rangle,$$

where now

$$\Gamma_{\mathbb{R}}(p, q) := pq^\top = \begin{pmatrix} \pm 1 & \mp 1 & \dots & \pm 1 \\ \mp 1 & \mp 1 & \dots & \mp 1 \\ \vdots & \vdots & \ddots & \vdots \\ \pm 1 & \mp 1 & \dots & \pm 1 \end{pmatrix}.$$



Full matrix representation of the Hilbert space vectors

Pick all $m + n$ Hilbert space unit vectors

$u_1, u_2, \dots, u_m, v_1, v_2, \dots, v_n \in H$ and represent them as



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Does this matrix look familiar to you?



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$$\begin{pmatrix} \langle u_1, v_1 \rangle & \langle u_1, v_2 \rangle & \dots & \langle u_1, v_n \rangle \\ \langle u_2, v_1 \rangle & \langle u_2, v_2 \rangle & \dots & \langle u_2, v_n \rangle \\ \vdots & \vdots & \vdots & \vdots \\ \langle u_m, v_1 \rangle & \langle u_m, v_2 \rangle & \dots & \langle u_m, v_n \rangle \end{pmatrix}$$

Does this matrix look familiar to you?

It is a part of something larger...



Full matrix representation of the Hilbert space vectors

Pick all $m + n$ Hilbert space unit vectors

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Namely:



Block matrix representation I

$$\left(\begin{array}{cccc} \langle u_1, v_1 \rangle & \langle u_1, v_2 \rangle & \dots & \langle u_1, v_n \rangle \\ \langle u_2, v_1 \rangle & \langle u_2, v_2 \rangle & \dots & \langle u_2, v_n \rangle \\ \vdots & \vdots & \vdots & \vdots \\ \langle u_m, v_1 \rangle & \langle u_m, v_2 \rangle & \dots & \langle u_m, v_n \rangle \end{array} \right)^T \left(\begin{array}{cccc} \langle u_1, v_1 \rangle & \langle u_1, v_2 \rangle & \dots & \langle u_1, v_n \rangle \\ \langle u_2, v_1 \rangle & \langle u_2, v_2 \rangle & \dots & \langle u_2, v_n \rangle \\ \vdots & \vdots & \vdots & \vdots \\ \langle u_m, v_1 \rangle & \langle u_m, v_2 \rangle & \dots & \langle u_m, v_n \rangle \end{array} \right)$$



Block matrix representation I

$$\begin{pmatrix} & & & \langle u_1, v_1 \rangle & \langle u_1, v_2 \rangle & \dots & \langle u_1, v_n \rangle \\ & & & \langle u_2, v_1 \rangle & \langle u_2, v_2 \rangle & \dots & \langle u_2, v_n \rangle \\ & & & \vdots & \vdots & \vdots & \vdots \\ & & & \langle u_m, v_1 \rangle & \langle u_m, v_2 \rangle & \dots & \langle u_m, v_n \rangle \\ \langle u_1, v_1 \rangle & \langle u_2, v_1 \rangle & \dots & \langle u_m, v_1 \rangle \\ \langle u_1, v_2 \rangle & \langle u_2, v_2 \rangle & \dots & \langle u_m, v_2 \rangle \\ \vdots & \vdots & \vdots & \vdots \\ \langle u_1, v_n \rangle & \langle u_2, v_n \rangle & \dots & \langle u_m, v_n \rangle \end{pmatrix}$$



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Block matrix representation II

$$\begin{pmatrix} \langle u_1, u_1 \rangle & \langle u_1, u_2 \rangle & \dots & \langle u_1, u_m \rangle & \langle u_1, v_1 \rangle & \langle u_1, v_2 \rangle & \dots & \langle u_1, v_n \rangle \\ \langle u_2, u_1 \rangle & \langle u_2, u_2 \rangle & \dots & \langle u_2, u_m \rangle & \langle u_2, v_1 \rangle & \langle u_2, v_2 \rangle & \dots & \langle u_2, v_n \rangle \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \langle u_m, u_1 \rangle & \langle u_m, u_2 \rangle & \dots & \langle u_m, u_m \rangle & \langle u_m, v_1 \rangle & \langle u_m, v_2 \rangle & \dots & \langle u_m, v_n \rangle \\ \langle v_1, u_1 \rangle & \langle v_1, u_2 \rangle & \dots & \langle v_1, u_m \rangle & \langle v_1, v_1 \rangle & \langle v_1, v_2 \rangle & \dots & \langle v_1, v_n \rangle \\ \langle v_2, u_1 \rangle & \langle v_2, u_2 \rangle & \dots & \langle v_2, u_m \rangle & \langle v_2, v_1 \rangle & \langle v_2, v_2 \rangle & \dots & \langle v_2, v_n \rangle \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \langle v_n, u_1 \rangle & \langle v_n, u_2 \rangle & \dots & \langle v_n, u_m \rangle & \langle v_n, v_1 \rangle & \langle v_n, v_2 \rangle & \dots & \langle v_n, v_n \rangle \end{pmatrix}$$



Block matrix representation III

$$\begin{pmatrix} \mathbf{1} & \langle u_1, u_2 \rangle & \dots & \langle u_1, u_m \rangle & \langle u_1, v_1 \rangle & \langle u_1, v_2 \rangle & \dots & \langle u_1, v_n \rangle \\ \langle u_2, u_1 \rangle & \mathbf{1} & \dots & \langle u_2, u_m \rangle & \langle u_2, v_1 \rangle & \langle u_2, v_2 \rangle & \dots & \langle u_2, v_n \rangle \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \langle u_m, u_1 \rangle & \langle u_m, u_2 \rangle & \dots & \mathbf{1} & \langle u_m, v_1 \rangle & \langle u_m, v_2 \rangle & \dots & \langle u_m, v_n \rangle \\ \langle v_1, u_1 \rangle & \langle v_1, u_2 \rangle & \dots & \langle v_1, u_m \rangle & \mathbf{1} & \langle v_1, v_2 \rangle & \dots & \langle v_1, v_n \rangle \\ \langle v_2, u_1 \rangle & \langle v_2, u_2 \rangle & \dots & \langle v_2, u_m \rangle & \langle v_2, v_1 \rangle & \mathbf{1} & \dots & \langle v_2, v_n \rangle \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \langle v_n, u_1 \rangle & \langle v_n, u_2 \rangle & \dots & \langle v_n, u_m \rangle & \langle v_n, v_1 \rangle & \langle v_n, v_2 \rangle & \dots & \mathbf{1} \end{pmatrix}$$



A refresher of a few definitions I

Let $n \in \mathbb{N}$. We put

$PSD(n; \mathbb{R}) := \{S : S \in \mathbb{M}(n \times n; \mathbb{R}) \text{ and } S \text{ is positive semidefinite}\}.$



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Recall that $PSD(n; \mathbb{R})$ is a closed convex cone which (by definition!) consists of **symmetric** matrices only.

Moreover, we consider the set

$C(n; \mathbb{R}) := \{S \in PSD(n; \mathbb{R}) \text{ such that } S_{ii} = 1 \text{ for all } i \in [n]\}$.



A refresher of a few definitions II

Let $d, k \in \mathbb{N}$ and $(H, \langle \cdot, \cdot \rangle)$ be an arbitrary d -dimensional Hilbert space (i. e. $H = \mathbb{R}^d$). Let $w_1, w_2, \dots, w_k \in H$. Put $w := (w_1, \dots, w_k)^\top \in H^k$ and $S := (w_1 | w_2 | \dots | w_k) \in \mathbb{M}(d \times k; \mathbb{R})$. The matrix $\Gamma_H(w, w) \in \text{PSD}(k; \mathbb{R})$, defined as

$$\Gamma_H(w, w)_{ij} := \langle w_i, w_j \rangle = (S^\top S)_{ij} \quad (i, j \in [k] := \{1, 2, \dots, k\})$$

is called **Gram matrix of the vectors** $w_1, \dots, w_k \in H$.



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Observe that

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is not a Gram matrix!



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Let $n \in \mathbb{N}$. Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and let $\xi := (\xi_1, \xi_2, \dots, \xi_n)^\top : \Omega \rightarrow \mathbb{R}^n$ be a random vector. Let $\mu := (\mu_1, \mu_2, \dots, \mu_n)^\top \in \mathbb{R}^n$ and $C \in \text{PSD}(n; \mathbb{R})$.



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Recall that ξ is an n -dimensional Gaussian random vector with respect to the “parameters” μ and C (short: $\xi \sim N_n(\mu, C)$) if and only if for all $a \in \mathbb{R}^n$ there exists $\eta_a \sim N_1(0, 1)$ such that

$$\langle a, \xi \rangle = \sum_{i=1}^n a_i \xi_i = \langle a, \mu \rangle + \sqrt{\langle a, Ca \rangle} \eta_a$$



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Note that we don't require here that C is invertible! Following Feller, the matrix $\mathbb{V}(\xi)$ defined as

$$\mathbb{V}(\xi)_{ij} := \mathbb{E}[\xi_i \xi_j] - \mathbb{E}[\xi_i] \mathbb{E}[\xi_j] \stackrel{(!)}{=} C_{ij} \quad (i, j \in [n])$$

is known as the *variance matrix of the Gaussian random vector* ξ .



Structure of correlation matrices I

Proposition

Let $n \in \mathbb{N}$ and $\Sigma = (\sigma_{ij}) \in \mathbb{M}(n \times n; \mathbb{R})$. TFAE:



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- (ii) $\Sigma \in C(n; \mathbb{R})$.
- (iii) There exist vectors $x_1, \dots, x_n \in S^{n-1}$ such that $\sigma_{ij} = \langle x_i, x_j \rangle$ for all $i, j \in [n]$.



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- In particular, *condition (i) implies* that $\sigma_{ij} \in [-1, 1]$ for all $i, j \in [n]$.



Structure of correlation matrices II

Observation

Let $k \in \mathbb{N}$. Then the sets $\{S : S = xx^\top \text{ for some } x \in \{-1, 1\}^k\}$
and $\{\Theta : \Theta \in C(k; \mathbb{R}) \text{ and } rk(\Theta) = 1\}$ coincide.



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Proposition (K. R. Parthasarathy (2002))

Let $k \in \mathbb{N}$. $C(k; \mathbb{R})$ is a compact and convex subset of the k^2 -dimensional vector space $\mathbb{M}(k \times k; \mathbb{R})$. Any $k \times k$ -correlation matrix of rank 1 is an extremal point of the set $C(k; \mathbb{R})$.



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Let $k \in \mathbb{N}$. Put

$$C_1(k; \mathbb{R}) := \{\Theta : \Theta \in C(k; \mathbb{R}) \text{ and } \text{rk}(\Theta) = 1\}.$$



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Having gained - important - additional structure by “enlarging” the $m \times n$ -matrix $\Gamma_H(u, v)$ to a $(m + n) \times (m + n)$ -**correlation** matrix, how could this gained information be used to rewrite Grothendieck’s inequality accordingly?



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Definition

Let $m, n \in \mathbb{N}$ and $A \in \mathbb{M}(m \times n; \mathbb{R})$ arbitrary. Put

$$\hat{A} := \frac{1}{2} \begin{pmatrix} \mathbf{0} & A \\ A^\top & \mathbf{0} \end{pmatrix}$$

Let us call $\mathbb{M}((m + n) \times (m + n); \mathbb{R}) \ni \hat{A}$ the **canonical block injection** of A .



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Observe that \hat{A} is symmetric, implying that $\hat{A} = \hat{A}^\top$.



A further equivalent rewriting of GT I

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Let $m, n \in \mathbb{N}$ and $A = (a_{ij}) \in \mathbb{M}(m \times n; \mathbb{R})$. Let $K > 0$. **TFAE:**



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$$\max_{\Sigma \in C(m+n; \mathbb{R})} |\langle \widehat{A}, \Sigma \rangle| \leq K \max_{\Theta \in C_1(m+n; \mathbb{R})} |\langle \widehat{A}, \Theta \rangle|.$$



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for *all* Hilbert spaces H over \mathbb{R} .

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$$\max_{\Sigma \in C(m+n; \mathbb{R})} |\langle \widehat{A}, \Sigma \rangle| \leq K \max_{\Theta \in C_1(m+n; \mathbb{R})} |\langle \widehat{A}, \Theta \rangle|.$$

We don't know whether condition (ii) holds for all matrices in $\mathbb{M}((m+n) \times (m+n); \mathbb{R})$.



GT versus NP-hard optimisation

Observation

On the left side of GT: a convex conic optimisation problem (since it is SDP) and hence of polynomial worst-case complexity (P):

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Thus, Grothendieck's constant $K_G^{\mathbb{R}}$ is precisely the “**integrality gap**”; i. e., the maximum ratio between the solution quality of the NP-hard Boolean optimisation on the right side of GT and of its SDP relaxation on the left side!



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Schur product and the matrix $f[A]$ I

Definition

Let $\emptyset \neq U \subseteq \mathbb{R}$ and $f : U \rightarrow \mathbb{R}$ a function. Let $A = (a_{ij}) \in \mathbb{M}(m \times n; \mathbb{R})$ such that $a_{ij} \in U$ for all $(i, j) \in [m] \times [n]$.



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The notation " $f[A]$ " is used to highlight the difference between the matrix $f(A)$ originating from the spectral representation of A (for normal matrices A) and the matrix $f[A]$, defined as above !



Schur product and the matrix $f[A]$ II

Theorem

For any $n \in \mathbb{N}$ the set $\mathbb{M}(n \times n; \mathbb{R})$ with the usual addition and the Schur multiplication $$ is a commutative Banach algebra under the operator norm. Moreover,*

$$PSD(n; \mathbb{R}) * PSD(n; \mathbb{R}) \subseteq PSD(n; \mathbb{R}) .^1$$

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The set $PSD(n; \mathbb{R})$ is a closed, convex, pointed, and solid cone in $\mathbb{M}(n \times n; \mathbb{R})$.

Corollary

Let $n \in \mathbb{N}$ Then

$$C(n; \mathbb{R}) * C(n; \mathbb{R}) \subseteq C(n; \mathbb{R}) .$$

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Correlation matrix transformation I

Corollary

Let $0 < r \leq \infty$ and $f : [-r, r] \rightarrow \mathbb{R}$ such that on $[-r, r]$

$$f(x) = \sum_{k=0}^{\infty} a_k x^k$$

for some **nonnegative coefficients** $a_k \geq 0$.



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If in addition $r \geq 1$ and $f \neq 0$ then $f(1) > 0$, and

$$\frac{f}{f(1)}[\cdot] : C(n, \mathbb{R}) \rightarrow C(n, \mathbb{R}) \text{ for every } n \in \mathbb{N}.$$



Correlation matrix transformation II

Example

Let $x \in [-1, 1]$.

$$g(x) := \frac{2}{\pi} \arcsin(x) = \frac{2}{\pi} \sum_{n=0}^{\infty} \frac{1}{4^n} \binom{2n}{n} \frac{x^{2n+1}}{2n+1}$$



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where for $a, b, c \in \mathbb{C}$, satisfying $\Re(c - (a + b)) > 0$ and $z \in \mathbb{D} = \{z \in \mathbb{C} : |z| < 1\}$

$${}_2F_1(a, b, c; z) := \frac{\Gamma(c)}{\Gamma(a)\Gamma(b)} \sum_{n=0}^{\infty} \frac{\Gamma(a+n)\Gamma(b+n)}{\Gamma(c+n) n!} z^n$$

denotes the **hypergeometric function**.



Correlation matrix transformation III

Example

Let H be an arbitrary separable Hilbert space with ONB $(x_n)_{n \in \mathbb{N}_0}$. Let $\psi \in H$ such that $\|\psi\| > 0$.



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Then $\frac{h_\psi}{\|\psi\|^2}[\cdot] : C(k, \mathbb{R}) \longrightarrow C(k, \mathbb{R})$ for every $k \in \mathbb{N}$.



Correlation matrix transformation IV

Theorem

Let $1 \leq r \leq \infty$. Let $g : [-r, r] \rightarrow \mathbb{R}$ be a function such that **for each** $n \in \mathbb{N}$ $g[\Sigma]$ is a $(n \times n)$ -correlation matrix **for all** $(n \times n)$ -correlation matrices Σ .



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Moreover, $g[A] \in \text{PSD}(n; \mathbb{R})$ **for all** $A \in \text{PSD}(n; [-r, r])$ and all $n \in \mathbb{N}$.



Correlation matrix transformation and Schoenberg's Theorem

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Theorem (Schoenberg (1942), Rudin (1959), Guillot and Rajaratnam (2012))

Let $0 < \alpha \leq \infty$ and $g : (-\alpha, \alpha) \rightarrow \mathbb{R}$ be an arbitrary function.

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Q: How can we link an NP-hard non-convex Boolean optimisation problem and its convex SDP relaxation?

A: Apply “suitable” correlation matrix transforms!



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Theorem (Grothendieck's identity - T. S. Stieltjes (1889),
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Grothendieck's identity II

Corollary

Let $k \in \mathbb{N}, k \geq 2$. Let $\Sigma \in C(k; \mathbb{R})$ an arbitrarily given correlation matrix.



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Let $k \in \mathbb{N}, k \geq 2$. Let $\Sigma \in C(k; \mathbb{R})$ an arbitrarily given correlation matrix. Then also $\frac{2}{\pi} \arcsin[\Sigma] \in C(k; \mathbb{R})$.



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$$\max_{\substack{\Theta \in C(k; \mathbb{R}) \\ \text{rank}(\Theta)=1}} |\langle \hat{A}, \Theta \rangle| \geq \mathbb{E}[|\langle \hat{A}, \Theta(\xi) \rangle|] \geq |\langle \hat{A}, \mathbb{E}[\Theta(\xi)] \rangle| = \frac{2}{\pi} |\langle \hat{A}, \arcsin[\Sigma] \rangle|.$$



Krivine's constant reproduced I

Example

$$f(x) := \sinh(x) = \sum_{n=0}^{\infty} \frac{x^{2n+1}}{(2n+1)!} \quad (x \in \mathbb{R})$$



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A bit more generally, the following (still special) case holds:



Krivine's constant reproduced II

Corollary

Let $m, n \in \mathbb{N}$, $A \in \mathbb{M}(m \times n; \mathbb{R})$, $u := (u_1, u_2, \dots, u_m)^\top \in S_H^m$ and $v := (v_1, v_2, \dots, v_n)^\top \in S_H^n$. Put $S := \Gamma_H(u, v)$. Let $0 < r \leq \infty$ and $f : (-r, r) \rightarrow \mathbb{R}$ be a function **such that f satisfies the “correlation assumptions”**.



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Hence,

$$\boxed{K_G^{\mathbb{R}} \leq \frac{\pi}{2c^*}}.$$

Krivine's constant reproduced III



Somewhat more generally, we have

Corollary

Let $m, n \in \mathbb{N}$, $A \in \mathbb{M}(m \times n; \mathbb{R})$, $u := (u_1, u_2, \dots, u_m)^\top \in S_H^m$ and $v := (v_1, v_2, \dots, v_n)^\top \in S_H^n$. Put $S := \Gamma_H(u, v)$. Let $0 < r \leq \infty$ and $f, g : (-r, r) \rightarrow \mathbb{R}$ be two functions **such that both, f and g satisfy the “correlation assumptions”**.



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- 1 *An important information for readers*
- 2 A very short glimpse at A. Grothendieck's work in functional analysis
- 3 A further reformulation of Grothendieck's inequality
- 4 $K_G^{\mathbb{R}}$ and correlation matrix transformations
- 5 Grothendieck's identity
- 6 Towards a computation of $K_G^{\mathbb{R}}$



Krivine rounding schemes revisited I

Natural Question

Can we possibly “remove” or cleverly substitute the arcsin function?



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Recall that the **invertible** function $\frac{2}{\pi} \arcsin : [-1, 1] \rightarrow [-1, 1]$ **transforming correlation matrices into correlation matrices** arrived as a result of an explicit hard calculation of the *non-trivial double integral*

$$H_{f,g}(t) := \mathbb{E}[f(\xi) g(\eta)],$$

where $\xi, \eta \sim N(0, 1)$ are correlated via $\mathbb{E}[\xi \eta] = t \in [-1, 1]$ and $f := g := \text{sign} = \mathbb{1}_{[0, \infty)} - \mathbb{1}_{(-\infty, 0)}$.



Krivine rounding schemes revisited II

Definition (Braverman, Makarychev, Makarychev, Naor (2011))

Fix $k \in \mathbb{N}$. Let $G_1, G_2 \sim N_k(0, I_k)$ be independent (standard) Gaussian random vectors. Let $t \in [-1, 1]$. Put $\tilde{f}(x) := f(\frac{1}{\sqrt{2}}x)$ and $\tilde{g}(y) := g(\frac{1}{\sqrt{2}}y)$, where $x, y \in \mathbb{R}^k$ and f, g are bounded.



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Corollary

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Fix $k \in \mathbb{N}$. Let $G \sim N_k(0, I_k)$ be a (standard) Gaussian random vector. Let $-1 < t < 1$ and g be as above.



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A bird's eye view - from the complex plane I

For the moment *assume that in addition* $f(-x) = -f(x)$ for all $x \in \mathbb{R}^k$ *or* $g(-y) = -g(y)$ for all $y \in \mathbb{R}^k$. Having Fourier transform techniques in mind, let us assume further that the function $z \mapsto H_{f,g}(z)$ can be analytically extended to a suitable domain in \mathbb{C} , containing $\pm i$.



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$$\frac{1}{i}H_{f,g}(i) = iH_{f,g}(-i) = \frac{1}{2^{k/2}} \int_{\mathbb{R}^k} \tilde{f}(x) \int_{\mathbb{R}^k} \tilde{g}(y) K(x,y) d^k y d^k x$$



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A bird's eye view - from the complex plane II

$$K(x, y) := \sin(\langle x, y \rangle) \varphi_{0, I_{2k}}(x, y)$$



A bird's eye view - from the complex plane II

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A similar non-trivial integral was explicitly calculated by H. König in 2001, leading to his conjecture whether $K_G^{\mathbb{R}} = \frac{\pi}{2 \ln(1+\sqrt{2})}$
- **which had been refuted in 2011 only (cf. [1])!**



Krivine rounding schemes revisited III

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Then $\chi_\alpha(x) \in \{-1, 1\}$ for all $x \in \mathbb{R}^k$, and

$$H_{\chi_\alpha, \chi_\beta}(t) \stackrel{(!)}{=} 1 - 2 \left(\prod_{i=1}^k \alpha_i + \prod_{i=1}^k \beta_i \right) + 4c_{\Sigma(t)}(\alpha, \beta),$$

where $c_{\Sigma(t)}$ denotes the **2k-dimensional Gaussian copula with respect to the correlation matrix $\Sigma(t)$!**



Krivine rounding schemes revisited IV

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A strong drawback: in general there is no closed form for values of multivariate Gaussian copulas available. One has to rely on approximation techniques and simulation methods here (such as standard Monte Carlo). One significant point to observe is that (by Sklar's Theorem) the structure of copulas requires a calculation of single quantile functions. Their values have to be implemented as upper bounds of (large) multi-dimensional integrals, originating from the underlying multi-dimensional Gaussian distribution.



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Krivine rounding schemes revisited V

Theorem

Let $l_2 \cong H$ be a separable Hilbert space, $m, n \in \mathbb{N}$, $k := m + n$ and $f, g : \mathbb{R}^k \rightarrow \mathbb{R}$ be bounded. Suppose the following conditions are satisfied:



Krivine rounding schemes revisited V

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Let $l_2 \cong H$ be a separable Hilbert space, $m, n \in \mathbb{N}$, $k := m + n$ and $f, g : \mathbb{R}^k \rightarrow \mathbb{R}$ be bounded. Suppose the following conditions are satisfied:

- (i) $H'_{f,g}(0) \neq 0$ and $H_{f,g}(0) \geq 0$.
- (ii) $\text{abs}(H_{f,g}^{-1})(c) = 1$, for some $c \equiv c(f, g) > 0$.



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Then for all $u_1, u_2, \dots, u_m, v_1, v_2, \dots, v_n \in S_H$ there exist k \mathbb{R}^k -valued random vectors $X_1, X_2, \dots, X_m, Y_1, Y_2, \dots, Y_n$ such that $X_i \sim N_k(0, I_k)$ for all $i \in [m]$ and $Y_j \sim N_k(0, I_k)$ for all $j \in [n]$ and

$$\frac{1}{c} \mathbb{E} \left[f \left(\frac{1}{\sqrt{2}} X_i \right) g \left(\frac{1}{\sqrt{2}} Y_j \right) \right] = \langle u_i, v_j \rangle_H$$

for all $(i, j) \in [m] \times [n]$.



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for all $(i, j) \in [m] \times [n]$. If $f, g : \mathbb{R}^k \rightarrow \{-1, +1\}$ then $K_G^{\mathbb{R}} \leq \frac{1}{c(f,g)}$.



A phrase of G. H. Hardy

“... at present I will say only that if a chess problem is, in the crude sense, 'useless', then that is equally true of most of the best mathematics; that very little of mathematics is useful practically, and that that little is comparatively dull. The 'seriousness' of a mathematical theorem lies, not in its practical consequences, which are usually negligible, but in the significance of the mathematical ideas which it connects...”

– *A Mathematician's Apology* (1940)



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Thank you for your attention!

Are there any questions, comments or remarks?