Entrywise positivity preservers:

covariance estimation, symmetric function identities, novel graph invariant

LAMA Lecture – ILAS 2019, Rio

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(Partly based on joint works with Alexander Belton, Dominique Guillot, Mihai Putinar, Bala Rajaratnam, and Terence Tao)

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- Moment sequences/Hankel matrices (measures on ℝ)
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- Positive definite functions on metric spaces, topological (semi)groups

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Question: Classify the positivity preservers in these settings.

Studied for the better part of a century.

Positivity and Analysis

Given $N\geqslant 1$ and $I\subset\mathbb{R}$, let $\mathbb{P}_N(I)$ denote the $N\times N$ positive semidefinite matrices, with entries in I. (Say $\mathbb{P}_N=\mathbb{P}_N(\mathbb{R})$.)

Problem: Given a function $f:I\to\mathbb{R}$, when is it true that $f[A]:=(f(a_{ij}))\in\mathbb{P}_N$ for all $A\in\mathbb{P}_N(I)$? (Long history!)

Apoorva Khare, IISc Bangalore

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(Long history!) The *Hadamard product* (or Schur, or entrywise product) of two matrices is given by: $A \circ B = (a_{ij}b_{ij})$.

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- Taking limits: if $f(x) = \sum_{k=0}^{\infty} c_k x^k$ is convergent and $c_k \geqslant 0$, then f[-] preserves positivity.

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Theorem (Schoenberg, Duke Math. J. 1942; Rudin, Duke Math. J. 1959)

Suppose I=(-1,1) and $f:I\to\mathbb{R}$. The following are equivalent:

- \bullet $f[A] \in \mathbb{P}_N$ for all $A \in \mathbb{P}_N(I)$ and all N.
- ② f is analytic on I and has nonnegative Maclaurin coefficients. In other words, $f(x) = \sum_{k=0}^{\infty} c_k x^k$ on (-1,1) with all $c_k \geqslant 0$.

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Such functions f are said to be **absolutely monotonic** on (0,1).

Motivations: Rudin was motivated by harmonic analysis and Fourier analysis on locally compact groups. On $G=S^1$, he studied preservers of *positive definite sequences* $(a_n)_{n\in\mathbb{Z}}$. This means the Toeplitz kernel $(a_{i-j})_{i,j\geqslant 0}$ is positive semidefinite.

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- Important parallel notion: moment sequences. Given positive measures μ on [-1,1], with moment sequences $\mathbf{s}(\mu) := (s_k(\mu))_{k\geqslant 0}, \qquad \text{where } s_k(\mu) := \int_{\mathbb{R}} x^k \ d\mu,$

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With Belton–Guillot–Putinar → a parallel result to Rudin:

Toeplitz and Hankel matrices (cont.)

Let $0 < \rho \leqslant \infty$ be a scalar, and set $I = (-\rho, \rho)$.

Theorem (Rudin, Duke Math. J. 1959)

Given a function $f: I \to \mathbb{R}$, the following are equivalent:

- f[-] preserves the set of positive definite sequences with entries in I.
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Theorem (Belton-Guillot-K.-Putinar, 2016)

Given a function $f: I \to \mathbb{R}$, the following are equivalent:

- \bullet f[-] preserves the set of moment sequences with entries in I.
- 2 f[-] preserves positivity on Hankel matrices of all sizes and rank ≤ 3 .
- 3 f is analytic on I and has nonnegative Maclaurin coefficients.

Positive semidefinite kernels

- These two results greatly weaken the hypotheses of Schoenberg's theorem

 only need to consider positive semidefinite matrices of rank ≤ 3.
- Note, such matrices are precisely the Gram matrices of vectors in a 3-dimensional Hilbert space. Hence Rudin (essentially) showed:
 - Let $\mathcal H$ be a real Hilbert space of dimension $\geqslant 3$. If f[-] preserves positivity on all Gram matrices in $\mathcal H$, then f is a power series on $\mathbb R$ with non-negative Maclaurin coefficients.

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 machine learning, via RKHS.
- Thus, Rudin (1959) classified positive semidefinite kernels on \mathbb{R}^3 , which is relevant in machine learning. (Now also via our parallel 'Hankel' result.)

Schoenberg's theorem in several variables

Let $I=(-\rho,\rho)$ for some $0<\rho\leqslant\infty$ as above. Also fix $m\geqslant 1$.

Given matrices $A_1, \ldots, A_m \in \mathbb{P}_N(I)$ and $f: I^m \to \mathbb{R}$, define

$$f[A_1, \ldots, A_m]_{ij} := f(a_{ij}^{(1)}, \ldots, a_{ij}^{(m)}), \quad \forall i, j = 1, \ldots, N.$$

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- \bullet $f[A_1,\ldots,A_m]\in\mathbb{P}_N$ for all $A_i\in\mathbb{P}_N(I)$ and all N.
- 2 The function f is real entire and absolutely monotonic: for all $\mathbf{x} \in \mathbb{R}^m$,

$$f(\mathbf{x}) = \sum_{\alpha \in \mathbb{Z}^m} c_{\alpha} \mathbf{x}^{\alpha}, \qquad \text{where } c_{\alpha} \geqslant 0 \,\, \forall \alpha \in \mathbb{Z}^m_+.$$

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 $((2) \Rightarrow (1)$ by Schur Product Theorem.) The test set can again be reduced:

Theorem (Belton-Guillot-K.-Putinar, 2016)

The above two hypotheses are further equivalent to:

3 f[-] preserves positivity on m-tuples of Hankel matrices of rank ≤ 3 .

Positivity and Metric geometry

Distance geometry

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- Now ubiquitous in science (mathematics, physics, economics, statistics, computer science...).
- Fréchet [Math. Ann. 1910]. If (X,d) is a metric space with |X|=n+1, then (X,d) isometrically embeds into $(\mathbb{R}^n,\ell_\infty)$.
- This avenue of work led to the exploration of metric space embeddings. Natural question: Which metric spaces isometrically embed into Euclidean space?

- Analysis: Schoenberg, Rudin, and measures
 Metric geometry: from spheres to correlations
- Fixed dimension results 2. Metric geometry: from spheres to correlations

Euclidean metric spaces and positive matrices

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- Menger [Amer. J. Math. 1931] and Fréchet [Ann. of Math. 1935] provided characterizations.
- Reformulated by Schoenberg, using...matrix positivity!

Theorem (Schoenberg, Ann. of Math. 1935)

Fix integers $n,r\geqslant 1$, and a finite metric space (X,d), where $X=\{x_0,\ldots,x_n\}$. Then (X,d) isometrically embeds into \mathbb{R}^r (with the Euclidean distance/norm) but not into \mathbb{R}^{r-1} if and only if the $n\times n$ matrix

$$A := (d(x_0, x_i)^2 + d(x_0, x_j)^2 - d(x_i, x_j)^2)_{i,j=1}^n$$

is positive semidefinite of rank r.

This is how Schoenberg connected metric geometry and matrix positivity.

Distance transforms: positive definite functions

• In the preceding result, the matrix

$$A=(d(x_0,x_i)^2+d(x_0,x_j)^2-d(x_i,x_j)^2)_{i,j=1}^n \text{ is positive semidefinite,}$$
 if and only if the matrix $A'_{(n+1)\times(n+1)}:=(-d(x_i,x_j)^2)_{i,j=0}^n$ is conditionally positive semidefinite: $u^TA'u\geqslant 0$ whenever $\sum_{j=0}^n u_j=0$.

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Now we move to transforms of positive matrices. Note that:

• Applying the function $-x^2$ entrywise sends any distance matrix from Euclidean space, to a conditionally positive semidefinite matrix A'.

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- Similarly, which entrywise maps send distance matrices to positive semidefinite matrices?

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- Similarly, which entrywise maps send distance matrices to positive semidefinite matrices? Such maps are called *positive definite functions*.
- Schoenberg was interested in embedding metric spaces into Euclidean spheres. This embeddability turns out to involve a *single* p.d. function!
 This is the cosine function.

Positive definite functions on spheres

Notice that the Hilbert sphere S^{∞} (hence every subspace such as S^{r-1}) has a rotation-invariant distance – arc-length along a great circle:

$$d(x,y) := \langle (x,y) = \arccos\langle x,y \rangle, \qquad x,y \in S^{\infty}.$$

Now applying $\cos[-]$ entrywise to any distance matrix on S^{∞} yields:

$$\cos[(d(x_i, x_j))_{i,j \geqslant 0}] = (\langle x_i, x_j \rangle)_{i,j \geqslant 0},$$

and this is a Gram matrix, so $\cos(\cdot)$ is positive definite on S^{∞} .

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Schoenberg then classified all continuous f such that $f \circ \cos(\cdot)$ is p.d.:

Theorem (Schoenberg, Duke Math. J. 1942)

Suppose $f:[-1,1]\to\mathbb{R}$ is continuous, and $r\geqslant 2$. Then $f(\cos\cdot)$ is positive definite on the unit sphere $S^{r-1}\subset\mathbb{R}^r$ if and only if

$$f(\cdot) = \sum_{k\geqslant 0} a_k C_k^{(\frac{r-2}{2})}(\cdot) \qquad \text{ for some } a_k\geqslant 0,$$

where $C_k^{(\lambda)}(\cdot)$ are the ultraspherical / Gegenbauer / Chebyshev polynomials.

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$$f(\cdot) = \sum_{k\geqslant 0} a_k C_k^{(\frac{r-2}{2})}(\cdot) \qquad \text{ for some } a_k\geqslant 0,$$

where $C_k^{(\lambda)}(\cdot)$ are the ultraspherical / Gegenbauer / Chebyshev polynomials.

Also follows from Bochner's work on compact homogeneous spaces [Ann. of Math. 1941] – but Schoenberg proved it directly with less 'heavy' machinery.

• Any Gram matrix of vectors $x_j \in S^{r-1}$ is the same as a rank $\leq r$ correlation matrix $A = (a_{ij})_{i,j=1}^n$, i.e.,

$$A = \begin{pmatrix} 1 & * & \\ & 1 & \\ & * & 1 \\ & & & 1 \end{pmatrix} = \begin{pmatrix} - & x_1^T & - \\ - & x_2^T & - \\ & \vdots & \\ - & x^T & - \end{pmatrix} \begin{pmatrix} | & | & | \\ x_1 & x_2 & \dots & x_n \\ | & | & & | \end{pmatrix} = (\langle x_i, x_j \rangle)_{i,j=1}^n.$$

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So.

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• If instead $r=\infty$, such a result would classify the entrywise positivity preservers on all correlation matrices. Interestingly, 70 years later the subject has acquired renewed interest because of its immediate impact in high-dimensional covariance estimation, in several applied fields.

Schoenberg's theorem on positivity preservers

And indeed, Schoenberg did make the leap from S^{r-1} to S^{∞} :

Theorem (Schoenberg, Duke Math. J. 1942)

Suppose $f:[-1,1]\to\mathbb{R}$ is continuous. Then $f(\cos\cdot)$ is positive definite on the Hilbert sphere $S^\infty\subset\mathbb{R}^\infty=\ell^2$ if and only if

$$f(\cos \theta) = \sum_{k \geqslant 0} c_k \cos^k \theta,$$

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For more information: A panorama of positivity – arXiv, Dec. 2018. (Survey, 80+ pp., by A. Belton, D. Guillot, A.K., and M. Putinar.)

- 3. Statistics: covariance estimation 4. Symmetric function theory
 - . Combinatorics: critical expone

Positivity and Statistics

- 3. Statistics: covariance estimation
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- Major challenge in science: detect structure in vast amount of data.
- Covariance/correlation is a fundamental measure of dependence between random variables:

$$\Sigma = (\sigma_{ij})_{i,j=1}^p, \qquad \sigma_{ij} = \operatorname{Cov}(X_i, X_j) = \mathbb{E}[X_i X_j] - \mathbb{E}[X_i] \mathbb{E}[X_j].$$

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- In modern-day settings (small samples, ultra-high dimension), covariance estimation can be very challenging.
- Classical estimators (e.g. sample covariance matrix (MLE)):

$$S = \frac{1}{n} \sum_{j=1}^{n} (x_j - \overline{x})(x_j - \overline{x})^T$$

perform poorly, are singular/ill-conditioned, etc.

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 Require some form of regularization – and resulting matrix has to be positive semidefinite (in the parameter space) for applications.

- 3. Statistics: covariance estimation
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Graphical models: Connections between statistics and combinatorics.

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- Not scalable to modern-day problems with 100,000+ variables (disease detection, climate sciences, finance. . .).

- 3. Statistics: covariance estimation
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Thresholding and regularization

Thresholding covariance/correlation matrices

True
$$\Sigma = \begin{pmatrix} 1 & 0.2 & 0 \\ 0.2 & 1 & 0.5 \\ 0 & 0.5 & 1 \end{pmatrix}$$
 $S = \begin{pmatrix} 0.95 & 0.18 & 0.02 \\ 0.18 & 0.96 & 0.47 \\ 0.02 & 0.47 & 0.98 \end{pmatrix}$

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Can be significant if p=1,000,000 and only, say, $\sim 1\%$ of the entries of the true Σ are nonzero.

- 3. Statistics: covariance estimation 4. Symmetric function theory
- 5 Combinatorics: critical exponer
- Entrywise functions regularization

More generally, we could apply a function $f:\mathbb{R}\to\mathbb{R}$ to the elements of the matrix S – regularization:

- 3. Statistics: covariance estimation
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(Example on previous slide is $f_{\epsilon}(x) = x \cdot \mathbf{1}_{|x| > \epsilon}$ for some $\epsilon > 0$.)

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Problem: For what functions $f: \mathbb{R} \to \mathbb{R}$, does f[-] preserve \mathbb{P}_N ?

- 3. Statistics: covariance estimation
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Preserving positivity in fixed dimension

Schoenberg's result characterizes functions preserving positivity for matrices of all dimensions: $f[A] \in \mathbb{P}_N$ for all $A \in \mathbb{P}_N$ and all N.

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Similar/related problems studied by many others, including:

- Bharali, Bhatia, Christensen, FitzGerald, Helson, Hiai, Holtz,
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- In applications: dimension of the problem is known.
 Unnecessarily restrictive to preserve positivity in all dimensions.

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Problems motivated by applications

• We revisit this problem with modern applications in mind.

- 3. Statistics: covariance estimation 4. Symmetric function theory
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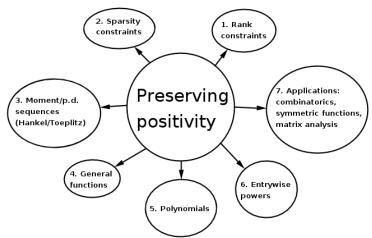
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Positivity and Symmetric functions

3. Statistics: covariance estimation4. Symmetric function theory

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Question: Find a power series with a negative coefficient, which preserves positivity on \mathbb{P}_N for some $N\geqslant 3$.

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Fix $I = (0, \rho)$ for $0 < \rho \leqslant \infty$, and $f : I \to \mathbb{R}$. Suppose $f[A] \in \mathbb{P}_N$ for all $A \in \mathbb{P}_N(I)$ Hankel of rank $\leqslant 2$, with N fixed.

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- Statistics: covariance estimation
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- 5. Combinatorics: critical expo

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Can c_N be negative? Sharp bound? (Not known to date.)

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- 3. Statistics: covariance estimation4. Symmetric function theory
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- Statistics: covariance estimation
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Consequences

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- 5 The proofs involve a deep result on Schur positivity.
- Further applications: Schubert cell-type stratifications, connections to Rayleigh quotients, thresholds for analytic functions and Laplace transforms, additional novel symmetric function identities,

Schur polynomials

Key ingredient in proof – representation theory / symmetric functions:

Given a decreasing N-tuple $n_{N-1} > n_{N-2} > \cdots > n_0 \geqslant 0$, the corresponding **Schur polynomial** over a field \mathbb{F} is the unique polynomial extension to \mathbb{F}^N of

$$s_{(n_{N-1},\dots,n_0)}(x_1,\dots,x_N) := \frac{\det(x_i^{n_{j-1}})}{\det(x_i^{j-1})}$$

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Example: If N = 2 and $\mathbf{n} = (m < n)$, then

$$s_{\mathbf{n}}(x_1, x_2) = \frac{x_1^n x_2^m - x_1^m x_2^n}{x_1 - x_2} = (x_1 x_2)^m (x_1^{n-m-1} + x_1^{n-m-2} x_2 + \dots + x_2^{n-m-1}).$$

Basis of homogeneous symmetric polynomials in x_1, \ldots, x_N .

- 3. Statistics: covariance estimation4. Symmetric function theory
- By-product: novel symmetric function identity

• Well-known identity of Cauchy: if
$$f_0(t) = 1/(1-t) = \sum_{k\geqslant 0} t^k$$
, then
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- We show this for *every* power series
 obtained by generalizing a matrix positivity computation of Loewner:

Theorem (K., 2018)

Fix a commutative unital ring R and let t be an indeterminate. Let $f(t) := \sum_{M \geqslant 0} f_M t^M \in R[[t]]$ be an arbitrary formal power series. Given vectors $\mathbf{u}, \mathbf{v} \in R^N$ for some $N \geqslant 1$, we have:

$$\det f[t\mathbf{u}\mathbf{v}^T] = V(\mathbf{u})V(\mathbf{v}) \sum_{M \geqslant \binom{N}{2}} t^M \sum_{\mathbf{n} = (n_{N-1}, \dots, n_0) \vdash M} s_{\mathbf{n}}(\mathbf{u})s_{\mathbf{n}}(\mathbf{v}) \prod_{k=0}^{N-1} f_{n_k}.$$

- 3. Statistics: covariance estimation
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Positivity and Combinatorics

- 3. Statistics: covariance estimation 4. Symmetric function theory
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Matrices with zeros according to graphs

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Study matrices with zeros according to graphs:

Given a graph G=(V,E) on N vertices, and $I\subset\mathbb{R},$ define

$$\mathbb{P}_G(I) := \{ A = (a_{ij}) \in \mathbb{P}_N(I) : a_{ij} = 0 \text{ if } i \neq j, \ (i,j) \notin E \}.$$

Note: a_{ij} can be zero if $(i, j) \in E$.

- 3. Statistics: covariance estimation
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Given a subset
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$$(f_G[A])_{ij} := \begin{cases} f(a_{ij}) & \text{if } i = j \text{ or } (i, j) \in E, \\ 0 & \text{otherwise.} \end{cases}$$

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- Previously known characterization for individual graphs: only for K_2 , i.e., \mathbb{P}_2 Vasudeva (1979).
- Only known characterization for sequence of graphs: $\{K_N:N\in\mathbb{N}\}$ [Schoenberg, Rudin]. Yields absolutely monotonic functions.

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We now explain how *powers* preserving positivity \leadsto a novel graph invariant.

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Distinguished family of functions: the power maps $x^{\alpha}, \alpha \in \mathbb{R}, \ x \geqslant 0$. (Here, $0^{\alpha} := 0$.)

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Can we do better?

- Statistics: covariance estimation
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Exploit the sparsity structure of \mathbb{P}_G .

Problem: Compute the set of powers preserving positivity on \mathbb{P}_G :

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- 3. Statistics: covariance estimation 4. Symmetric function theory
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- How do CE(G) and \mathcal{H}_G depend on the geometry of G? Compute CE(G) for a family containing complete graphs and trees?

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Not Chordal

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Let $K_r^{(1)}$ be the 'almost complete' graph on r nodes – missing one edge. Let r=r(G) be the largest integer such that either K_r or $K_r^{(1)}$ is an induced subgraph of G.

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If G is chordal with $|V| \geqslant 2$, then $\mathcal{H}_G = \mathbb{N} \cup [r-2, \infty)$.

In particular, CE(G) = r - 2.

Unites complete graphs, trees, band graphs, split graphs...

- 4. Symmetric function theory
- 5. Combinatorics: critical exponent

Non-chordal graphs

Example: Band graphs with bandwidth d: $CE(G) = \min(d, n-2)$.

$$\text{So for } T_5 = \begin{pmatrix} 1 & 0.6 & 0.5 & 0 & 0 \\ 0.6 & 1 & 0.6 & 0.5 & 0 \\ 0.5 & 0.6 & 1 & 0.6 & 0.5 \\ 0 & 0.5 & 0.6 & 1 & 0.6 \\ 0 & 0 & 0.5 & 0.6 & 1 \end{pmatrix} \text{ as above, all powers } \geqslant 2 = d \text{ work.}$$

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Other graphs? (Talk by Dominique Guillot in MS18-iii.)

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Other graphs? (Talk by $Dominique\ Guillot$ in MS18-iii.) CE(G) in terms of other graph invariants? Not clear.



















- 3. Statistics: covariance estimation 4. Symmetric function theory
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Selected publications

- D. Guillot, A. Khare, and B. Rajaratnam:
- [1] Preserving positivity for rank-constrained matrices, Trans. AMS, 2017.
- [2] Preserving positivity for matrices with sparsity constraints, Tr. AMS, 2016.
- [3] Critical exponents of graphs, J. Combin. Theory Ser. A, 2016.
- [4] Complete characterization of Hadamard powers preserving Loewner positivity, monotonicity, and convexity, J. Math. Anal. Appl., 2015.

A. Belton, D. Guillot, A. Khare, and M. Putinar:

- [5] Matrix positivity preservers in fixed dimension. I, Advances in Math., 2016.
- [6] Moment-sequence transforms, Preprint, 2016.
- [7] A panorama of positivity (survey), Shimorin volume + Ransford-60 proc.
- [8] On the sign patterns of entrywise positivity preservers in fixed dimension, (With T. Tao) Preprint, 2017.
- [9] Smooth entrywise positivity preservers, a Horn–Loewner master theorem, and Schur polynomials, Preprint, 2018.