

# Extremal Positive Semidefinite Matrices for graphs without $K_5$ minors

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Joint work with Liam Solus and Caroline Uhler

# Outline

- 1 Series-Parallel Graphs
- 2 Three Convex Bodies
- 3 Facet-Ray Identification Property
- 4 Open problems

# Series-Parallel Graph

## Definition

A two-terminal series-parallel graph (TTSPG) is a graph that may be constructed by a sequence of series and parallel compositions starting from a set of copies of a single-edge graph  $K_2$  with assigned terminals.

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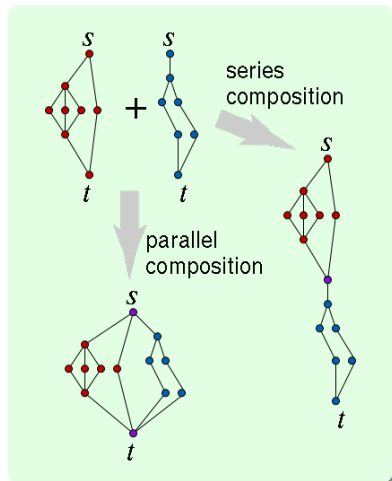
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# Cut Polytopes

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A **cut** of the graph  $G$  is a bipartition of the vertices,  $(U, U^c)$ , and its associated **cutset** is the collection of edges  $\delta(U) \subset E$  with one endpoint in each block of the bipartition. To each cutset we assign a  $(\pm 1)$ -vector in  $\mathbb{R}^E$  with a  $-1$  in coordinate  $e$  if and only if  $e \in \delta(U)$ . The  $(\pm 1)$ -cut polytope of  $G$  is the convex hull in  $\mathbb{R}^E$  of all such vectors.

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- Maximizing over the polytope  $\text{cut}^{\pm 1}(G)$  is equivalent to solving the max-cut problem for  $G$ .
- The max-cut problem is known to be NP-hard.
- However, it is possible to optimize in polynomial time over a (often times non-polyhedral) positive semidefinite relaxation of  $\text{cut}^{\pm 1}(G)$ , known as an **elliptope**.

# Elliptopes

## Elliptopes

Let  $\mathbb{S}^p$  denote the real vector space of all real  $p \times p$  symmetric matrices, and let  $\mathbb{S}_{\succeq 0}^p$  denote the cone of all positive semidefinite matrices in  $\mathbb{S}^p$ . The  **$p$ -elliptope** is the collection of all  $p \times p$  **correlation matrices**, i.e.

$$\mathcal{E}_p = \{X \in \mathbb{S}_{\succeq 0}^p \mid X_{ii} = 1 \text{ for all } i \in [p]\}.$$

The elliptope  $\mathcal{E}_G$  is defined as the projection of  $\mathcal{E}_p$  onto the edge set of  $G$ . That is,

$$\mathcal{E}_G = \{\mathbf{y} \in \mathbb{R}^E \mid \exists Y \in \mathcal{E}_p \text{ such that } Y_e = y_e \text{ for every } e \in E(G)\}.$$

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## Notes

The elliptope  $\mathcal{E}_G$  is a positive semidefinite relaxation of the cut polytope  $\text{cut}^{\pm 1}(G)$ , and thus maximizing over  $\mathcal{E}_G$  can provide an approximate solution to the max-cut problem.

# Cone of Concentration Matrices

## Concentration Matrices

Consider the **Graphical Gaussian model**  $N(\mu, \Sigma)$  where  $\mu \in \mathbb{R}^p$  is the mean and  $\Sigma \in \mathbb{R}^{p \times p}$  is the correlation matrix for the model. The concentration matrix of  $\Sigma$  is  $K = \Sigma^{-1}$ .

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## Definition

The **sparsity order** of  $G$  is defined as the maximum rank of an extremal matrix in  $\mathcal{K}_G$ .

# $\text{cut}^{\pm 1}(G)$ and $\mathcal{K}_G$

## Goal

Want to show that the facets of  $\text{cut}^{\pm 1}(G)$  identify extremal rays of  $\mathcal{K}_G$  for any graph  $G$  without  $K_5$  minor and to compute the sparsity order of any series-parallel graph  $G$ .

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The dual body of the elliptope  $\mathcal{E}_G$  is

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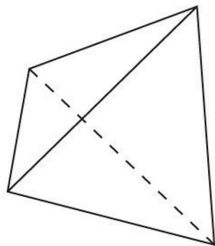
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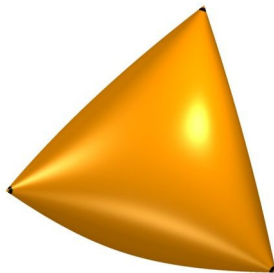
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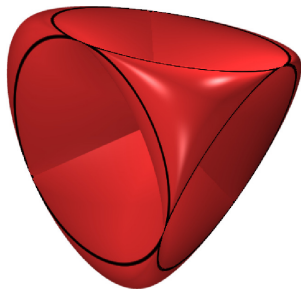
## Example: 3-cycle



(a)  $CUT^{\pm 1}(G)$



(b)  $\mathcal{E}_G$



(c)  $\mathcal{E}_G^V$

$$CUT^{\pm 1}(G) = \text{conv}((1, 1, 1), (-1, -1, 1), (-1, 1, -1), (1, -1, -1))$$

$$\mathcal{E}_G = \left\{ \begin{pmatrix} 1 & x_1 & x_3 \\ x_1 & 1 & x_2 \\ x_3 & x_2 & 1 \end{pmatrix} \succeq 0 \right\} \quad \mathcal{E}_G^V = \left\{ \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} : \begin{pmatrix} a & y_1 & y_3 \\ y_1 & b & y_2 \\ y_3 & y_2 & 2 - a - b \end{pmatrix} \succeq 0 \right\}$$

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- The PD-completeness problem would become easier for  $G$  with smaller sparsity order (i.e. where the max rank of an extremal ray is small).
- Our computations of the facets of  $\text{cut}^{\pm 1}(G)$  for  $G$  series-parallel together with the proof of facet-ray identification tells us all these ranks are encoded nicely in the supporting hyperplanes of  $\text{cut}^{\pm 1}(G)$ .

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## Theorem [Solus, Uhler, Y. 2015]

Graphs without  $K_5$  minors have the facet-ray identification property.

## Cut Polytope for the 4-cycle: an example

$G := C_4$ , identify  $\mathbb{R}^{E(G)} \simeq \mathbb{R}^4$  by identifying edge  $\{i, i+1\}$  with coordinate  $i$  for  $i = 1, 2, 3, 4$ . The cut polytope of  $G$  is the convex hull of  $(-1, 1)$ -vectors in  $\mathbb{R}^4$  containing precisely an even number of  $-1$ 's.

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### Facets

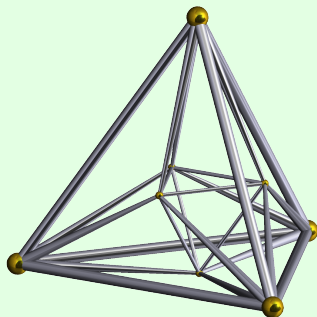
$\text{cut}^{\pm 1}(G)$  is the 4-cube  $[-1, 1]^4$  with truncations at the eight vertices containing an odd number of  $-1$ 's with sixteen facets supported by the hyperplanes

$$\pm x_i = 1, \quad \text{and} \quad \langle v_T, x \rangle = 2,$$

where  $T$  is an odd cardinality subset of  $[4]$ , and  $v_T$  is the corresponding vertex of  $[-1, 1]^4$  with an odd number of  $-1$ 's.

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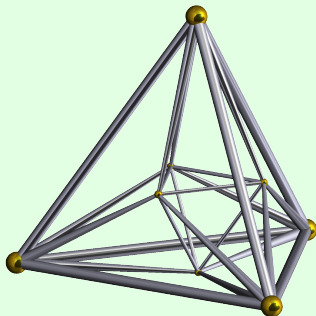
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Schlegel diagram of the cut polytope for the 4-cycle.

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## Notes

It has 8 demicubes (tetrahedra) 8 tetrahedra as its facets.

## 4-cycle: an example

The facets supported by the hyperplanes  $\pm x_1 = 1$  correspond to the rank 1 extremal matrices

$$Y = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{and} \quad Y = \begin{bmatrix} 1 & -1 & 0 & 0 \\ -1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

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The facets  $\langle v_T, x \rangle = 2$  for  $v_T = (1, -1, 1, 1)$  and  $v_T = (1, -1, -1, -1)$  respectively correspond to the rank 2 extremal matrices

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The facets  $\langle v_T, x \rangle = 2$  for  $v_T = (1, -1, 1, 1)$  and  $v_T = (1, -1, -1, -1)$  respectively correspond to the rank 2 extremal matrices

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These four matrices respectively project to the four extreme points in  $\mathcal{E}_G^\vee$

$$(1, 0, 0, 0), \quad (-1, 0, 0, 0), \quad \frac{1}{3}(-1, 1, -1, -1), \quad \text{and} \quad \frac{1}{3}(-1, 1, 1, 1),$$

# Outline

- 1 Series-Parallel Graphs
- 2 Three Convex Bodies
- 3 Facet-Ray Identification Property
- 4 Open problems**

# Open problems

## Problem

Determine all graphs  $G$  with the facet-ray identification property for which the facets of  $\text{cut}^{\pm 1}(G)$  characterize all extremal ranks of  $\mathbb{S}_{\geq 0}^p(G)$ .

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Determine facet-defining inequalities of  $\text{cut}^{\pm 1}(G)$  that can never identify extremal matrices in  $\mathbb{S}_{\geq 0}^p(G)$ .

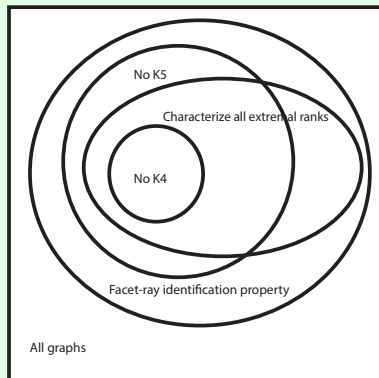
# Open problems

## Problem

Determine all graphs  $G$  with the facet-ray identification property for which the facets of  $\text{cut}^{\pm 1}(G)$  characterize all extremal ranks of  $\mathbb{S}_{\geq 0}^p(G)$ .

## Problem

Determine facet-defining inequalities of  $\text{cut}^{\pm 1}(G)$  that can never identify extremal matrices in  $\mathbb{S}_{\geq 0}^p(G)$ .



THANK YOU FOR YOUR  
ATTENTION!

*Questions?*

Reference: <http://arxiv.org/abs/1506.06702>

$K_{3,3}$

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Grone and Pierce (1990) characterized the extremal rays of  $\mathbb{S}_{\geq 0}^p(G)$ , and it is shown that  $G$  has extremal rays of ranks 1, 2, and 3.



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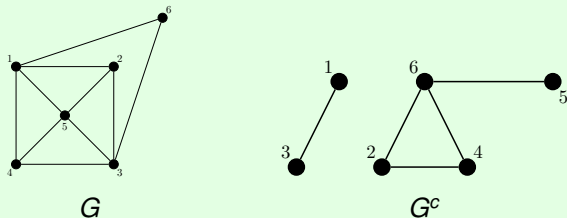
However, with the help of `Polymake` we see that the facet-supporting hyperplanes of  $\text{cut}^{\pm 1}(G)$  are  $x_e = \pm 1$  for each edge  $e \in E(G)$  together with  $\langle v^F, x \rangle = m - 2$  as  $C_m$  varies over the nine (chordless) 4-cycles within  $G$ . Thus, the constant terms of the facet-supporting hyperplanes only capture extreme ranks 1 and 2, but not 3.

## Graph $G$ with a $K_4$ minor but no $K_5$ minor

This is an example of a graph  $G$  with a  $K_4$  minor but no  $K_5$  minor for which the extremal ranks of  $\mathbb{S}_{\geq 0}^p(G)$  are characterized by the facets of  $\text{cut}^{\pm 1}(G)$ .

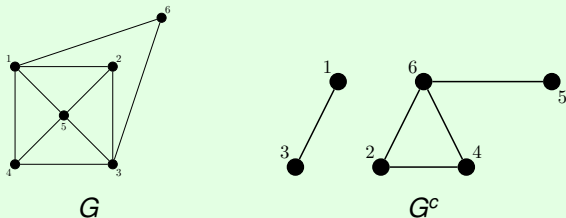
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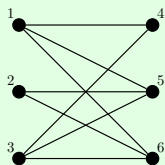
Recall that a  $k$ -block is a graph  $P$  of order  $k$  that has no proper induced subgraph of order  $k$ . Agler et al. characterized all 3-blocks in terms of their complements. It follows immediately from this theorem that  $G$  contains no induced 3-block. Thus,  $\text{ord}(G) \leq 2$ , and since  $G$  is not a chordal graph we see that  $\text{ord}(G) = 2$ . By Theorem the facets of  $\text{cut}^{\pm 1}(G)$  identify extremal rays of rank 1 and 2. Thus, all possible extremal ranks of  $G$  are characterized by the facets of  $\text{cut}^{\pm 1}(G)$ .

## Graph $G$ with no $K_{3,3}$ minor

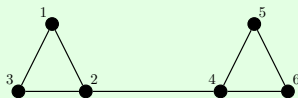
Are graphs with no  $K_{3,3}$  minor the collection of graphs for which the facets characterize the extremal ranks of  $\mathbb{S}_{\Sigma_0}^p(G)$ ? Answer is no.

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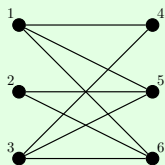
$G$



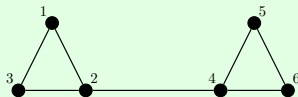
$G^c$

## Graph $G$ with no $K_{3,3}$ minor

Are graphs with no  $K_{3,3}$  minor the collection of graphs for which the facets characterize the extremal ranks of  $\mathbb{S}_{\geq 0}^p(G)$ ? Answer is no.



$G$



$G^c$

Notice that  $G$  contains no  $K_{3,3}$  minor, but it does contain a  $K_4$  minor. By Agler et al,  $G$  is a 3-block since its complement graph is two triangles connected by an edge. Thus,  $G$  has an extremal ray of rank 3, but by Theorem, the facets of  $\text{cut}^{\pm 1}(G)$  only detect extremal rays of ranks 1 and 2.

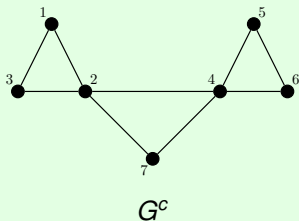
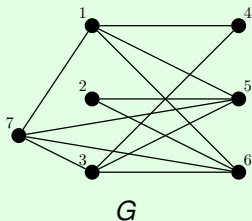
# Facet-ray identification property with $K_5$ minor

A graph with a  $K_5$  minor whose facets characterize all extremal rays.



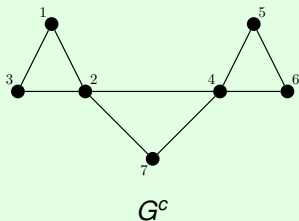
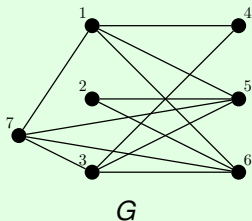
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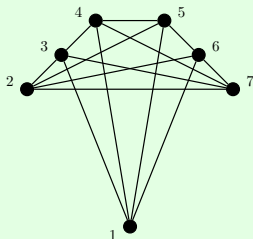
$G$  has the facet-ray identification property, and the facets identify extreme rays of rank 1, 2, and 3.

# Graph without facet-ray identification property

Not all graphs have facet-ray identification property.

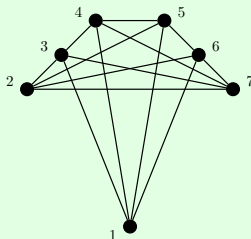
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$$X_{13} + X_{14} + X_{15} + X_{16} + X_{25} + X_{26} + X_{27} + X_{37} + X_{47} - X_{23} - X_{34} - X_{45} - X_{56} - X_{67} \leq 4$$

is not a facet-defining inequality.