The facets of the cut polytope and the extreme rays of cone of concentration matrices of series-parallel graphs

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Joint work with Liam Solus and Caroline Uhler

Outline

Series-Parallel Graph

2 Three Convex Bodies

3 Facet-Ray Identification Property

Definition

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A graph *G* is called **seriesparallel** if it has no subgraph homeomorphic to K_4 , the complete graph on four vertices

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Example

A cycle graph with *p* vertices.









3 Facet-Ray Identification Property

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 (± 1) -vector in \mathbb{R}^E with a -1 in coordinate *e* if and only if $e \in \delta(U)$. The (± 1) -cut polytope of *G* is the convex hull in \mathbb{R}^E of all such vectors.

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Max-Cut Problem

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- Maximizing over the polytope cut^{±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 cut^{±1} (G), known as an elliptope.

 $G := C_4$, 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

 $\operatorname{cut}^{\pm 1}(G)$ 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

$$\pm x_i = 1$$
, and $\langle v_T, x \rangle = 2$,

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.

Cut Polytope



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.

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Let \mathbb{S}^p denote the real vector space of all real $p \times p$ symmetric matrices, and let $\mathbb{S}^p_{\geq 0}$ 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.

$$\mathcal{E}_{\rho} = \{ X \in \mathbb{S}^{\rho}_{\succ 0} | X_{ii} = 1 \text{ for all } i \in [\rho] \}.$$

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

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

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Notes

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

C₄-Elliptopes



C₄-Elliptopes



Level curves of the rank 2 locus of \mathcal{E}_{C_4} . The value of x_4 varies from 0 to 1 as we view the figures from left-to-right and top-to-bottom.

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 Σ is $K = \Sigma^{-1}$.

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A concentration matrix *K* is a $p \times p$ positive semidefinite matrices with zeros in all entries corresponding to nonedges of *G*.

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A concentration matrix K is a $p \times p$ positive semidefinite matrices with zeros in all entries corresponding to nonedges of G.

Cone of Concentration Matrices

Let \mathcal{K}_G is the set of all concentration matrices K corresponding to G. Then \mathcal{K}_G is a convex cone in \mathbb{S}^p called the **cone of concentration matrices**.

Goal

Want to show that the facets of $cut^{\pm 1}$ (G) identify extremal rays of \mathcal{K}_G for any series parallel graph *G*.

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- The PD-completability 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 cut^{±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 cut^{±1} (G).

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Theorem [Solus, Uhler, Y. 2015]

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

$$\mathcal{E}_G^{\vee} = \{ x \in \mathbb{R}^E \mid \exists X \in \mathcal{K}_G \text{ such that } X_E = x \text{ and } \operatorname{tr}(X) = 2 \}.$$

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An immediate consequence of this theorem is that the extreme points in \mathcal{E}_G^{\vee} are projections of extreme matrices in \mathcal{K}_G .

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Facet-Ray Identification Property

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- If all singular points on the boundary of *E_G* are also singular points on the boundary of cut^{±1} (G) then the supporting hyperplanes of facets of cut^{±1} (G) will be translations of facets of *E_G*, i.e. extreme sets of *E_G* with positive Lebesgue measure in a codimension one affine subspace of the ambient space.

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- It follows that the outward normal vectors to the facets of cut^{±1} (G) generate the normal cones to these regular points and facets of *E_G*.
- Dually, the normal vectors to the facets of cut^{±1} (G) are then extreme points of *E*[∨]_G, and consequently projections of extreme matrices of *K*_G.
- Thus, we can expect to find extremal matrices in *K_G* whose off-diagonal entries are given by the normal vectors to the facets of cut^{±1} (G).

Example: 3-cycle



$$CUT^{\pm 1}(G) = conv((1, 1, 1), (-1, -1, 1), (-1, 1, -1), (1, -1, -1))$$
$$\mathcal{E}_{G} = \left\{ \begin{pmatrix} 1 & x_{1} & x_{3} \\ x_{1} & 1 & x_{2} \\ x_{3} & x_{2} & 1 \end{pmatrix} \succeq 0 \right\} \quad \mathcal{E}_{G}^{V} = \left\{ \begin{pmatrix} y_{1} \\ y_{2} \\ y_{3} \end{pmatrix} : \begin{pmatrix} a & y_{1} & y_{3} \\ y_{1} & b & y_{2} \\ y_{3} & y_{2} & 2 - a - b \end{pmatrix} \succeq 0 \right\}$$

Facet-Ray Identification Property Definition

Let *G* be a graph. For each facet *F* of cut^{±1} (G) let $\alpha^F \in \mathbb{R}^E$ denote the normal vector to the supporting hyperplane of *F*. We say that *G* has the facetray identification property (or FRIP) if for every facet *F* of cut^{±1} (G) there exists an extremal matrix $M = [m_{ij}]$ in \mathcal{K}_G for which either $m_{ij} = \alpha_{ij}^F$ for every $\{i, j\} \in E(G)$ or $m_{ij} = -\alpha_{ij}^F$ for every $\{i, j\} \in E(G)$.

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Theorem [Solus, Uhler, Y. 2015]

Let $p \ge 3$. The cycle C_p on p vertices has the facet-ray identification property. Moreover, the cut polytope cut^{±1} (C_p) is the p-halfcube which has two types of facets, halfcubical and simplicial. If the extremal matrix M is identified by a halfcubical facet then it is rank 1, and if it is identified by a simplicial facet it is rank p - 2.

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Theorem [Solus, Uhler, Y. 2015]

Every series-parallel graph has the facet-ray identification property. Moreover, the rank of the extremal ray is given by the constant term of the supporting hyperplane of the facet.

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4-cycle: an example

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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

$$Y = \frac{1}{3} \begin{bmatrix} 1 & -1 & 0 & -1 \\ -1 & 2 & 1 & 0 \\ 0 & 1 & 1 & -1 \\ -1 & 0 & -1 & 2 \end{bmatrix} \text{ and } Y = \frac{1}{3} \begin{bmatrix} 1 & -1 & 0 & 1 \\ -1 & 2 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 2 \end{bmatrix}.$$

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

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

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- R package
 - R package algstat is available via CRAN or at Github https://github.com/dkahle/algstat

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Questions?