# Separation for the Max-Cut Problem on General Graphs 

## Thorsten Bonato

Research Group Discrete and Combinatorial Optimization University of Heidelberg

Joint work with:
Michael Jünger (University of Cologne) Gerhard Reinelt (University of Heidelberg) Giovanni Rinaldi (IASI, Rome)
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## Outline

(1) Max-Cut Problem
(2) Separation using Graph Contraction
(3) Computational Results

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## Max-Cut Problem

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Finding a cut with maximum aggregate edge weight is known as max-cut problem.

## Related Polytopes

## Cut polytope CUT(G)

Convex hull of all incidence vectors of cuts of $G$.

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Convex hull of all incidence vectors of cuts of $G$.

## Semimetric polytope MET(G)

Relaxation of the max-cut IP formulation described by two inequality classes:

$\operatorname{CUT}\left(K_{3}\right)$

Odd-cycle: $\quad x(F)-x(C \backslash F) \leq|F|-1, \quad$ for each cycle $C$ of $G$, for all $F \subseteq C,|F|$ odd.
Trivial:

$$
0 \leq x_{e} \leq 1, \quad \text { for all } e \in E
$$

## Exact Solution Methods

## Algorithms

- Branch\&Cut,
- Branch\&Bound using SDP relaxations.

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- Branch\&Bound using SDP relaxations.

Certain separation procedures only work for dense/complete graphs.


## How to handle sparse graphs

- Trivial approach:
artificial completion using edges with weight 0 .
- Drawback:
increases number of variables and thus the computational difficulty.


## Outline

## (1) Max-Cut Problem

(2) Separation using Graph Contraction
(3) Computational Results

## Outline of the Separation using Graph Contraction

Input: LP solution $z \in \operatorname{MET}(G) \backslash \operatorname{CUT}(G)$.

|  |  <br> Separate |  | $G$ <br> $\bar{G}$ |
| :---: | :---: | :---: | :---: |

## Outline of the Separation using Graph Contraction

Transform 1-edges into 0-edges.


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## Outline of the Separation using Graph Contraction

Contract 0-edges.


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## Outline of the Separation using Graph Contraction

Introduce artificial LP values for non-edges.


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## Outline of the Separation using Graph Contraction

Separate extended LP solution.


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## Outline of the Separation using Graph Contraction

Project out nonzero coefficients related to non-edges.

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## Outline of the Separation using Graph Contraction

Lift inequality.

\begin{tabular}{|c|c|c|c|}
\hline  \& Separate \&  \& $G$
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$\bar{G}^{\prime}$ <br>
\hline
\end{tabular}

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Contraction allows heuristic odd-cycle separation.

## Extension

Given a contracted LP solution $\bar{z} \in \operatorname{MET}(\bar{G})$, assign artificial LP values to the non-edges.
Goal: extended LP solution $\bar{z}^{\prime} \in \operatorname{MET}\left(\bar{G}^{\prime}\right)$.


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Feasible artificial LP values of non-edge uv
Range: [ $\left.\max \left\{0, L_{u v}\right\}, \min \left\{U_{u v}, 1\right\}\right] \subseteq[0,1]$ with

$$
\begin{aligned}
& L_{u v}:=\max \{\bar{z}(F)-\bar{z}(P \backslash F)-|F|+1 \mid P(u, v) \text {-path, } F \subseteq P,|F| \text { odd }\} \\
& U_{u v}:=\min \{-\bar{z}(F)+\bar{z}(P \backslash F)+|F| \quad \mid P(u, v) \text {-path, } F \subseteq P,|F| \text { even }\} .
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Odd-cycle inequality derived from arg max (resp. arg min) is called a lower (resp. upper) inequality of $u v$.

## Projection

Consider a valid inequality $\bar{a}^{\prime T} \bar{x}^{\prime} \leq \bar{\alpha}^{\prime}$ violated by the extended LP solution $\bar{z}^{\prime}$.

$$
\left(\begin{array}{lll}
\cdots & \bar{a}_{\mathrm{uv}}^{\prime} & \cdots \\
\bar{a}_{\mathrm{st}}^{\prime} & \cdots, \bar{\alpha}^{\prime}
\end{array}\right)
$$ Non-edges may have nonzero coefficients!

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## Project out coefficient of non-edge uv

Add a lower inequality if $\bar{a}_{u v}^{\prime}>0$ resp. an upper inequality if $\bar{a}_{u v}^{\prime}<0$.

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\begin{aligned}
& \left(\cdots \quad \bar{a}_{\mathrm{uv}}^{\prime} \cdots \quad \overline{\mathrm{a}}_{\mathrm{st}}^{\prime} \cdots, \bar{\alpha}^{\prime}\right) \\
& +\left(\cdots-\overline{\mathbf{a}}_{\mathrm{uv}}^{\prime} \cdots \quad \cdots \cdots, \overline{\boldsymbol{\beta}}_{1}^{\prime}\right) \\
& +\left(\cdots \quad \cdots \cdots-\overline{\mathbf{a}}_{\mathrm{st}}^{\prime} \cdots, \overline{\boldsymbol{\beta}}_{2}^{\prime}\right)
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Project out coefficient of non-edge uv
$=\left(\begin{array}{lllll}\cdots & 0 & \cdots & 0 & \cdots, \bar{\gamma}\end{array}\right)$
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## Problem

If the added inequalities are not tight at $\bar{z}^{\prime}$ then the projection reduces the initial violation $\bar{a}^{\prime} T \bar{z}^{\prime}-\bar{\alpha}^{\prime}$.

## Adaptive Extension

Artificial LP values $\bar{z}_{u v}^{\prime}$ adapt to the sign of the corresponding coefficient in a given inequality $\bar{a}^{\prime} T \bar{x}^{\prime} \leq \bar{\alpha}^{\prime}$, i. e.,

$$
\bar{z}_{u v}^{\prime}= \begin{cases}L_{u v} & \text { if } \bar{a}_{u v}^{\prime}>0 \\ U_{u v} & \text { otherwise }\end{cases}
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## Trivial modification case

For a given class of inequalities, all nonzero coefficients have identical sign.
E. g., bicycle- $p$-wheel inequalities: $x(B) \leq 2 p$ (set $\bar{z}_{u v}^{\prime}=L_{u v}$ for all non-edges $u v$ ).


## Adaptive Extension: Target Cuts (1/2)

Input for separation framework [Buchheim, Liers, and Oswald]

- Associated polyhedron $Q=\operatorname{conv}\left\{x_{1}, \ldots, x_{s}\right\}+\operatorname{cone}\left\{y_{1}, \ldots, y_{t}\right\}$,
- Interior point $q \in Q$,
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Obtain facet defining inequality $a^{T}(x-q) \leq 1$ by solving the LP

$$
\begin{array}{ll}
\max & a^{T}(z-q) \\
\text { s.t. } & a^{T}\left(x_{i}-q\right) \leq 1, \text { for all } i=1, \ldots, s \\
& a^{T} y_{j} \leq 0, \text { for all } j=1, \ldots, t \\
& a \in \mathbb{R}^{m}
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For max-cut we set $Q=\operatorname{CUT}(G(W))$ for a subset $W \subseteq V$.

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W.I.o.g. let the last $\ell$ vector entries correspond to the non-edges.

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& z^{\prime}:=\left(z_{1}, \ldots, z_{m-\ell}, \quad L_{1}, \quad \ldots, L_{\ell}, \quad U_{1}, \quad \ldots, U_{\ell}\right), \\
& x_{i}^{\prime}:=\left(x_{i 1}, \ldots, x_{i, m-\ell}, \quad x_{i, m-\ell+1}, \ldots, x_{i m}, \quad x_{i, m-\ell+1}, \ldots, x_{i m}\right) \text {, } \\
& q^{\prime}:=\left(q_{1}, \ldots, q_{m-\ell}, \quad q_{m-\ell+1}, \ldots, q_{m}, \quad q_{m-\ell+1}, \ldots, q_{m}\right) \text {, } \\
& Q^{\prime}:=\operatorname{conv}\left\{x_{1}^{\prime}, \ldots, x_{s}^{\prime}\right\}+\operatorname{cone}\left\{-e_{m-\ell+k}, e_{m+k} \mid k=1, \ldots, \ell\right\} .
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\end{array} U_{1}, \quad \ldots, U_{\ell}\right.
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Resulting target cut separation LP

$$
\begin{aligned}
\max & a^{\prime T}\left(z^{\prime}-q^{\prime}\right) \\
\text { s.t. } & a^{\prime T}\left(x_{i}^{\prime}-q^{\prime}\right) \leq 1, \text { for all } i=1, \ldots, s \\
- & a_{m-\ell+k}^{\prime}, a_{m+k}^{\prime} \leq 0, \text { for all } k=1, \ldots, \ell \\
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\end{aligned}
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In an optimum solution $a^{\prime *}$ at most one of $a_{m-\ell+k}^{\prime *}$ and $a_{m+k}^{\prime *}$ can be nonzero for each $k=1, \ldots, \ell$.

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## Computational Experiments

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Separation schemes

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odd-cycles (spanning-tree heuristic, 3- / 4-cycles, exact separation).


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- Contraction:
standard scheme + contraction as heuristic OC-separator.


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odd-cycles (spanning-tree heuristic, 3- / 4-cycles, exact separation).
- Contraction:
standard scheme + contraction as heuristic OC-separator.
- Extension:
contraction scheme + separation of bicycle- $p$-wheels, hypermetric inequalities and target cuts on the extended LP solution.


## Unconstrained Quadratic 0/1-Optimization Problems

Running time of Beasley instances (250 nodes, density 0.1)

[Intel Xeon 2.8 GHz, 8GB shared RAM.]

## Spin Glass Problems with Uniformly Distributed $\pm 1$-Weights

Average running time of 10 random instances per grid size

[Intel Xeon 2.8 GHz , 8GB shared RAM. Running time capped to 10 h per instance.]

## Spin Glass Problems with Gaussian Distributed Integral Weights

Average running time of 10 random instances per grid size

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## Conclusion and Future Work

## Separation using graph contraction

- Enables the use of separation techniques for dense / complete graphs on sparse graphs.
- Accelerates the exact solution of the max-cut problem for the examined classes of spin glass problems.
- Acceleration is mainly due to the use of contraction as heuristic odd-cycle separator.


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- Determine good parameter settings.
- Further computational experiments.


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## Thank you for your attention!

