Hard Combinatorial Problems, Doubly Nonnegative Relaxations, Facial Reduction, and Alternating Direction Method of Multipliers

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Two Main References

- [6] N. Graham, H. Hu, J. Im, X. Li, and H. Wolkowicz, *A restricted dual Peaceman-Rachford splitting method for QAP*, Tech. report, Waterloo, Ontario, 2020.
- [7] X. Li, T.K. Pong, H. Sun, and H. Wolkowicz, *A strictly contractive Peaceman-Rachford splitting method for the doubly nonnegative relaxation of the minimum cut problem*, Comput. Optim. Appl. **78** (2021), no. 3, 853–891. MR4221619

- Solving hard combinatorial/discrete optimization problems requires: efficient upper/lower bounding techniques.
- These problems are often modelled using quadratic objectives and/or quadratic constraints, i.e., QQPs.
- Lagrangian relaxations of QQPs lead to Semidefinite Programming, SDP, and SDP relaxations, e.g., Handbook on SDP [10].
- SDP relaxations are expensive to solve using interior-point approaches. This becomes *doubly* expensive when cutting planes are added, e.g., using Doubly Nonnegative, DNN, relaxations

Outline/Background/Motivation II

- Strict feasibility fails for many of the SDP relaxations of these hard combinatorial problems.
  (Compare Rademacher Theorem: Loc. Lip. functions are differentiable a.e.)
  Facial reduction, FR , e.g., [2, 3, 4, 5] provides a means of regularizing the SDP relaxations.

- FR appears to provide a natural splitting of variables for the application of Alternating Direction Method of Multipliers, ADMM , type methods for large scale problems;
  and for exploiting structure.

- Classes of Problems:
  Min-Cut; Maxcut; and Graph Partitioning;
  and QAP,

Hard Combinatorial Problems and Modelling with Quadratic Functions; Importance of Duality

Instance /Modelling with Quadratic Functions

$$\begin{array}{rlll} \min & q_0(x) & & (= x^T H x + 2g^T x + \alpha) \\ \text{s.t.} & Ax = b & & \text{(linear constraint)} \\ & x \in K \subseteq \mathbb{R}^N & & (K \text{ hard constraints}) \end{array}$$

Hard (Combinatorial) Constraints: e.g.,

- both $0,1$ and ± 1 modelled with quadratic const., resp.,

$$\begin{array}{ccc} K := \{0,1\}^N & \text{or} & K := \{\pm 1\}^N \\ q_i(x) := x_i^2 - x_i = 0, \forall i & \text{or} & q_i(x) := x_i^2 - 1 = 0, \forall i \end{array}$$

- K is partition matrices, $x \in \mathcal{M}_m$, (GP)
- K is permutation matrices, $x \in \Pi_n$, (QAP)

Can Close the Duality Gap by Changing Model

Example: (Lagrangian) Duality Gap for QP

$$\begin{aligned} 1 = p^* &= \max\{-x_1^2 + x_2^2 : x_2 = 1\} \\ &< \infty = d^* \\ &= \inf_\lambda \max_x L(x,\lambda) = -x_1^2 + x_2^2 - \lambda(x_2 - 1) \end{aligned}$$

BUT with a Model Change (same problem)

$$\begin{aligned} 1 = p^* &= \max\left\{-x_1^2 + x_2^2 : \boxed{(x_2 - 1)^2 = 0}\right\} \\ &= d^* = \inf_\lambda \max_x \{-x_1^2 + x_2^2 - \lambda(x_2 - 1)^2\} \end{aligned}$$

since stationarity and the Lagrangian function value satisfy:

$$0 = 2x_2 - 2\lambda(x_2 - 1) \implies x_2 = \frac{\lambda}{\lambda - 1} \to 1;$$

$$L(x,\lambda) = x_2^2 - \lambda(x_2 - 1)^2 = \frac{\lambda^2}{(\lambda - 1)^2} - \lambda \frac{1}{(\lambda - 1)^2} = \frac{\lambda}{\lambda - 1} \to 1$$

Further Example: Close Duality Gap

- Let $A = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$, $B = \begin{bmatrix} 3 & 0 \\ 0 & 4 \end{bmatrix}$, $\quad X^* = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

$$10 = p^* = \begin{array}{ll} \min & \operatorname{trace} AXBX^T \\ \text{s.t.} & XX^T = I,\ X \in \mathbb{R}^{n \times n} \end{array}$$

- $L(X,S) = \operatorname{trace} AXBX^T + \operatorname{trace} S(XX^T - I), S \in \mathcal{S}^n$
  $\operatorname{trace} AXBX^T = x^T(B \otimes A)x,\ x = \operatorname{vec} X$

$$\text{Lagrangian dual:} \qquad d^* = \max_{S \in \mathcal{S}^n} \min_{X} L(X,S)$$

-

$$10 = p^* > 9 = d^* = \begin{array}{ll} \max & -\operatorname{trace} S \\ \text{s.t.} & B \otimes A + I \otimes S \succeq 0, \quad S \in \mathcal{S}^n \end{array}$$

$$\text{where } B \otimes A = \begin{bmatrix} 3 & 0 & 0 & 0 \\ 0 & 6 & 0 & 0 \\ 0 & 0 & 4 & 0 \\ 0 & 0 & 0 & 8 \end{bmatrix} \implies S_{11} \geq -3, S_{22} \geq -6$$

Change Model; Add Redundant Constraint; Increase Number of Lagrange Dual Multipliers

Duplicate orthogonality constraint

Add: $X^TX = I$ closes duality gap by exploiting the new Lagrange multipliers in $T \in \mathcal{S}^n$

$$10 = p^* = 10 = d^* = \begin{array}{ll} \max & \text{trace}\, -S - T \\ \text{s.t.} & B \otimes A + I \otimes S + T \otimes I \succeq 0, \end{array}$$

Theorem (Anstreicher, W. '95, [1])

Strong duality holds for

$$\begin{array}{ll} \min & \text{trace}\, AXBX^T \\ s.t. & XX^T = I, X^TX = I,\ X \in \mathbb{R}^{n \times n} \end{array}$$

QP: Obtain Strong Duality in General? A Modelling Issue

$H \in \mathcal{S}^n$, A, $m \times n, m < n$, K compact

Theorem (Poljak, Rendl, W. '95, [8])

$$\begin{array}{rcll} p^* & = & \max_x & \{q_0(x) := x^T H x + 2g^T x + \alpha : Ax = b, x \in K\} \\ & = & \max_x & \{q_0(x) : \|Ax - b\|^2 = 0, x \in K\} \\ & = & d^* & = \boxed{\min_\lambda} \phi(\lambda) \end{array}$$

where the dual functional is:

$$\phi(\lambda) := \max_{x \in K} L(x, \lambda) := q_0(x) - \lambda \|Ax - b\|^2$$

□

Summary: To strengthen the Lagrangian dual

- linear constraints $Ax - b = 0$ to quadratic $\|Ax - b\|^2 = 0$
- Add redundant constraints

Model with Quadratics Details; Homogenize, and Lift to Matrix Space

Homogenize using $x_0 \in \mathbb{R}$ with $x_0^2 - 1 = 0$

$$\begin{cases} \min q_0(x, x_0) = x^T H x + 2g^T x x_0 + \alpha x_0^2 \\ \quad Ax - b = 0 \quad \cong \quad \|Ax - bx_0\|_2^2 = 0 \end{cases}$$

Lifting (linearization): $\mathbb{R}^{N+1} \rightarrow \mathbb{S}^{N+1}$

$$y = \begin{pmatrix} x_0 \\ x \end{pmatrix}, \; Y = yy^T \in \mathbb{S}_+^{N+1}, \quad \text{symmetric, psd,} \quad Y_{00} = 1$$

obj. fn. $\quad y^T \begin{bmatrix} \alpha & g^T \\ g & H \end{bmatrix} y = \operatorname{trace} \begin{bmatrix} \alpha & g^T \\ g & H \end{bmatrix} Y, \qquad \operatorname{rank}(Y) = 1$

Relaxation to Convex Problem:

Discard the (hard) rank one constraint on Y

Lifting with QQP and FACIAL REDUCTION

Lifting Linear Equality Constraint

$$\begin{aligned} 0 &= \|Ax - bx_0\|_2^2 = \left\| \begin{bmatrix} -b & A \end{bmatrix} \begin{pmatrix} x_0 \\ x \end{pmatrix} \right\|_2^2 \\ &= \begin{pmatrix} x_0 \\ x \end{pmatrix}^T \begin{bmatrix} -b^T \\ A^T \end{bmatrix} \begin{bmatrix} -b & A \end{bmatrix} \begin{pmatrix} x_0 \\ x \end{pmatrix} \\ &= \operatorname{trace} \begin{bmatrix} \|b\|^2 & -b^T A \\ -A^T b & A^T A \end{bmatrix} Y = 0 \end{aligned}$$

EXPOSING VECTOR $W \in \mathbb{S}_+^{N+1}$, with: spectr. decomp., FR

$$W := \begin{bmatrix} \|b\|^2 & -b^T A \\ -A^T b & A^T A \end{bmatrix} = \begin{bmatrix} V & U \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & D \end{bmatrix} \begin{bmatrix} V & U \end{bmatrix}^T, \; D \in \mathbb{S}_+^{N+1-r}$$

$$\begin{aligned} Y \text{ feasible} \quad &\Longrightarrow \quad YW = 0 \quad \text{(Strict feasibility (Slater) fails)} \\ &\Longrightarrow \quad Y = VRV^T, \; R \in \mathbb{S}_+^r \quad \text{(facial reduction)} \end{aligned}$$

Hard Discrete Constraints

Zero-One; Homogenize with x_0, $x_0^2 - 1 = 0$

$$q_i(x, x_0) := x_i^2 - x_i x_0 = 0, \ \forall i$$

Lifting (linearization): $\mathbb{R}^{N+1} \to \mathbb{S}^{N+1}$

$$y = \begin{pmatrix} x_0 \\ x \end{pmatrix}, \ Y = yy^T \in \mathbb{S}_+^{N+1}, \quad \text{symmetric, psd,} \quad Y_{00} = 1$$

$$\text{constr. for } \{0,1\}: \qquad \text{arrow}(Y) = e_0 := \begin{pmatrix} 1 \\ 0 \end{pmatrix} \in \mathbb{R}^{n+1}$$

$$(\mathrm{diag}\,(Y) = Y_{:,0})$$

Adjoint: $\text{Arrow} \cong \text{arrow}^*$

$$\langle \text{Arrow}(v), S \rangle = \langle v, \text{arrow}(S) \rangle, \quad \forall v \in \mathbb{R}^{N+1}, \forall S \in \mathbb{S}^{N+1}$$

Splitting Methods, Facial Reduction, FR

Natural Splitting? $Y \in \mathcal{P},\ R \in \mathcal{R} \subseteq \mathbb{S}^r_+ \quad Y = VRV^T$

$$Y \in \mathcal{P} \subset \mathbb{S}^{N+1}_+, \qquad R \in \mathcal{R} \subseteq \mathbb{S}^r_+, \quad r < N+1$$

Facial reduction generally provides a reduction in dimension and a guarantee that strict feasibility holds.
There is a natural separation of constraints where

$$Y \in \mathcal{P} \text{ polyhedral} \qquad R \in \mathcal{R} \text{ convex set}$$

Adding Redundant Constraints Back

- FR results in many constraints becoming redundant; and these are deleted for e.g., interior-point methods.
- However, after the splitting, many of the redundant constraints can be added back to the separate split problems to form sets $\mathcal{P}, \mathcal{R}$.

Instance: Minimum Cut, MC, Problem

Given: Undirected Graph $G = (\mathcal{V}, \mathcal{E})$

edge set $\mathcal{E}$ and node set $|\mathcal{V}| = n$
$m = (m_1 \ m_2 \ \ldots \ m_k)^T$, $\sum_{i=1}^{k} m_i = n$; given partition into k sets

MC Problem:

partition vertex set $\mathcal{V}$ into k subsets with given sizes in m
to *minimize the cut* after removing the k-th set;
X is the unknown $0, 1$ partition matrix.

Applications

re-orderings for sparsity patterns; microchip design and circuit board, floor planning and other layout problems.
($k = 3$, vertex separator problem)

Quadratic-Quadratic Model/Homogenized

Include Many Redundant Constraints

$$
\begin{array}{rclll}
\operatorname{cut}(m) & = & \min & \frac{1}{2}\operatorname{trace} AXBX^T & \\
& & \text{s.t.} & X \circ X = x_0 X & \in \{0,1\} \\
& & & \|Xe - x_0 e\|^2 = 0 & \text{row sums } = 1 \\
& & & \|X^T e - x_0 m\|^2 = 0 & \text{column sums} \\
& & & X_{:i} \circ X_{:j} = 0, \ \forall i \neq j & \text{col. elem. orth.} \\
& & & X^T X - M = 0 & \text{scaled orth.} \\
& & & \operatorname{diag}(XX^T) - e = 0 & \text{unit norm rows} \\
& & & x_0 e_n^T X e_k - n = 0 & n \text{ vertices} \\
& & & x_0^2 = 1 & \text{homog.}
\end{array}
$$

- e_j is the vector of ones of dimension j; $M = \operatorname{Diag}(m)$.
- $u \circ v$ Hadamard (elementwise) product.

SDP Constraints, FR and Exposing Vectors

Trace constraints (from linear equality constraints

$$\operatorname{trace} D_1 Y = 0, \qquad D_1 := \begin{bmatrix} n & -e_k^T \otimes e_n^T \\ -e_k \otimes e_n & (e_k e_k^T) \otimes I_n \end{bmatrix},$$

$$\operatorname{trace} D_2 Y = 0, \qquad D_2 := \begin{bmatrix} m^T m & -m^T \otimes e_n^T \\ -m \otimes e_n & I_k \otimes (e_n e_n^T) \end{bmatrix},$$

e_j vector of ones of dimension j; $D_i \succeq 0, i = 1, 2$; nullspaces of these matrices yield the facial reduction $Y = VRV^T$.

Block: trace, diagonal and off-diagonal

$$\begin{aligned} \mathcal{D}_t(Y) &:= \left(\operatorname{trace} \overline{Y}_{(ij)}\right) = M \in \mathbb{S}^k; \\ \mathcal{D}_d(Y) &:= \sum_{i=1}^k \operatorname{diag} \overline{Y}_{(ii)} = e_n \in \mathbb{R}^n; \\ \mathcal{D}_o(Y) &:= \left(\sum_{s \neq t} \left(\overline{Y}_{(ij)}\right)_{st}\right) = \hat{M} \in \mathbb{S}^k, \end{aligned}$$

where $\hat{M} := mm^T - M$.

SDP Constraints cont...

trace $Y = n + 1$; and Gangster constraints on Y

The Hadamard product and orthogonal type constraints lead to

gangster constraints

i.e., simple constraints that restrict elements to be zero (shoot holes in the matrix) and/or restrict entire blocks.
gangster and restricted gangster constraint on Y:

$$\mathcal{G}_H(Y) = 0,$$

for specific index sets H.

SDP Relaxation

SDP Relaxation with Many (some redundant) Constraints

$$
\begin{array}{rll}
\mathrm{cut}(m) \geq p^*_{\mathrm{SDP}} := \min & \frac{1}{2}\,\mathrm{trace}\, L_A Y \\
\text{s.t.} & \mathrm{arrow}(Y) = e_0 \\
& \mathrm{trace}\, D_1 Y = 0,\ \mathrm{trace}\, D_2 Y = 0 \\
& \mathcal{G}_{J_0}(Y) = 0,\ Y_{00} = 1 \\
& \mathcal{D}_t(Y) = M,\ \mathcal{D}_d(Y) = e,\ \mathcal{D}_o(Y) = \widehat{M} \\
& Y \in \mathbb{S}^{kn+1}_+
\end{array}
$$

Equivalent FR greatly simplified SDP; with $Y = \widetilde{V} R \widetilde{V}^T$

$$
\begin{array}{rcll}
\mathrm{cut}(m) \geq p^*_{\mathrm{SDP}} & = & \min & \frac{1}{2}\,\mathrm{trace}\left(\widetilde{V}^T L_A \widetilde{V}\right) R \\
& & \text{s.t.} & \mathcal{G}_{\widehat{J}_{\mathcal{I}}}(\widetilde{V} R \widetilde{V}^T) = \mathcal{G}_{\widehat{J}_{\mathcal{I}}}(e_0 e_0^T) \\
& & & R \in \mathbb{S}^{(k-1)(n-1)+1}_+
\end{array}
$$

Primal-Dual Strong Duality (Regularity) for FR SDP

Theorem

1. *(Generalized) slater point for the primal:*

$$\widetilde{R} = \left[\begin{array}{c|c} 1 & 0 \\ \hline 0 & \frac{1}{n^2(n-1)}\left(n\mathrm{Diag}\,(\hat{m}_{k-1}) - \hat{m}_{k-1}\hat{m}_{k-1}^T\right) \otimes \left(nI_{n-1} - E_{n-1}\right) \end{array}\right] \in \mathbb{S}_{++}^{(k-1)(n-1)+1}.$$

   Moreover, Robinson regularity holds.

2. *The dual problem*

$$\begin{array}{ll} \max & \frac{1}{2} w_{00} \\ \text{s.t.} & \widetilde{V}^T \mathcal{G}^*_{\hat{J}_{\mathcal{I}}}(w) \widetilde{V} \preceq \widetilde{V}^T L_A \widetilde{V}. \end{array}$$

   satisfies strict feasibility.

Motivation

Difficulties for Primal-dual interior-point Methods for SDP

- solving large problems
- obtaining high accuracy solutions
- exploiting sparsity
- adding on nonnegativity and other cutting plane constraints

First order operator splitting methods for SDP

- FR provides a natural (successful) splitting, $Y = VRV^T$, (Y polyhedral, R cone/convex)
- Flexibility in dealing with additional constraints
- separable/split optimization steps are inexpensive

Strengthen model with redundant constraint

Set Constraints, Low Rank (helps with early stopping)

$$\mathcal{R} := \{R \in \mathbb{S}_+^{(k-1)(n-1)+1} : \text{trace } R = n+1\},$$
$$\mathcal{Y} := \{Y \in \mathbb{S}^{nk+1} : 1 \geq Y(J^c) \geq 0,$$
$$\mathcal{G}_{\bar{J}}(Y) = \mathcal{G}_{\bar{J}}(e_0 e_0^T)$$
$$\mathcal{D}_o(Y) = \widehat{M},\ e^T Y_{(i0)} = m_i, \forall i\}$$

Strengthened model

$$(\text{DNN}) \quad p^*_{DNN} = \begin{array}{ll} \min & \frac{1}{2}\text{trace } L_A Y + \mathbb{1}_{\mathcal{Y}}(Y) + \mathbb{1}_{\mathcal{R}}(R) \\ \text{s.t.} & Y = \widehat{V} R \widehat{V}^T, \end{array}$$

where $\mathbb{1}_{\mathcal{S}}(\cdot)$ is indicator function of set $\mathcal{S}$.

Splitting Method

Augmented Lagrangian Function, $\mathcal{L}_\beta(R, Y, Z) =$

$$= f_{\mathcal{R}}(R) + g_{\mathcal{Y}}(Y) + \langle Z, Y - \widehat{V}R\widehat{V}^T \rangle + \frac{\beta}{2}\left\| Y - \widehat{V}R\widehat{V}^T \right\|^2$$

- $\beta > 0$ penalty parameter for quadratic penalty term,
- (L_s diagonally scaled objective $L_s := \frac{1}{2}L + \alpha I \succ 0$)

$$f_{\mathcal{R}}(R) = \mathbb{1}_{\mathcal{R}}(R), \quad g_{\mathcal{Y}}(Y) = \operatorname{trace} L_s Y + \mathbb{1}_{\mathcal{Y}}(Y).$$

sPRSM, Strictly Contractive Peaceman-Rachford Splitting

i.e., alternate minimization of $\mathcal{L}_\beta$ in the variables Y and R interlaced by an update of the Z variable.
In particular, we update the dual variable Z both after the R-update *and* the Y-update (both of which have unique solutions).

FRSMR, FR Splitting Method with Redundancies

- Pick any $Y^0, Z^0 \in \mathbb{S}^{nk+1}$. Fix $\beta > 0$ and $\gamma \in (0,1)$. Set $t = 0$.
- For each $t = 0, 1, \ldots$, update

$$
\begin{aligned}
\bullet R^{t+1} &= \operatorname{argmin}_{R \in \mathcal{R}} \mathcal{L}_\beta(R, Y^t, Z^t) \\
&= \operatorname{argmin}_R f_{\mathcal{R}}(R) - \langle Z^t, \widehat{V} R \widehat{V}^T \rangle + \frac{\beta}{2} \left\| Y^t - \widehat{V} R \widehat{V}^T \right\|^2 \\
\bullet Z^{t+\frac{1}{2}} &= Z^t + \gamma\beta(Y^t - \widehat{V} R^{t+1} \widehat{V}^T), \\
\bullet Y^{t+1} &= \operatorname{argmin}_{Y \in \mathcal{Y}} \mathcal{L}_\beta(R^{t+1}, Y, Z^{t+\frac{1}{2}}) \\
&= \operatorname{argmin}_Y g_{\mathcal{Y}}(Y) + \langle Z^{t+\frac{1}{2}}, Y \rangle + \frac{\beta}{2} \left\| Y - \widehat{V} R^{t+1} \widehat{V}^T \right\|^2, \\
\bullet Z^{t+1} &= Z^{t+\frac{1}{2}} + \gamma\beta(Y^{t+1} - \widehat{V} R^{t+1} \widehat{V}^T).
\end{aligned}
$$

Global convergence

Theorem

Let $\{R^t\}$, $\{Y^t\}$ and $\{Z^t\}$ be the generated sequences from FRSMR. *Then $\{(R^t, Y^t)\}$ converges to an optimal solution (R^*, Y^*) of the* DNN *relaxation, $\{Z^t\}$ converges to some Z^*, and (R^*, Y^*, Z^*) satisfies the optimality conditions of the* DNN *relaxation*

$$\begin{aligned} 0 &\in -\widehat{V}^T Z^* \widehat{V} + \mathcal{N}_{\mathcal{R}}(R^*), \\ 0 &\in L_s + Z^* + \mathcal{N}_{\mathcal{Y}}(Y^*), \\ Y^* &= \widehat{V} R^* \widehat{V}^T, \end{aligned}$$

where $\mathcal{N}_S(x)$ denotes the normal cone of S at x. □

1. Explicit solution for R^{t+1}

With the assumption that $\widehat{V}^T\widehat{V} = I$

$$
\begin{aligned}
R^{t+1} &= \operatorname{argmin}_{R\in\mathcal{R}} -\langle Z, \widehat{V}R\widehat{V}^T\rangle + \frac{\beta}{2}\left\| Y^t - \widehat{V}R\widehat{V}^T \right\|^2 \\
&= \mathcal{P}_{\mathcal{R}}(\widehat{V}^T(Y^t + \tfrac{1}{\beta}Z^t)\widehat{V}),
\end{aligned}
$$

where $\mathcal{P}_{\mathcal{R}}$ denotes the projection (nearest point) onto the intersection of the SDP cone $\mathbb{S}_+^{(k-1)(n-1)+1}$ and the hyperplane $\{R \in \mathbb{S}^{(k-1)(n-1)+1} : \text{trace}\, R = n+1\}$.

(diagonalize; then project eigenvalues onto simplex)

2. Explicit solution of Y^{t+1}

The Y-subproblem yields a closed form solution by projection onto the polyhedral set $\mathcal{Y}$, i.e.,

$$Y^{t+1} = \operatorname{argmin}_{Y \in \mathcal{Y}} \frac{\beta}{2} \left\| Y - \boxed{\widehat{V} R^{t+1} \widehat{V}^T - \frac{1}{\beta}(L_s + Z^{t+\frac{1}{2}})} \right\|^2.$$

Note that the update (projection of $\tilde{Y}$) satisfies e.g.,

$$(Y^{t+1})_{ij} = \begin{cases} 1 & \text{if } i = j = 0 \\ 0 & \text{if } ij \in J \backslash \{00\} \\ 0 & \text{if } ij \in J^c,\ Y_{ij} \leq 0 \\ \tilde{Y}_{ij} & \text{if } ij \in J^c,\ 0 < Y_{ij}. \end{cases}$$

Lower bound from Inaccurate Solutions

Theorem (Fenchel Dual)

Define modified dual functional
$g(Z) := \min_{Y \in \widetilde{\mathcal{Y}}} \langle L_s + Z, Y \rangle - (n+1)\lambda_{\max}(\widehat{V}^T Z \widehat{V})$,
with $\widetilde{\mathcal{Y}} :=$

$$\{Y \in \mathbb{S}^{nk+1} : \mathcal{G}_{\widehat{J}_0}(Y) = \mathcal{G}_{\widehat{J}_0}(e_0 e_0^T),\ 0 \le \mathcal{G}_{\widehat{J}_0^c}(Y) \le 1,$$
$$\mathcal{D}_o(Y) = \widehat{M},\ \mathcal{D}_t(Y) = M,\ e^T Y_{(i0)} = m_i, i = 1, \ldots, k\}.$$

Then

$$p^*_{\mathrm{DNN}} = d^*_Z := \max_Z g(Z),$$

and the latter (dual) problem is attained, i.e., strong duality holds. □

The Lower Bound

Evaluating $g(Z^t)$ always yields a lower bound for the DNN relaxation optimal value

$$p^*_{\mathrm{DNN}} \ge g(Z^t)$$

Upper bound from feasible solution

Approx. output Y^{out}

- Obtain a vector $v = (v_0 \ \bar{v})^T \in \mathbb{R}^{nk+1}$, $v_0 \neq 0$ from Y^{out}
- Reshape $\bar{v}$; get $n \times k$ matrix X^{out}
- Since X implies $\operatorname{trace} X^T X = n$, a constant, we get

$$\left\| X^{\text{out}} - X \right\|^2 = -2 \operatorname{trace} X^T X^{\text{out}} + \text{constant}.$$

- Solve the linear program (transportation problem)

$$\hat{X} \in \operatorname{argmax} \left\{ \langle X^{\text{out}}, X \rangle : Xe = e, X^T e = m, X \geq 0 \right\}$$

- Upper bound $= \frac{1}{2} \operatorname{trace} A\hat{X}B\hat{X}^T$

Choosing the vector v for X^{out} for upper bound

rank $Y = 1 \implies$ column/eigenvector 0 yields opt. X

1. column 0 of Y^{out};
2. eigenvector corresponding to largest eigenvalue of Y^{out};
3. random sampling/repeated: sum of random weighted-eigenvalue eigenvectors of Y^{out},
$$v = \sum_{i=1}^{r} w_i \lambda_i v_i,$$
where ordered eigenpairs of Y^{out} and ordered weights; r here is the *numerical rank* of Y^{out}.

Numerical Tests from [7,6]

Tests using:

Matlab R2017a on a ThinkPad X1 with an Intel CPU (2.5GHz) and 8GB RAM running Windows 10.

Three classes of problems:

(a) random structured graphs (compare with previous results in Pong et al. [9])

(b) partially random graphs with various sizes classified by the number of 1's, $|\mathcal{I}|$, in the vector m (similar to QAP)

(c) vertex separator instances

Lifting Linear Equality Constraint

Table: Data terminology

imax	maximum size of each set
k	number of sets
n	number of nodes (sum of sizes of sets)
p	density of graph
u_0	known lower bound
$l = e^T m_{\text{one}}$	number of 1's in m
Iters	number of iterations
CPU	time in seconds
Bounds	best lower and upper bounds and relative gap
Residuals	*final* values of: $\left\lVert Y^{t+1} - \widehat{V} R^{t+1} \widehat{V}^T \right\rVert$ $(\cong \Delta Z)$; $\left\lVert Y^{t+1} - Y^t \right\rVert$ $(\cong \Delta Y)$

Numerical Tests

Comparison small structured graphs with Pong et al

Data				Lower bounds		Upper bounds		Rel-gap		Time (cpu)	
n	k	$\|E\|$	u_0	FRSMR	Mosek	FRSMR	Mosek	FRSMR	Mosek	FRSMR	Mosek
20	4	136	6	6	6	6	6	0.00	0.00	0.21	3.96
25	4	222	8	8	8	8	8	0.00	0.00	0.20	10.94
25	5	170	14	14	14	14	14	0.00	0.00	0.31	34.19
31	5	265	22	22	22	22	22	0.00	0.00	1.28	149.49

Numerics cont... Random Graphs

\# ones, $\mathcal{I} = \emptyset$, mean over 3 instances

Specifications					Iter	cpu	Bounds			Residuals	
imax	*k*	*n*	*p*	*l*			low	up	rel-gap	prim.	dual
5	6	19.0	0.49	0	333.33	0.89	38.0	38.33	0.01	4.15e-03	6.18e-03
6	7	24.67	0.44	0	500.0	3.03	60.0	61.67	0.02	4.86e-03	8.74e-03
7	8	31.0	0.37	0	966.67	9.53	68.33	71.0	0.04	8.44e-04	3.74e-04
8	9	40.0	0.31	0	833.33	22.75	100.33	110.67	0.09	1.43e-03	6.92e-04
9	10	50.33	0.23	0	1100.0	75.26	119.67	132.33	0.09	1.53e-03	6.81e-04

Numerics cont... Random Graphs

$k \notin \mathcal{I} \neq \emptyset$, mean over 4 instances

Specifications					Iters	cpu	Bounds			Residuals	
imax	k	n	p	l			lower	upper	rel-gap	primal	dual
5	6	16.25	0.51	1.50	450.00	1.02	22.25	23.00	0.03	2.36e-03	1.64e-03
6	7	17.00	0.43	3.25	325.00	1.18	23.00	23.25	0.00	3.75e-02	5.90e-02
7	8	21.00	0.38	3.50	625.00	4.98	34.50	36.00	0.02	3.66e-03	1.95e-03
8	9	21.75	0.30	5.00	400.00	3.36	20.75	21.25	0.01	8.37e-02	9.51e-02
9	10	38.00	0.23	3.25	775.00	25.84	55.25	63.50	0.11	3.26e-03	1.37e-03

Numerics Cont... Random Graphs

$k \in \mathcal{I} \neq \mathcal{K}$, mean 5 instances

Specifications					Iters	cpu	Bounds			Residuals	
imax	*k*	*n*	*p*	*l*			lower	upper	rel-gap	primal	dual
5	6	13.60	0.49	2.80	160.00	0.33	22.60	22.60	0.00	2.55e-02	3.02e-02
6	7	18.00	0.42	3.40	460.00	1.99	37.80	39.00	0.02	5.66e-02	7.10e-02
7	8	22.20	0.39	3.80	560.00	3.96	57.80	60.20	0.02	1.04e-02	1.19e-02
8	9	22.60	0.30	5.20	540.00	4.92	37.20	38.00	0.01	3.48e-02	4.29e-02
9	10	31.00	0.23	4.80	700.00	16.78	61.80	68.00	0.06	1.44e-02	1.01e-02

$\mathcal{I} = \mathcal{K}$, mean 6 instances

Specifications				Iters	Time (cpu)	Bounds			Residuals	
k	*n*	*p*	*l*			lower	upper	rel-gap	primal	dual
6	6.00	0.59	6.00	100.00	0.06	4.67	4.67	0.00	5.12e-03	5.10e-03
7	7.00	0.48	7.00	100.00	0.08	5.67	5.67	0.00	8.66e-02	1.27e-01
8	8.00	0.41	8.00	150.00	0.18	7.17	7.17	0.00	2.64e-01	1.68e-01
9	9.00	0.34	9.00	233.33	0.37	7.83	8.00	0.03	1.88e-01	3.99e-02
10	10.00	0.25	10.00	266.67	0.56	7.50	7.50	0.00	6.28e-02	8.71e-02

Numerics Cont...

Table: Comparisons on the bounds for MC and bounds for the cardinality of separators

Name	n	$\|E\|$	m_1	m_2	m_3	MC by SDP_4		MC by DNN-final		Separator by SDP_4		Separator by DNN-final	
						lower	upper	lower	upper	lower	upper	lower	upper
Example 1	93	470	42	41	10	0.07	1	0	1	11	11	11	11
bcspwr03	118	179	58	57	3	0.56	1	0	2	4	5	4	5
Smallmesh	136	354	65	66	5	0.13	1	0	1	6	6	6	6
can-144	144	576	70	70	4	0.90	6	0	6	5	6	5	8
can-161	161	608	73	72	16	0.31	2	0	2	17	18	17	18
can-229	229	774	107	107	15	0.40	6	0	6	16	19	16	19
gridt(15)	120	315	56	56	8	0.29	4	0	4	9	11	9	12
gridt(17)	153	408	72	72	9	0.17	4	0	4	10	13	10	13
grid3dt(5)	125	604	54	53	18	0.54	2	0	4	19	19	19	22
grid3dt(6)	216	1115	95	95	26	0.28	4	0	4	27	30	27	31
grid3dt(7)	343	1854	159	158	26	0.60	22	0	27	27	37	27	44

Conclusion

- We discussed strategies for finding new, strengthened lower and upper bounds, for hard discrete optimization problems.
- In particular, we exploited the fact that strict feasibility fails for many of these problems and that facial reduction, FR, leads to a natural splitting approach for ADMM, sPRSM, type methods.
- The FR makes many constraints redundant and simplifies the problem. We strengthened the subproblems in the splitting by *returning* redundant constraints.
- A special scaling, and a random sampling provided strengthened lower and upper bounds from low approximate solutions from our approach. (Allowing for early stopping.

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Thanks for your attention!

Hard Combinatorial Problems,
Doubly Nonnegative Relaxations,
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and
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MS40: SDP Approaches to Combinatorial and Global Optimization - Part II of III