

# Lift-and-Project Methods

Recall the lifted-SDP representation of  $TH(G)$ :

$$TH(G) = \{ x \in \mathbb{R}^V; Y \in \mathcal{S}_+^{iso \times V}, Y_{e_0} = \begin{pmatrix} x \\ x \end{pmatrix} = \text{diag}(Y), Y_{ij} = 0 \forall i, j \notin E \}$$

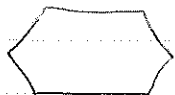
this set is in a much higher dimensional space compared to  $STAB(G)$

$\mathbb{R}^3$



5 facets

projection onto  $\mathbb{R}^2$



6 facets

Sometimes going from an  $n$ -dimensional space to an  $n^2$  or  $n^3$ -dim. space can result in exponential gain in terms of representations of facets of the polytope in  $\mathbb{R}^d$

Let's try to generalize this SDP rep. for  $TH(G)$  which is used for  $STAB(G)$ , to arbitrary polytopes with  $o$  extreme points.

Note that in the SDP rep. of  $TH(G)$ ,

$$Y = \begin{bmatrix} 1 & \dots & x_i \\ \vdots & & \vdots \\ x_i & \dots & x_i \end{bmatrix}$$

If  $x_i = 0, Y \succeq 0 \Rightarrow Y_{e_i} = 0$

If  $x_i > 0, \frac{1}{x_i} Y_{e_i} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$

$j^{th}$  component is zero  $\forall i, j \in E$

If  $Y = \begin{pmatrix} x \\ x \end{pmatrix} (1 \ x^T)$

$\Rightarrow \begin{pmatrix} x \\ x \end{pmatrix} \in \{0, 1\}^{iso \times V}$

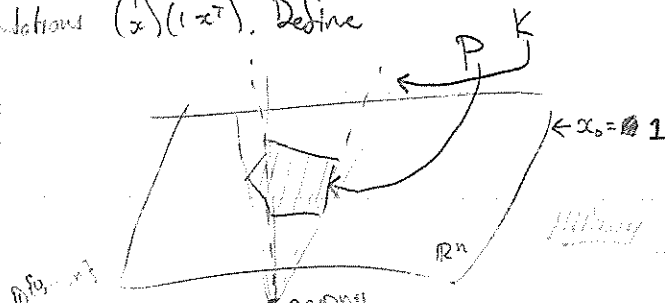
$\Rightarrow$  col. of  $Y, Y_{e_i} = x_i \begin{pmatrix} 1 \\ x \end{pmatrix}$

Suppose we are given polytope  $P \subseteq [0, 1]^n$  (like  $FRAC(G)$ ). We are interested in  $P_I := \text{conv}(P \cap \{0, 1\}^n)$ . (like  $STAB(G)$ )

Think about  $\{0, 1\}$  vectors  $x$  in  $P_I$  and their representations  $\begin{pmatrix} x \\ x \end{pmatrix} (1 \ x^T)$ . Define

$$K := \{ \lambda \begin{pmatrix} x \\ x \end{pmatrix}; x \in P, \lambda > 0 \}$$

$$N_+(K) := \{ Y_{e_0}; Y \in \mathcal{S}_+^{n+1}, Y_{e_0} = \text{diag}(Y), Y_{e_i}^* = Y_{e_0 - e_i} \in K \}$$



\*encodes  $\{0, 1\}$  if  $\text{rank}(Y) = 1$

If  $Y = \begin{pmatrix} 1 \\ x \end{pmatrix} (1 \ x^T)$ , then  $Y(e_0 - e_i) = \begin{pmatrix} 1 \\ x \end{pmatrix} - x_i \begin{pmatrix} 1 \\ x \end{pmatrix} = (1 - x_i) \begin{pmatrix} 1 \\ x \end{pmatrix}$ .

$N_+(K) \subseteq K$  since  $Y e_0 = \underbrace{Y(e_0 - e_i)}_{\in K} + \underbrace{Y e_i}_{\in K \leftarrow \text{conv}}$

Further note that

$$Y(e_0 - e_i) = \begin{bmatrix} 1 - x_i \\ \vdots \\ x_i \\ \vdots \\ x_i \end{bmatrix} \quad Y e_i = x_i \begin{bmatrix} 1 \\ \vdots \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

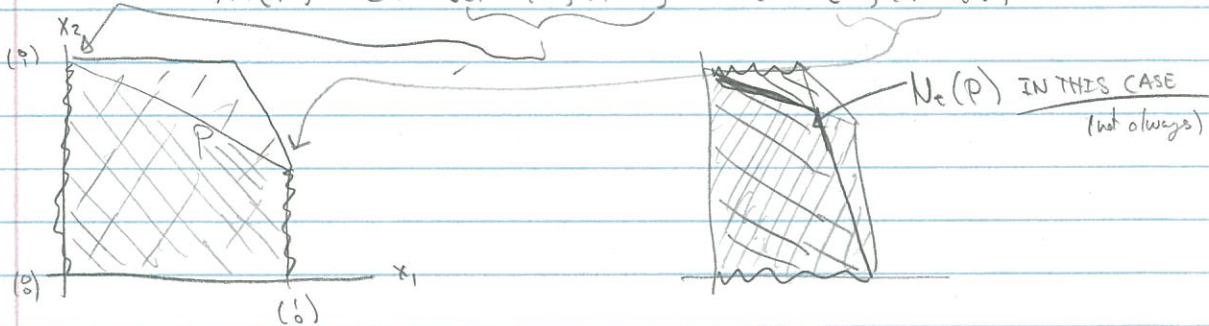
$$\hookrightarrow \in K \cap \left\{ \begin{pmatrix} x_0 \\ x \end{pmatrix} \in \mathbb{R}^{n+1}; x_i = 0 \right\} \quad \hookrightarrow \in K \cap \left\{ \begin{pmatrix} x_0 \\ x \end{pmatrix} \in \mathbb{R}^{n+1}; x_i = x_0 \right\}$$

in  $\mathbb{R}^n \quad P \cap \{x \in \mathbb{R}^n; x_i = 1\}$

$$\Rightarrow N_+(K) \subseteq \left( K \cap \left\{ \begin{pmatrix} x_0 \\ x \end{pmatrix}; x_i = 0 \right\} \right) + \left( K \cap \left\{ \begin{pmatrix} x_0 \\ x \end{pmatrix}; x_i = x_0 \right\} \right)$$

In the space of  $P, P_I$ ,

$$N_+(P) \subseteq \text{conv} \left( (P \cap \{x; x_i = 0\}) \cup (P \cap \{x; x_i = 1\}) \right)$$



Theorem 7.10:  $P \supseteq N_+(P) \supseteq N_+^2(P) \supseteq \dots \supseteq N_+^n(P) = P_I$ .

Theorem: If  $\exists$  a poly time separation oracle for  $P$ , then we can optimize any linear function over  $N_+^k(P)$ , approximately, in poly. time for all  $k = O(n)$ . 2014 07 29

spelling

The above method is due to Lovász & Schrijver (1991). There are many other approaches methods, including one due to Sherali and Adams.

$$P := \{x \in \mathbb{R}^n; Ax \leq b, 0 \leq x \leq \bar{e}\}$$

Multiply each inequality by

$$f(J_1, J_2) := \prod_{i \in J_1} x_i \prod_{j \in J_2} (1 - x_j) \geq 0 \quad \forall x \in [0, 1]^n$$

where  $J_1, J_2 \subseteq \{1, 2, \dots, n\}$ ,  $J_1 \cap J_2 = \emptyset$ .  $|J_1| + |J_2| \leq \min\{k+1, n\}$ .

We obtain a system of poly. inequalities.

Replace  $x_i^2$  by  $x_i$   $\forall i$   $\forall$  monomials ( $x_i^2 = x_i, \forall x_i \in \{0, 1\}$ )

Replace  $\prod_{i \in J} x_i$  by  $y_J$  (linearization) for  $|J| \geq 2$

$\rightarrow$  a relaxation of  $P = \{x \in \mathbb{R}^n; \hat{A}x + By \leq d\}, \exists y \in \mathbb{R}^M\}$   
 $SA^k(P)$

This kind of approach can be generalized to solving the problems of optimizing a continuous function over a compact set.

Let  $F \subset \mathbb{R}^n$  be a compact set, let  $f$  be a cont. function over  $F$ .

$$\begin{aligned} \min_{x \in F} f(x) &= \min_{x_0} \left. \begin{aligned} f(x) \leq x_0 \\ x \in F \\ l.b. \leq x_0 \leq u.b. \end{aligned} \right\} \begin{aligned} (x_0, x) &\in F \subset \mathbb{R}^{n+1} \\ &\uparrow \\ &\text{compact} \end{aligned} \end{aligned}$$

So, our problem is  $\min_{x \in F} c^T x = \min_{x \in \text{conv}(F)} c^T x$

For almost all  $c$ ,  $\exists$  a unique solution for the second problem (when  $F \neq \emptyset$ ) and such solution(s) are optimal for the first problem.

Every compact set  $F$  in  $\mathbb{R}^n$  admits a representation as the solution set of a system of (possibly infinite) quadratic inequalities.

Suppose  $F$  is given by

$$F = \{x \in \mathbb{R}^n; x^T Q x + 2q^T x + \gamma \leq 0 \forall (Q, q, \gamma) \in \mathcal{P}\} \quad \text{possibly infinite}$$

$\mathcal{P} = \langle \begin{bmatrix} q^T & \gamma \end{bmatrix}, \begin{bmatrix} 1 & x^T \\ x & x^T \end{bmatrix} \rangle$

Suppose  $\mathcal{P}$  contains  $(I, 0, M)$ ,  $M \in \mathbb{R}_{++}$ .

We may assume  $\mathcal{P}$  is a convex cone. We may also focus on  $\text{ext}(\mathcal{P})$ , if we like.

$\{x \in \mathbb{R}^n; x^T Q x + 2q^T x + \gamma \leq 0\}$  is convex  $\Leftrightarrow Q \succeq 0$

Let  $\mathcal{Q}_+ = \{\begin{bmatrix} q^T & \gamma \end{bmatrix} \in \mathbb{S}^{n+1}; Q \succeq 0\}$

Theorem 9.4: With the above notation and assumptions,

$$\begin{aligned} \text{conv}(F) &\subseteq \{x \in \mathbb{R}^n; x^T Q x + 2q^T x + \gamma \leq 0 \forall (Q, q, \gamma) \in \text{cone}(\mathcal{P}) \cap \mathcal{Q}_+\} \\ &= \{x \in \mathbb{R}^n; \langle \begin{bmatrix} q^T & \gamma \end{bmatrix}, \begin{bmatrix} 1 & x^T \\ x & x^T \end{bmatrix} \rangle \leq 0 \forall (Q, q, \gamma) \in \text{ext}(\mathcal{P}), \begin{bmatrix} q^T & \gamma \end{bmatrix} \in \mathcal{Q}_+\} \end{aligned}$$