A Different Perspective on Perspective Cuts

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Indicator MINLPs

- We focus on (convex) MINLPs that are driven by 0-1 indicator variables $z_i, i \in \mathcal{I}$
- Each indicator variable i controls a collection of variables V_i
- If $z_i = 0$, the components of x controlled by z_i must collapse to a point: $z_i = 0 \Rightarrow x_{V_i} = \hat{x}_{V_i}$
  - WLOG $\hat{x}_{V_i} = 0$ from now on
- If $z_i = 1$, the components of x controlled by z_i belong to a convex set $z_i = 1 \Rightarrow x_{V_i} \in \Gamma_i$
- Γ_i is specified by (convex) nonlinear inequality constraints and bounds on the variables

$$\Gamma_i \stackrel{\text{def}}{=} \{x_{V_i} \mid f_k(x_{V_i}) \leq 0 \ \forall k \in K_i, l \leq x_{V_i} \leq u\}.$$

Indicator MINLPs

$$
\begin{array}{llll}
\min & c^T x + d^T z & & \\
\text{s.t.} & g_m(x,z) & \leq 0 & \forall m \in M \\
& z_i f_k(x_{V_i}) & \leq 0 & \forall i \in \mathcal{I} \;\; \forall k \in K_i \\
& \ell_j z_i \leq x_j & \leq u_j z_i & \forall i \in \mathcal{I} \;\; \forall j \in V_i \\
& x \in X & z \in Z \cap \mathbb{B}^p, &
\end{array}
$$

- X, Z polyhedral sets
- Typically, $g_m(x,z) = \bar{g}_m(x) + a_m^T z$ is linear in z, or even $a_m = 0$.

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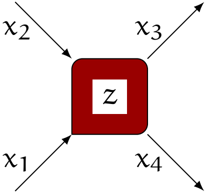
- X, Z polyhedral sets
- Typically, $g_m(x,z) = \bar{g}_m(x) + a_m^T z$ is linear in z, or even $a_m = 0$.
- If $z \in Z \cap \mathbb{B}^p$ is fixed, then the problem is convex.

Indicators Everywhere

Process Flow Applications

- $z = 0 \Rightarrow x_1 = x_2 = x_3 = x_4 = 0$
- $z = 1 \Rightarrow f(x_1, x_2, x_3, x_4) \leq 0$



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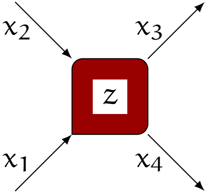

Separable Function Epigraphs

$$y_i \geq f_i(x_i) \ \forall i \in \mathcal{I}$$

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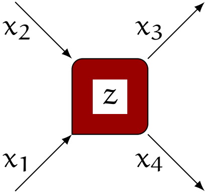

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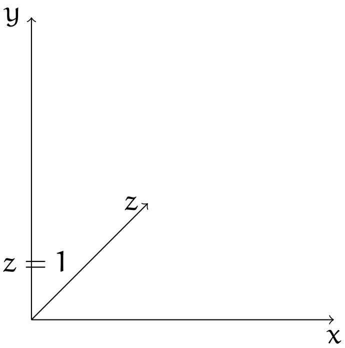
- Note that here I am already lying
- $z = 0$ does not imply $y = 0$
- Nevertheless, results apply to epigraph-type indicator MINLPs.

A Very Simple Example

$$R \stackrel{\text{def}}{=} \left\{(x, y, z) \in \mathbb{R}^2 \times \mathbb{B} \mid y \geq x^2, 0 \leq x \leq uz\right\}$$



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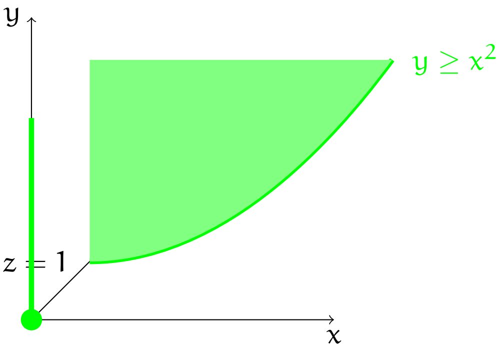

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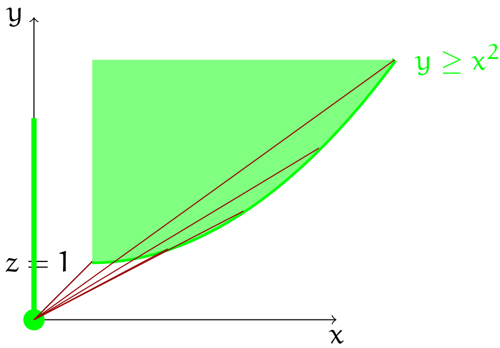

Deep Insights

- $\text{conv}(R) \equiv$ line connecting $(0, 0, 0)$ to $y = x^2$ in the $z = 1$ plane

Characterization of Convex Hull

- Work out the algebra to get:

Deep Theorem #1

$$\mathrm{conv}(R) = \left\{ (x, y, z) \in \mathbb{R}^3 \mid yz \geq x^2, 0 \leq x \leq uz, 0 \leq z \leq 1, y \geq 0 \right\}$$

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Second Order Cone Programming

- There are effective and robust algorithms for optimizing linear objectives over $\text{conv}(R)$

Higher Dimensions

- Using an extended formulation, we can describe the convex hull of a higher-dimensional analogue of R:

$$Q \stackrel{\text{def}}{=} \left\{ (w, x, z) \in \mathbb{R}^{1+n} \times \mathbb{B}^n \mid w \geq \sum_{i=1}^{n} q_i x_i^2,\ u_i z_i \geq x_i \geq 0, \forall i \right\}$$

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- First we write an extended formulation of Q, introducing variables y_i:

$$\bar{Q} \stackrel{\text{def}}{=} \left\{(w, x, y, z) \in \mathbb{R}^{1+3n} \mid w \geq \sum_{i} q_i y_i, (x_i, y_i, z_i) \in R_i,\ \forall i\right\}$$

$$R_i \stackrel{\text{def}}{=} \left\{(x_i, y_i, z_i) \in \mathbb{R}^2 \times \mathbb{B} \mid y_i \geq x_i^2, 0 \leq x_i \leq u_i z_i\right\}$$

Extended Formulations

- $\bar{Q}$ is indeed an extended formulation in the sense that projecting out the y variables from $\bar{Q}$ gives Q: $\mathrm{Proj}_{(w,x,z)}\,\bar{Q} = Q$.

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- The convex hull of $\bar{Q}$ is obtained by replacing R_i with its convex hull description $\text{conv}(R_i)$:

$$\text{conv}(\bar{Q}) = \Big\{ w \in \mathbb{R},\ x \in \mathbb{R}^n, y \in \mathbb{R}^n, z \in \mathbb{R}^n \ :\ w \geq \sum_i q_i y_i, \\ (x_i, y_i, z_i) \in \text{conv}(R_i), \quad i = 1, 2, \ldots, n \Big\}.$$

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- Again, the description of $\text{conv}(\bar{Q})$ is SOC-representable.
- You get one rotated cone for each i

Descriptions in the Original Space

- We can also write also write a convex hull description in the original space of variables, by projecting out y:

$$Q^c = \Big\{ (w, x, z) \in \mathbb{R}^{1+n+n} :$$

$$w \prod_{i \in S} z_i \geq \sum_{i \in S} \left(q_i x_i^2 \prod_{l \in S \setminus \{i\}} z_l \right) \quad S \subseteq \{1, 2, \ldots, n\}$$

$$u_i z_i \geq x_i \geq 0, \quad x_i \geq 0, \quad i = 1, 2, \ldots, n \Big\} \quad (\Pi)$$

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Theorem

$$\mathrm{Proj}_{(w,x,z)}(\bar{Q}^c) = Q^c = \mathrm{conv}(Q).$$

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Theorem

$$\text{Proj}_{(w,x,z)}(\bar{Q}^c) = Q^c = \text{conv}(Q).$$

- Q^c consists of an exponential number of nonlinear inequalities.

Extending the Intuition

- To deal with general convex sets, let $W = W^1 \cup W^0$:

$$W^0 = \{(x, z) \in \mathbb{R}^{n+1} \mid x = 0, z = 0\}$$
$$W^1 = \{(x, z) \in \mathbb{R}^{n+1} \mid f_k(x) \le 0 \text{ for } k \in K, u \ge x \ge 0, z = 1\}$$

- Write an extended formulation (XF) for $\text{conv}(W)$

$$\Big\{(x, x_0, x_1, z, z_0, z_1, \alpha) \in \mathbb{R}^{3n+4} \mid 1 \ge \alpha \ge 0, x^0 = 0, z^0 = 0$$
$$x = \alpha x^1 + (1-\alpha)x^0, z = \alpha z^1 + (1-\alpha)z^0,$$
$$f_i(x^1) \le 0 \text{ for } i \in I, u \ge x^1 \ge 0, z^1 = 1\Big\}.$$

Simplify, Simplify, Simplify

- Substitute out x^0, z^0 and z^1: They are fixed in (XF)
- $z = \alpha$ after these substitutions, so substitute it out as well.
- $x = \alpha x^1 = z x^1$, so we can eliminate x^1 by replacing it with x/z provided that $z > 0$.

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Lemma

If W^1 is convex, then $\text{conv}(W) = W^- \cup W^0$, where

$$W^- = \left\{(x, z) \in \mathbb{R}^{n+1} \mid f_k(x/z) \leq 0 \ \forall k \in K, uz \geq x \geq 0, 1 \geq z > 0\right\}$$

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Lemma Extension

$$\mathrm{conv}(W) = \mathrm{closure}(W^-)$$

Convexify, Convexify, Convexify

- Note: $f_k(x/z)$ is not necessarily convex, even if $f_k(x)$ is.
- However, $zf_k(x/z)$ is convex if $f_k(x)$ is.
- Multiplying both sides of the inequality by $z > 0$ doesn't change the set W^-:

$$W^- = \left\{(x, z) \in \mathbb{R}^{n+1} \mid zf_k(x/z) \leq 0 \ \forall k \in K, uz \geq x \geq 0, 1 \geq z > 0\right\}$$

- You can, if you wish, multiply by z^p

Giving You Some Perspective

- For a convex function $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}$, the function

$$\mathcal{P}(f(z, x)) = zf(x/z)$$

  is known as the perspective function of f
- The epigraph of $\mathcal{P}(f(z, x))$ is a cone pointed at the origin whose lower shape is $f(x)$

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Exploiting Your Perspective

- If z_i is an indicator that the (nonlinear, convex) inequality $f(x) \leq 0$ must hold, (otherwise $x = 0$), replace the inequality with its perspective version:

$$z_i f(x/z_i) \leq 0$$

- The resulting (convex) inequality is a much tighter relaxation of the feasible region.

An Axioma Connection

Stubbs (1996)

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Ceria and Soares (1999)

- Describe $K = \cup_{i \in M} K_i$, with $K_i = \{x \mid f_i(x) \leq 0\}$ in a higher-dimensional space.
- $x \in \mathrm{conv}(K) \Leftrightarrow$

$$x = \sum_{i \in M} \lambda_i x_i, \mathcal{P}(f_i(\lambda_i, x_i)) \leq 0, \lambda \in \Delta_{|M|}$$

Other Smart People

Frangioni and Gentile (2006)

- Study: $y \geq f(x), x \leq uz$, give perspective cut:

$$y \geq f(x) + \nabla f(x)^T (x - \hat{x}) - (\hat{x}^T \nabla f(\hat{x}) + f(\hat{x}))(z - 1)$$

- This is first-order Taylor expansion of perspective $zf(x/z) + y \leq 0$ about $(\hat{x}, f(\hat{x}), 1)$
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Aktürk, Atamtürk, and Gürel (2007)

- Apply perspective reformulation (of epigraph indicator MINLP) to nonlinear machine scheduling problem
- Explain that formulations are representable as SOCP.

Facility Location

- M: Facilities
- N: Customers
- x_{ij}: percentage of customer i's demand served from facility j
- $z_i = 1 \Leftrightarrow$ facility i is opened
- Fixed cost for opening facility i
- Quadratic cost for serving j from i
- Problem studied by Günlük, Lee, and Weismantel ('07), and classes of strong cutting planes derived

Separable Quadratic UFL—Formulation

$$z^* \stackrel{\text{def}}{=} \min \sum_{i \in M} c_i z_i + \sum_{i \in M} \sum_{j \in N} q_{ij} x_{ij}^2$$

subject to

$$\begin{aligned} x_{ij} &\leq z_i && \forall i \in M, \forall j \in N \\ \sum_{i \in M} x_{ij} &= 1 && \forall j \in N \\ x_{ij} &\geq 0 && \forall i \in M, \forall j \in N \\ z_i &\in \{0, 1\} && \forall i \in M \end{aligned}$$

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Strength of Relaxations

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- z_{GLW}: Value of NLP relaxation after GLW cuts
- z_P: Value of perspective relaxation
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$\|M\|$	N	z_R	z_{GLW}	z_P	z^*
10	30	140.6	326.4		348.7
15	50	141.3	312.2		384.1
20	65	122.5	248.7		289.3
25	80	121.3	260.1		315.8
30	100	128.0	327.0		393.2

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Woo Hoo!

Design of Uncongested Network

- Capacitated directed network: $G = (N, A)$
- Set of commodities: K
- Node demands: b_i^k $\forall i \in N, \forall k \in K$
- Each arc $(i, j) \in A$ has
  - Fixed cost: c_{ij}
  - Capacity: u_{ij}
  - Queueing weight: r_{ij}

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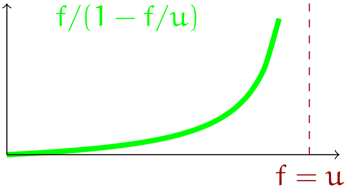
- $z_{ij} \in \{0,1\}$: Indicates whether arc $(i,j) \in \mathcal{A}$ is opened.
- x_{ij}^k: The quantity of commodity k routed on arc (i,j)

Network Design

- Let $f_{ij} \stackrel{\text{def}}{=} \sum_{k \in K} x_{ij}^k$ be the flow on arc (i,j).
- A measure of queueing delay is:

$$\rho(f) \stackrel{\text{def}}{=} \sum_{(i,j) \in A} r_{ij} \frac{f_{ij}}{1 - f_{ij}/u_{ij}}$$



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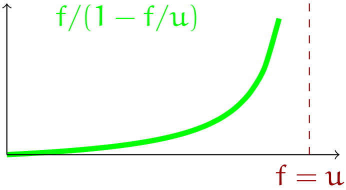

Our Network Design Problem

Design network to keep total queueing delay less than a given value β, and this is to be accomplished at minimum cost.

Network Design Formulation

$$\min \sum_{(i,j)\in A} c_{ij} z_{ij}$$

$$
\begin{aligned}
\text{s.t.} \quad \sum_{(j,i)\in A} x_{ij}^k - \sum_{(i,j)\in A} x_{ij}^k &= b_i^k && \forall i \in N, \forall k \in K \\
\sum_{k\in K} x_{ij}^k - f_{ij} &= 0 && \forall (i,j) \in A \\
f_{ij} &\le u_{ij} z_{ij} && \forall (i,j) \in A \\
y_{ij} &\ge \frac{r_{ij} f_{ij}}{1 - f_{ij}/u_{ij}} && \forall (i,j) \in A \\
\sum_{(i,j)\in A} y_{ij} &\le \beta
\end{aligned}
$$

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- Consider the nonlinear inequality:

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$$y/z \geq \frac{rf/z}{1 - f/zu} \Leftrightarrow ruzf \leq y(uz - f)$$

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$$y \geq \frac{rf}{1 - f/u} \Leftrightarrow ruf \leq y(u - f)$$

- Since $z_{ij} = 0 \Rightarrow f_{ij} = 0$, we can write the perspective reformulation:

$$y/z \geq \frac{rf/z}{1 - f/zu} \Leftrightarrow ruzf \leq y(uz - f)$$

Cones Are Everywhere!

- The inequalities $ruf \leq y(u - f)$ and $urfz \leq y(uz - f)$ are SOC-representable:

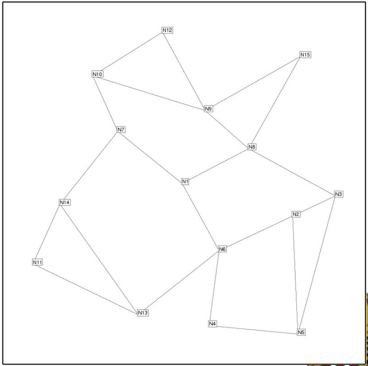
$$\begin{aligned} ruf \leq y(u - f) \quad &\Leftrightarrow \quad rf^2 \leq (y - rf)(u - f) \\ rufz \leq y(uz - f) \quad &\Leftrightarrow \quad rf^2 \leq (y - rf)(uz - f) \end{aligned}$$

since $y \geq rf$, $u \geq f$, $uz \geq f$

Results (Under Construction)

- ZIB SNDLIB instance: ATL.
- $|N| = |K| = 15$, $|A| = 22$
- Instance solved using (beta) version of Mosek (v5) conic MIP solver
- No fancy cutting planes (cut-set inequalities) added

ATL Network



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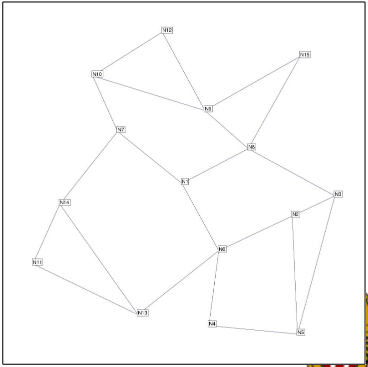

Results

	Nodes	Time
No Perspective	3686	517.1
W/Perspective	414	52.5

Conclusions

Other Conclusions

- Strong reformulations for MINLPs are likely to be just as important as they are for MILPs
- Strong formulations for MINLPs may require nonlinear inequalities. (Duh!)
- Much of the work we present here has (recently) found its way into the literature.

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- Strong reformulations for MINLPs are likely to be just as important as they are for MILPs
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Our "contributions"

- Give convex hull for the union of a (general) bounded convex set and a point
- Give description in original space of variables
- Exploit SOC-representability of strong reformulations to solve instances much more effectively