A General Framework for Convex Relaxation of Polynomial Optimization Problems over Cones

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Contents

1. **Convex relaxation of global optimization problems**

2. **Existing convex relaxation methods**

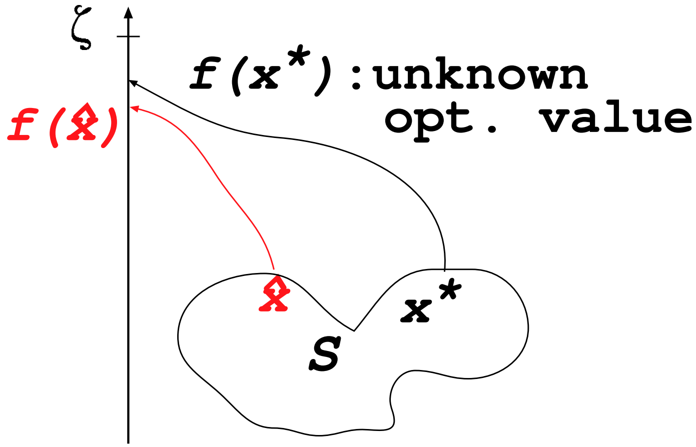
3. **Polynomial optimization problems over cones and their linearization**

4. **General framework for convex relaxation**

5. **Basic theory**
   — Relation to Lagrangian dual relaxation

1. Convex relaxation of global optimization problems

(1) max. $f(x)$ sub.to $x \in S$, where $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and $S \subset \mathbb{R}^n$.



To solve (1) approximately, we need

(a) a feasible solution $\hat{x} \in S$ with a larger objective value $f(\hat{x})$

(b) a smaller upper bound ζ for the unknown optimal value $f(x^*)$

$\Longrightarrow$ a main role of convex relaxation

If $\zeta - f(\hat{x})$ is smaller, we can accept $\hat{x}$ as a higher quality approximate optimal solution.

1. Convex relaxation of global optimization problems

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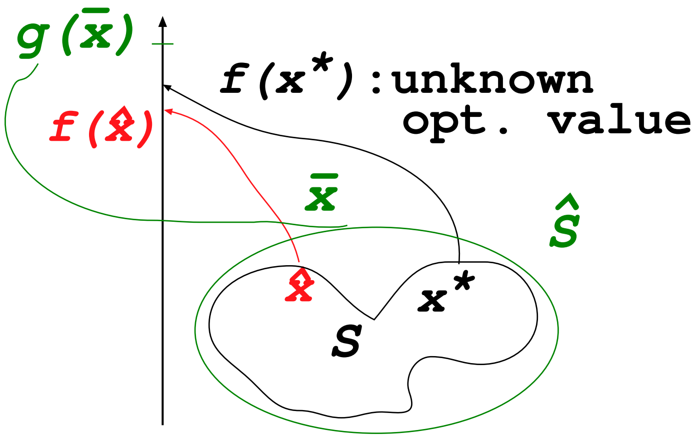


The common basic idea behind convex relaxation methods is:

(i) Replace S by a convex set $\hat{S}$ which includes S.

(ii) Replace f by a linear function g such that $f(x) \leq g(x)$ for $\forall x \in S$.

(iii) Solve the resulting convex optimization problem

$$\text{max. } g(x) \;\; \text{sub.to } x \in \hat{S}$$

to compute an optimal solution $\bar{x}$ whose objective value $\zeta = g(\bar{x})$ serves as an upper bound for $f(x^*)$.

2. Existing convex relaxation methods

- **One-step methods for 0-1 IPs, nonconvex QPs and polynomial programs**

(a) SDP-based, *e.g.*, Grötschel-Lovász-Schrijver'88, Shor'90, Goemans-Willianson'95.

(b) LP-based, *e.g.*, Reformulation-Linearization-Technique (Sherali et.al'92).

- **Successive applications of convex relaxation**

(c) Lovász-Schrijver'91 for 0-1 IPs, the lift-and-project procedure for 0-1 IPs by Balas-Ceria-Cornuéjols'93.

(d) SCRM (Successive Convex Relaxation Method) for QOPs by Kojima-Tunçel'00.

(e) Hierarchical SDP relaxation by Lasserre'01 for polynomial programming.

- Theoretically very powerful: the optimal value can be approximated in arbitrary accuracy by solving a finite number of SDP relaxations under a moderate condition.
- Practically very expensive: we need to solve a sequence of large scale SDPs.

The purpose of this talk is to present

a general framework for convex relaxation methods

which includes most of the existing methods.

The main ingredients are:

(a) Polynomial Optimization Problems $\supset$ QOPs and 0-1 IPs

$\Downarrow$(b) Add valid constraints and reformulate

(c) Polynomial Optimization Problems over Cones

$\Downarrow$ (d) Linearization

(e) Linear Optimization Problems over Cones

I will talk about

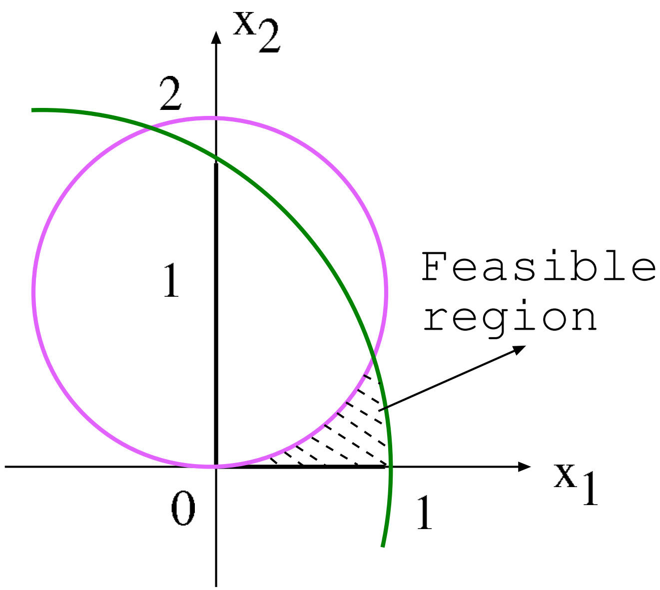
- **An illustrative example**
- **(c) $\Rightarrow$ (d) $\Rightarrow$ (e)**
- **(b)**

An illustrative example

Original problem: max. $-2x_1 + x_2$

sub.to $x_1 \geq 0, \; x_2 \geq 0, \; x_1^2 + x_2^2 - 2x_2 \geq 0,$

$$\left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2 \text{ (SOCP constraint)}$$



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$\Downarrow$ Valid constraints and/or reformulation

$$\begin{array}{ll} \text{max.} & -2x_1 + x_2 \\ \text{sub.to} & x_1 \geq 0,\ x_2 \geq 0,\ x_1^2 \geq 0,\ x_1 x_2 \geq 0,\ x_2^2 \geq 0,\ x_1^2 + x_2^2 - 2x_2 \geq 0, \\ & \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2,\ \left\| \begin{pmatrix} x_1^2 + x_1 \\ x_1 x_2 \end{pmatrix} \right\| \leq 2x_1,\ \left\| \begin{pmatrix} x_1 x_2 + x_2 \\ x_2^2 \end{pmatrix} \right\| \leq 2x_2. \end{array}$$

$\Downarrow$ Linearization: Keep the linear terms,
but replace each nonlinear term by a single independent variable

$$\begin{array}{ll} \text{max.} & -2x_1 + x_2 \\ \text{sub.to} & x_1 \geq 0,\ x_2 \geq 0,\ X_{11} \geq 0,\ X_{12} \geq 0, X_{22} \geq 0, \\ & X_{11} + X_{22} - 2x_2 \geq 0, \\ & \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2, \left\| \begin{pmatrix} X_{11} + x_1 \\ X_{12} \end{pmatrix} \right\| \leq 2x_1, \left\| \begin{pmatrix} X_{12} + x_2 \\ X_{22} \end{pmatrix} \right\| \leq 2x_2. \end{array}$$

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$\Downarrow$ **Valid constraints and/or reformulation**

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$\Uparrow$ $X_{11} = x_1 x_1, X_{12} = x_1 x_2, X_{22} = x_2 x_2$

$$\begin{array}{ll} \text{max.} & -2x_1 + x_2 \\ \text{sub.to} & x_1 \geq 0,\ x_2 \geq 0,\ X_{11} \geq 0,\ X_{12} \geq 0, X_{22} \geq 0, \\ & X_{11} + X_{22} - 2x_2 \geq 0, \\ & \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2, \left\| \begin{pmatrix} X_{11} + x_1 \\ X_{12} \end{pmatrix} \right\| \leq 2x_1, \left\| \begin{pmatrix} X_{12} + x_2 \\ X_{22} \end{pmatrix} \right\| \leq 2x_2. \end{array}$$

3. Polynomial optimization problems over cones and their linearization

$$\max.\ f_0(x) \text{ sub.to } f(x) \in \mathcal{K}, \quad \text{where}$$

$\mathcal{K}$: a closed convex cone in $\mathbb{R}^m$,
$x = (x_1, \ldots, x_n)$: a variable vector, $f(x) \equiv (f_1(x), \ldots, f_m(x))$,
$f_j(x)$: a polynomial in $x_1, \ldots, x_n$ $(j = 0, 1, \ldots, m)$.

Typical examples of $\mathcal{K}$: $\mathbb{R}^m_+$: the nonnegative orthant of $\mathbb{R}^m$.

$\mathbb{S}^\ell_+$: the cone of $\ell \times \ell$ psd symmetric matrices, where we identify each $\ell \times \ell$ matrix as an $\ell \times \ell$ dim vector.

$$\mathbb{N}^{1+\ell}_p \equiv \left\{ v = (v_0, v_1, \ldots, v_\ell) \in \mathbb{R}^{1+\ell} : \sum_{i=1}^{\ell} |v_i|^p \leq v_0^p \right\}$$

: the pth order cone $(p \geq 1)$.

$\mathbb{N}^{1+\ell}_2$: the second order cone.

When $f_j(x)$ $(j = 0, 1, 2, \ldots, m)$ are linear,

$$\mathcal{K} = \mathbb{S}^\ell_+ \Rightarrow \text{SDP (Semidefinite Program)},$$
$$\mathcal{K} = \mathbb{N}^{1+\ell}_2 \Rightarrow \text{SOCP (Second-Order Cone Program)}$$

3. Polynomial optimization problems over cones and their linearization

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$f_j(x)$: a polynomial in $x_1, \ldots, x_n$ $(j = 0, 1, \ldots, m)$.

Linearization — Keep the linear terms, but replace each nonlinear term by a single independent variable.

Example 1:

$$f(x_1, x_2) = \begin{pmatrix} 1 - 2x_1 + 3x_2 + 4x_1^2 + 5x_1x_2 + 6x_2^2 \\ 9 + 8x_1 + 7x_2 + 6x_1^2 - 5x_1x_2 - 4x_2^2 \end{pmatrix} \in \mathcal{K}$$

$\Downarrow$ Linearization

$$F(x_1, x_2, X_{11}, X_{12}, X_{22}) = \begin{pmatrix} 1 - 2x_1 + 3x_2 + 4X_{11} + 5X_{12} + 6X_{22} \\ 9 + 8x_1 + 7x_2 + 6X_{11} - 5X_{12} - 4X_{22} \end{pmatrix} \in \mathcal{K}$$

Here the three new variables X_{11}, X_{12} and X_{22} are introduced.

3. Polynomial optimization problems over cones and their linearization

$$\max.\ f_0(x)\ \text{sub.to}\ f(x) \in \mathcal{K}, \quad \text{where}$$

$\mathcal{K}$: a closed convex cone in $\mathbb{R}^m$,

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$f_j(x)$: a polynomial in $x_1, \ldots, x_n$ $(j = 0, 1, \ldots, m)$.

Linearization — Keep the linear terms, but replace each nonlinear term by a single independent variable.

Example 2:

$$f(x_1, x_2, x_3) = \begin{pmatrix} 1 - 2x_1 + 3x_2 + 4x_1^2 x_3 + 5x_1x_2x_3 + 6x_3^4 \\ 9 + 8x_1 + 7x_2 + 6x_1^2 x_3 - 5x_1x_2x_3 - 4x_3^4 \end{pmatrix} \in \mathcal{K}$$

$\Downarrow$ Linearization

$$F(x_1, x_2, U, V, W) = \begin{pmatrix} 1 - 2x_1 + 3x_2 + 4U + 5V + 6W \\ 9 + 8x_1 + 7x_2 + 6U - 5V - 4W \end{pmatrix} \in \mathcal{K}$$

Here the new variables U, V and W are introduced. In general, we need a systematic method of assigning a new variable to each nonlinear term.

3. Polynomial optimization problems over cones and their linearization

$$\max.\ f_0(x) \text{ sub.to } f(x) \in \mathcal{K}, \quad \text{where}$$

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$f_j(x)$: a polynomial in $x_1, \ldots, x_n$ $(j = 0, 1, \ldots, m)$.

Linearization — Keep the linear terms, but replace each nonlinear term by a single independent variable.

Systematic method of assigning a new variable to each nonlinear term:

$$\text{a nonlinear term } x_1^{\alpha} x_2^{\beta} \cdots x_n^{\zeta} \Rightarrow y_{(\alpha,\beta,\ldots,\zeta)} \in \mathbb{R} \text{ a new variable}$$

For example,

$$n = 5,\ x_1^2 x_2 x_3^3 x_5^4 = x_1^2 x_2^1 x_3^3 x_4^0 x_5^4 \Rightarrow y_{(2,1,3,0,4)}.$$

In theory, any method of assigning a new variable to each nonlinear term works. $\Rightarrow$ This method is not essential.

4. General framework for convex relaxation

Original QOP, 0-1 IP, Polynomial programs to be solved

$\Downarrow$ **Valid constraints and/or reformulate**

POP: max. $f_0(x)$ sub.to $f(x) \in \mathcal{K}$, where

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$\Downarrow$ **Linearization — Keep the linear terms, but replace each**
$\Downarrow$ **nonlinear term by a single independent variable.**

LOP: max. $F_0(x, y)$ sub.to $F(x, y) \in \mathcal{K}$, where

y denotes a new variable vector whose elements correspond to nonlinear terms appeared in the polynomials $f_j(x)$ $(j = 0, 1, \ldots, m)$.

An illustrative example

Original problem:

$$\begin{array}{ll} \text{max.} & -2x_1 + x_2 \\ \text{sub.to} & x_1 \geq 0,\ x_2 \geq 0,\ x_1^2 + x_2^2 - 2x_2 \geq 0, \\ & \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2 \text{ (SOCP constraint)} \end{array}$$

⇓ Valid constraints and/or reformulation

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⇓ Valid constraints and/or reformulation

$$
\begin{array}{ll}
\text{max.} & -2x_1 + x_2 \\
\text{sub.to} & x_1 \geq 0,\ x_2 \geq 0,\ x_1^2 + x_2^2 - 2x_2 \geq 0, \\
& \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2,\ \begin{pmatrix} 1 \\ x_1 \\ x_2 \end{pmatrix} \begin{pmatrix} 1 & x_1 & x_2 \end{pmatrix} \equiv \begin{pmatrix} 1 & x_1 & x_2 \\ x_1 & x_1^2 & x_1 x_2 \\ x_2 & x_1 x_2 & x_2^2 \end{pmatrix} \succeq O.
\end{array}
$$

⇓ Linearization

$$
\begin{array}{ll}
\text{max.} & -2x_1 + x_2 \qquad \text{— SDP} \\
\text{sub.to} & x_1 \geq 0,\ x_2 \geq 0,\ X_{11} + X_{22} - 2x_2 \geq 0, \\
& \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2,\ \begin{pmatrix} 1 & x_1 & x_2 \\ x_1 & X_{11} & X_{12} \\ x_2 & X_{12} & X_{22} \end{pmatrix} \succeq O.
\end{array}
$$

Given a problem, there are various ways of adding valid constraints and reformulating the problem. They usually yield different convex relaxations.

In the previous illustrative example:

$$\text{Original problem: max. } -2x_1 + x_2$$
$$\text{sub.to } x_1 \geq 0,\ x_2 \geq 0,\ x_1^2 + x_2^2 - 2x_2 \geq 0, \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2 \text{ (SOCP constraint)},$$

we obtained two distinct convex relaxations.

$$\begin{array}{ll} \text{max.} & -2x_1 + x_2 \qquad \text{— SOCP} \\ \text{sub.to} & x_1 \geq 0,\ x_2 \geq 0,\ X_{11} \geq 0,\ X_{12} \geq 0, X_{22} \geq 0, \\ & X_{11} + X_{22} - 2x_2 \geq 0, \\ & \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2, \left\| \begin{pmatrix} X_{11} + x_1 \\ X_{12} \end{pmatrix} \right\| \leq 2x_1, \left\| \begin{pmatrix} X_{12} + x_2 \\ X_{22} \end{pmatrix} \right\| \leq 2x_2. \end{array}$$

$$\begin{array}{ll} \text{max.} & -2x_1 + x_2 \qquad \text{— SDP} \\ \text{sub.to} & x_1 \geq 0,\ x_2 \geq 0, X_{11} + X_{22} - 2x_2 \geq 0, \\ & \left\| \begin{pmatrix} x_1 + 1 \\ x_2 \end{pmatrix} \right\| \leq 2, \begin{pmatrix} 1 & x_1 & x_2 \\ x_1 & X_{11} & X_{12} \\ x_2 & X_{12} & X_{22)} \end{pmatrix} \succeq O. \end{array}$$

$$\textbf{Original problem: max.} \quad -2x_1 + x_2$$
$$\textbf{sub.to} \quad x_1 \geq 0,\; x_2 \geq 0,\; x_1^2 + x_2^2 - 2x_2 \geq 0,$$
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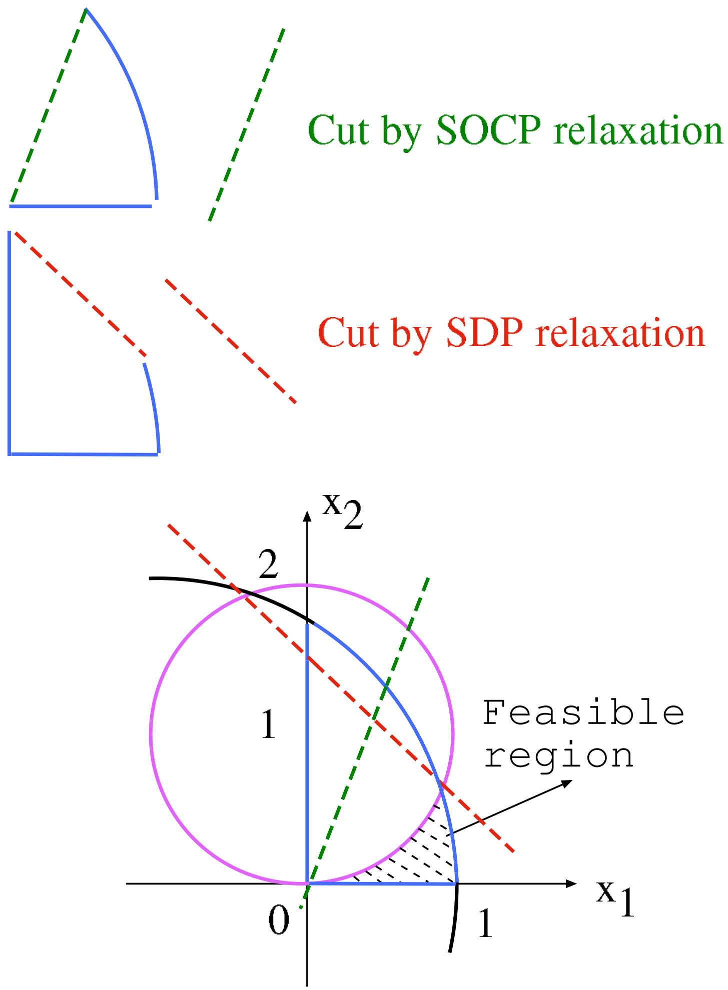

Some examples of valid constraints — 1

- **Universally valid constraints.**

(a) SDP type:

$$u(x)u(x)^T = \begin{pmatrix} 1 & x_1 & x_2 & x_1^2 & x_1x_2 & x_2^2 \\ x_1 & x_1^2 & x_1x_2 & x_1^3 & x_1^2x_2 & x_1x_2^2 \\ x_2 & x_1x_2 & x_2^2 & x_1^2x_2 & x_1x_2^2 & x_2^3 \\ x_1^2 & x_1^3 & x_1^2x_2 & x_1^4 & x_1^3x_2 & x_1^2x_2^2 \\ x_1x_2 & x_1^2x_2 & x_1x_2^2 & x_1^3x_2 & x_1^2x_2^2 & x_1x_2^3 \\ x_2^2 & x_1x_2^2 & x_2^3 & x_1^2x_2^2 & x_1x_2^3 & x_2^4 \end{pmatrix} \succeq O,$$

where $u(x) = \begin{pmatrix} 1 & x_1 & x_2 & x_1^2 & x_1x_2 & x_2^2 \end{pmatrix}^T$

More generally, take a row vector consisting of a basis of the polynomials in $x_1, \ldots, x_n$ with degree ℓ for $u(x)$. [Lasserre'01].

(b) SOCP (Second-Order Cone Programming) type:

$$\forall\ f_1, f_2 : \mathbb{R}^n \to \mathbb{R}, \ \left\| \begin{pmatrix} f_1(x)^2 - f_2(x)^2 \\ 2f_1(x)f_2(x) \end{pmatrix} \right\| \leq f_1(x)^2 + f_2(x)^2$$

Some examples of valid constraints — 2

- **Deriving valid constraints, "multiplication" of valid constraints:**

$$\begin{array}{rcl} \text{original constraints} & & \text{new constraints} \\ \mathbb{R} \ni f(x) \geq 0,\ \mathbb{R} \ni g(x) \geq 0 & \Rightarrow & f(x)g(x) \geq 0 \text{ [Sherali et.al'92]} \\ f(x) \geq 0,\ G(x) \succeq O & \Rightarrow & f(x)G(x) \succeq 0 \text{ [Lasserre'01]} \end{array}$$

$$\begin{array}{rcl} F(x) \succeq O,\ G(x) \succeq O & \Rightarrow & F(x) \otimes G(x) \succeq 0 \text{ (Kronecker product)} \\ \left. \begin{array}{r} \|f(x)\| \leq f_0(x),\ f(x) \in \mathbb{R}^\ell \\ \|g(x)\| \leq g_0(x),\ g(x) \in \mathbb{R}^\ell \end{array} \right\} & \Rightarrow & \|f(x) \circ g(x)\| \leq f_0(x) g_0(x) \\ \text{(SOCP constraints)} & & \text{(component-wise product)} \end{array}$$

5. Basic theory

POP: max. $f_0(x)$ sub.to $f(x) \in \mathcal{K}$, where

$\mathcal{K}$: a closed convex cone in $\mathbb{R}^m$, $f(x) \equiv (f_1(x), \ldots, f_m(x))$.

$\Downarrow$ Linearization — Keep the linear terms, but replace each
$\Downarrow$ nonlinear term by a single independent variable.

LOP: max. $F_0(x, y)$ sub.to $F(x, y) \in \mathcal{K}$, where

y denotes a new variable vector whose elements correspond to nonlinear terms appeared in the polynomials $f_j(x)$ $(j = 0, 1, \ldots, m)$.

Lagrangian funct: $L(x, v) \equiv f_0(x) + \sum_{j=1}^m v_j f_j(x)$ for $\forall x \in \mathbb{R}^n, v \in \mathcal{K}^*$

Under the Slater condition ($\exists x$; $f(x) \in$ int $\mathcal{K}$), if $\bar{\zeta}$ is the optimal value of LOP then there exists $\bar{v} \in \mathcal{K}^*$ satisfying

$$L(x, \bar{v}) = \bar{\zeta} \text{ for } \forall x \in \mathbb{R}^n$$

$$\begin{aligned} \text{Hence } \bar{\zeta} &= \max\{L(x, \bar{v}) : x \in \mathbb{R}^n\} \text{ (a Lagrangian relaxation)} \\ &\geq \min_{v \in \mathcal{K}^*} \max\{L(x, v) : x \in \mathbb{R}^n\} \text{ (Lagrangian dual relaxation)} \end{aligned}$$

6. Concluding remarks

The framework proposed in this talk for convex relaxation is quite general.

But we need to investigate various issues.

- **Effectiveness — How do we generate better bounds?**
- **Low cost — Resulting relaxed problems need to be solved cheaply**
- **How to combine this framework with other methods like the branch-and-bound method**
- **Parallel computation?**