

# Theory and Application of $p$ -regularized subproblems for $p > 2$

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# Outline

- 1 Introduction
- 2 Characterization of the Global Minimizers
- 3 Characterization of the Local Non-global Minimizer
- 4 Application to  $(p - RS)$  subject to linear inequality constraints for  $p = 4$
- 5 Conclusions

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# Introduction

$$\min_{x \in \mathbb{R}^n} c^T x + \frac{1}{2} x^T H x + \frac{\sigma}{p} \|x\|_2^p \quad (p - RS)$$

$\sigma > 0, p > 2$ .  $H \in \mathbb{R}^{n \times n}$  symmetric.

**Subproblem for Unconstrained Optimization:**  $\min f(x)$

$$f(x) \approx f(x_k) + f'(x_k)(x - x_k) + \frac{1}{2}(x - x_k)^T H_k (x - x_k)$$

Regularization term: (Penalty term)

$$\|x - x_k\|_2^p$$

# Why $p > 2$ ?

## Self Adaptive Property of $\|x\|^p$

Define  $g(x) = c^T x + \frac{1}{x} x^T H x + \frac{\sigma}{p} \|x\|^p$ . As a penalty function,  $g(x)$

- When  $\|x\| \rightarrow +\infty$ ,

$$\lim_{\|x\| \rightarrow +\infty} g(x) = +\infty.$$

- When  $x \rightarrow 0$ ,

$$g(x) \sim c^T x + \frac{1}{2} x^T H x$$



# Previous Works

## Cubic Regularization: $p = 3$

$$\min_{x \in \mathcal{R}} c^T x + \frac{1}{2} x^T H x + \frac{\sigma}{3} \|x\|_2^3$$

Griewank (1981)

Nesterov and Polyak (2006)

Weiser, Deufhard and Erdmann (2007)

Cartis, Gould and Toint (2011)

**quartic regularization:  $p = 4$ ,**  
Fang, Gao, Lin Sheu, Xing (2012)

**general  $p$ – regularization for  $p > 2$ :**  
Gould, Robinson and Thorne (2010)

# Related Problem: Trust Region Subproblem

## Trust region Subproblem

$$\begin{aligned}
 (\text{TRS}) \quad & \min \quad \frac{1}{2}x^T Hx + c^T x \\
 \text{s.t.} \quad & \|x\|_2^2 \leq \Delta, \quad x \in \mathbb{R}^n.
 \end{aligned}$$

## Quadratic regularization: (Levenberg-Marquardt Technique)

$$\min \frac{1}{2}x^T Hx + c^T x + \frac{\sigma}{2}\|x\|_2^2 \quad (2 - RS)$$

Relations between (TRS) and (2-RS): Gay(1981), Moré and Sorenson(1983).

**Interesting Properties of (TRS)** Local minimizers, global minimizers  
 Martinez(1994): necessary conditions for local non-global minimizers.

# Motivation

Properties of (p-RS) for general  $p > 2$ :

- Conditions for local minimizers and global minimizers
- conditions for local non-global minimizers
- number of local non-global minimizers

## Notations.

- $\text{Diag}(x)$ : diagonal matrix with components  $x_1, \dots, x_n$ .
- $\lambda_i(P)$  is the  $i$ th smallest eigenvalue of  $P$
- $\|x\| = \|x\|_2$

# Necessary Condition for a Local Minimizer

## Lemma

*Assume that  $\underline{x}$  is a local minimizer of (p-RS),  $p > 2$ . It holds that*

$$\nabla g(\underline{x}) = \left( H + \sigma \|\underline{x}\|^{p-2} I \right) \underline{x} + \underline{c} = 0, \quad (1)$$

$$\nabla^2 g(\underline{x}) = (H + \sigma \|\underline{x}\|^{p-2} I) + \sigma(p-2) \|\underline{x}\|^{p-4} \underline{x} \underline{x}^T \succeq 0, \quad (2)$$

*where  $\nabla g$ ,  $\nabla^2 g$  denote the gradient and the Hessian of  $g(x)$ , respectively.*

direct calculations

# Necessary and Sufficient Conditions for Global Minimizer

## Theorem

*The point  $x^*$  is a global minimizer of (p-RS) for  $p > 2$  if and only if it is a critical point satisfying  $\nabla g(x^*) = 0$  and  $H + \sigma \|x^*\|^{p-2} I \succeq 0$ . Moreover, the  $\ell_2$  norms of all the global minimizers are equal.*

## Proof

**Necessary:** See Gould, Robinson and Thorne(2010).

N.I.M. Gould, D.P. Robinson and H.S. Thorne, On solving trust region and other regularised subproblems in optimization, *Mathematical Programming Computation*, 2(2010) pp.21-57.

**Sufficient:**

If  $x^* = 0_n$ , then  $\sigma \|x^*\|^{p-2} = 0$  so that  $c = -(H + \sigma \|x^*\|^{p-2}I)x^* = 0$  and  $H = H + \sigma \|x^*\|^{p-2}I \succeq 0$ . Consequently,  $x^T H x \geq 0, \forall x \in \mathbb{R}^n$ . Thus,  $x^* = 0_n$  is a global minimizer since

$$g(x) = \frac{1}{2}x^T H x + c^T x + \frac{\sigma}{p}\|x\|^p \geq \frac{\sigma}{p}\|x\|^p > 0 = g(0), \forall x \neq 0_n = x^*.$$

Now, Assume  $\|x^*\| > 0$ .

Define  $Q = H + \sigma \|x^*\|^{p-2}I$ .  $Q \succeq 0$ . For any  $x \in \mathbb{R}^n$  and  $x \neq x^*$ ,

$$\begin{aligned} g(x) &= \frac{1}{2}x^T H x + c^T x + \frac{\sigma}{p}\|x\|^p \\ &= \frac{1}{2}x^T Q x + c^T x + \frac{\sigma}{p}\|x^*\|^p \left( \left( \frac{\|x\|^2}{\|x^*\|^2} \right)^{\frac{p}{2}} - \frac{p}{2} \frac{\|x\|^2}{\|x^*\|^2} \right) \quad (3) \end{aligned}$$

Define  $f(t) = t^{\frac{p}{2}}$ ,  $p > 2$ . It is strictly convex for  $t > 0$ . Therefore,

$$f(t) = t^{\frac{p}{2}} \geq f(1) + f'(1)(t - 1) = 1 + \frac{p}{2}(t - 1), \quad \forall t > 0.$$

By substituting  $t$  with  $\frac{\|x\|^2}{\|x^*\|^2}$ , we have

$$\left( \frac{\|x\|^2}{\|x^*\|^2} \right)^{\frac{p}{2}} - \frac{p}{2} \frac{\|x\|^2}{\|x^*\|^2} \geq 1 - \frac{p}{2}.$$

Then,

$$g(x) \geq \frac{1}{2}x^T Qx + c^T x + \frac{\sigma}{p} \|x^*\|^p \left(1 - \frac{p}{2}\right). \quad (4)$$

By  $Q \succeq 0$ , the lower bounding function of  $g$  in the right hand side of (4) is convex quadratic in terms of  $x$ . Since  $x^*$  satisfies  $(H + \sigma \|x^*\|^{p-2}I)x^* = Qx^* = -c$ ,  $x^*$  is a global minimizer of the convex function in the right hand side of (4). As a consequence,

$$g(x) \geq \frac{1}{2}(x^*)^T Qx^* + c^T x^* + \frac{\sigma}{p} \|x^*\|^p (1 - \frac{p}{2}) = g(x^*)$$

and  $x^*$  is a global minimizer of (p-RS).

Finally, from (3), if  $\hat{x}$  is also a global minimizer of (p-RS),  $\hat{x}$  must minimize both  $\frac{1}{2}x^T Qx + c^T x$  and  $\left(\frac{\|x\|^2}{\|x^*\|^2}\right)^{\frac{p}{2}} - \frac{p}{2} \frac{\|x\|^2}{\|x^*\|^2}$  simultaneously. This can happen if and only if  $Q\hat{x} = -c$  and  $\|\hat{x}\| = \|x^*\|$ .



# Set of Global Minimizers

## Theorem

*The set of global minimizers of (p-RS) is either a singleton or a  $k$ -dimensional sphere centered at  $(0, \dots, 0, -\frac{c_{k+1}}{\alpha_{k+1}-\alpha_1}, \dots, -\frac{c_n}{\sigma_n-\sigma_1})$  with the radius  $\sqrt{\left(\frac{\alpha_1}{\sigma}\right)^{\frac{2}{p-2}} - \sum_{i=k+1}^n \frac{c_i^2}{(\alpha_i-\alpha_1)^2}}$ .*

# Ideas of Proof

## Consider Diagonal $H$

Assume  $H$  is diagonal, i.e.,

$$H = \text{Diag}(\alpha_1, \dots, \alpha_n), \quad (5)$$

where

$$\alpha_1 = \dots = \alpha_k < \alpha_{k+1} \leq \dots \leq \alpha_n$$

and  $k$  is the multiplicity of the smallest eigenvalue  $\alpha_1$ .

Otherwise let  $H = U\Sigma U^T$ , and let  $y = U^T x$

## Outlines of the Proof

- Define  $t^* = \|x^*\|^{p-2} \geq 0$ , independent of  $x^*$ .
- $t^* \in (\max\{-\frac{\alpha_1}{\sigma}, 0\}, +\infty)$ .
- Solution  $x^*$  satisfying  $(H + \sigma t^* I)x^* = -c$

**If  $H + \sigma t^* I$  is invertible**

- $x_i^* = \frac{-c_i}{\alpha_i + \sigma t^*}$ ,  $i = 1, \dots, n$ .



$$h(t) = \sum_{i=1}^n \frac{c_i^2}{(\alpha_i + \sigma t)^2} - t^{\frac{2}{p-2}}, \quad t \in I_g = \left( \max\left\{-\frac{\alpha_1}{\sigma}, 0\right\}, +\infty \right). \quad (6)$$

$h(t)$  can only have a unique root on  $I_g$ , which must be  $t^*$ .

**If  $H + \sigma t^* I$  is singular**

- $t^* = \frac{-\alpha_1}{\sigma} \implies (\alpha_1 \leq 0)$
- $c_1^2 + \dots + c_k^2 = 0$ , and  $\alpha_i + \sigma t^* > 0$ ,  $i = k+1, k+2, \dots, n$  such that

$$\hat{x}^* = \left( 0, 0, \dots, 0, \frac{-c_{k+1}}{\alpha_{k+1} - \alpha_1}, \dots, \frac{-c_n}{\alpha_n - \alpha_1} \right)^T \quad (7)$$

is one trivial solution to  $(H - \alpha_1 I)x^* = -c$ .

- $\hat{h}(t) = \sum_{i=k+1}^n \frac{c_i^2}{(\alpha_i + \sigma t)^2} - t^{\frac{2}{p-2}}$ ,  $t \in I_{\hat{g}} = \left[ -\frac{\alpha_1}{\sigma}, +\infty \right)$ .

$\hat{h}(t)$ : strictly decreasing on  $I_{\hat{g}}$  and  $\lim_{t \rightarrow +\infty} \hat{h}(t) = -\infty$ .

If  $h\left(-\frac{\alpha_1}{\sigma}\right) = 0$

- $t^* = \frac{-\alpha_1}{\sigma}$  is the only root of  $\hat{h}(t)$  on  $I_{\hat{g}}$ .
- $\hat{x}^*$  defined in (7) is the unique global minimizer of (p-RS).

If  $\hat{h}\left(-\frac{\alpha_1}{\sigma}\right) < 0$

- $\hat{h}(t) = 0$  has no solution
- the trivial solution  $\hat{x}^*$  to  $(H - \alpha_1 I)x^* = -c$  does not satisfy  $t^* = \frac{-\alpha_1}{\sigma} = \|\hat{x}^*\|^{p-2}$ .
- Any  $x^*$  satisfying

$$(x_1^*)^2 + \dots + (x_k^*)^2 + \sum_{i=k+1}^n \frac{c_i^2}{(\alpha_i - \alpha_1)^2} = \left(\frac{-\alpha_1}{\sigma}\right)^{\frac{2}{p-2}}$$

is a global minimizer of (p-RS).

# Hidden Convexity

## Lemma

*Suppose  $H$  is diagonal. Let  $x^*$  be any global minimizer of (RS), then*

$$c_i x_i^* \leq 0, \quad i = 1, \dots, n.$$

## Proof

Comparing  $x^*$  with  $\tilde{x} = (-x_1^*, x_2^*, x_3^*, \dots, x_n^*)$ , we immediately have

$$0 \geq g(x^*) - g(\tilde{x}) = c_1(x_1^* - \tilde{x}_1) = 2c_1 x_1^*.$$

A similar argument applying to all other components yields the result.

□

By the above lemma,

$$\begin{aligned} \min \quad & \sum_{i=1}^n \left\{ \frac{\alpha_i}{2} x_i^2 + c_i x_i \right\} + \frac{\sigma}{p} \left( \sum_{i=1}^n x_i^2 \right)^{\frac{p}{2}} \\ \text{s.t.} \quad & c_i x_i \leq 0, \quad i = 1, \dots, n. \end{aligned} \quad (8)$$

and (p-RS) share the same optimal solution set.  
Using the nonlinear one-to-one map:

$$x_i = \begin{cases} \sqrt{z_i}, & \text{if } c_i \leq 0, \\ -\sqrt{z_i}, & \text{if } c_i > 0, \end{cases} \quad i = 1, \dots, n, \quad (9)$$

we convert the problem (8) into the following convex program:

$$\begin{aligned} \min \quad & - \sum_{i=1}^n |c_i| \sqrt{z_i} + \frac{1}{2} \sum_{i=1}^n \alpha_i z_i + \frac{\sigma}{p} \left( \sum_{i=1}^n z_i \right)^{\frac{p}{2}} \\ \text{s.t.} \quad & z_i \geq 0, \quad i = 1, \dots, n. \end{aligned} \quad (10)$$

# Ramark

$$h'(t) = \sum_{i=1}^n \frac{-2\sigma c_i^2}{(\alpha_i + \sigma t)^3} - \frac{2}{p-2} t^{\frac{4-p}{p-2}}$$

$$h''(t) = \sum_{i=1}^n \frac{6\sigma^2 c_i^2}{(\alpha_i + \sigma t)^4} - \frac{2(4-p)}{(p-2)^2} t^{\frac{6-2p}{p-2}}.$$

- For  $p \geq 4$ ,  $h(t)$  is strictly decreasing on  $I_g$  and convex.
- For  $p = 3$ , if  $H \not\equiv 0$  (which ensures that  $c \neq 0$ ) and  $h$  is restricted to a finite subinterval of  $I_g$  covering  $t^*$ , by properly choosing the regularization parameter  $\sigma$ ,  $h(t)$  can be made convex.
- Notice that the secular function for (TRS) is always convex.

# Necessary Condition for Local Non-global Minimizer

Assume

- $H$  is diagonal.
- $\alpha_1 < 1$
- $n \geq 2$

## Lemma

*Suppose  $\underline{x}$  is a local non-global minimizer of (p-RS). It holds that  $\underline{x}_1 \neq 0$ ,  $\alpha_1 < \alpha_2$  and*

$$\alpha_2 + \sigma \|\underline{x}\|^{p-2} > 0. \quad (11)$$



# Proof of the Lemma

$\underline{x}$  is a local but non-global minimizer,  $H + \sigma \|\underline{x}\|^{p-2} \not\geq 0$ . Thus,  
 $\alpha_1 + \sigma \|\underline{x}\|^{p-2} < 0$ .

Second order necessary conditions imply

$$\begin{bmatrix} \alpha_1 + \sigma \|\underline{x}\|^{p-2} & 0 \\ 0 & \alpha_2 + \sigma \|\underline{x}\|^{p-2} \end{bmatrix} + \sigma(p-2)\|\underline{x}\|^{p-4} \begin{bmatrix} \underline{x}_1^2 & \underline{x}_1 \underline{x}_2 \\ \underline{x}_1 \underline{x}_2 & \underline{x}_2^2 \end{bmatrix} \succeq 0.$$

This gives  $x_1 \neq 0$  and

$$(\alpha_1 + \sigma \|\underline{x}\|^{p-2})(\underline{x}_2)^2 + (\alpha_2 + \sigma \|\underline{x}\|^{p-2})(\underline{x}_1)^2 \geq 0.$$

Therefore  $\alpha_2 + \sigma \|\underline{x}\|^{p-2} \geq 0$ .

But  $\alpha_1 + \sigma \|\underline{x}\|^{p-2} < 0$ , thus,  $\alpha_1 \neq \alpha_2$ .

Prove  $\alpha_2 + \sigma \|\underline{x}\|^{p-2} > 0$  **by contradiction**. Assume  $\alpha_2 + \sigma \|\underline{x}\|^{p-2} = 0$ .

$$H - \alpha_2 I + \sigma(p-2)\|\underline{x}\|^{p-4} \underline{x} \underline{x}^T \succeq 0.$$

By  $\alpha_1 - \alpha_2 < 0$  and

$$\begin{aligned} & \det \left\{ \begin{bmatrix} \alpha_1 - \alpha_2 & 0 \\ 0 & 0 \end{bmatrix} + \sigma(p-2)\|\underline{x}\|^{p-4} \begin{bmatrix} \underline{x}_1^2 & \underline{x}_1 \underline{x}_2 \\ \underline{x}_1 \underline{x}_2 & \underline{x}_2^2 \end{bmatrix} \right\} \\ &= \sigma(p-2)\|\underline{x}\|^{p-4}(\alpha_1 - \alpha_2)\underline{x}_2^2 \geq 0, \end{aligned}$$

it implies that  $\underline{x}_2 = 0$  and, first order necessary condition gives

$$\underline{x}_1 = \frac{-c_1}{\alpha_1 + \sigma \|\underline{x}\|^{p-2}} = \frac{c_1}{\alpha_2 - \alpha_1}.$$

w.l.o.g. assume  $c_1 > 0$  and  $\underline{x}_1 > 0$ . Define

$$k(t) = \sqrt{\underline{x}_1^2 - t^2}, \quad t \in [-\underline{x}_1, \underline{x}_1]$$

and consider the following parametric curve in  $\mathbb{R}^n$ :

$$\gamma(t) = \{(k(t), t, \underline{x}_3, \dots, \underline{x}_n) \mid t \in [-\underline{x}_1, \underline{x}_1]\}. \quad (13)$$

Notice that  $\gamma(0) = \gamma(\underline{x}_2) = \underline{x}$ , i.e.,  $\gamma(t)$  passes through  $\underline{x}$  at  $t = 0$ . Evaluating  $g(x)$  on  $\gamma(t)$ , we have

$$g(\gamma(t)) = \frac{\sigma}{p} \left( \underline{x}_1^2 + \sum_{i=3}^n \underline{x}_i^2 \right)^{\frac{p}{2}} + \frac{\alpha_1}{2} \underline{x}_1^2 + \sum_{i=3}^n \frac{\alpha_i}{2} \underline{x}_i^2 + \frac{\alpha_2 - \alpha_1}{2} t^2 + c_1 \sqrt{\underline{x}_1^2 - t^2} + \sum_{i=3}^n c_i \underline{x}_i.$$

Since  $\underline{x}$  is a local minimizer of  $g(x)$ ,  $t = 0$  must be a local minimum point of  $g(\gamma(t))$ . However, this implication contradicts to the fact that

$$\frac{d^i}{dt^i} g(\gamma(0)) = 0 (i = 1, 2, 3), \quad \frac{d^4}{dt^4} g(\gamma(0)) = -\frac{3(\alpha_2 - \alpha_1)}{\underline{x}_1^2} < 0.$$

□

# Necessary and Sufficient Conditions for local non-global Minimizers

## Theorem

$\underline{x}$  is a local non-global minimizer of (p-RS) if and only if

$$\underline{x} = -(H + \sigma \underline{t}^* I)^{-1} c, \quad (14)$$

where  $\underline{t}^*$  is a root of the secular function

$$h(t) = \| (H + \sigma t I)^{-1} c \|^2 - t^{\frac{2}{p-2}}, \quad t \in \left( \max \left\{ -\frac{\alpha_2}{\sigma}, 0 \right\}, -\frac{\alpha_1}{\sigma} \right) \quad (15)$$

such that  $h'(\underline{t}^*) > 0$ .

# Proof: Necessary

local non-global minimizer  $\underline{x}$  satisfies

$$-\alpha_2 < \sigma \|\underline{x}\|^{p-2} < -\alpha_1.$$

First order necessary condition gives

$$\underline{x}_i = \frac{-c_i}{\alpha_i + \sigma \|\underline{x}\|^{p-2}}, \quad i = 1, \dots, n \quad (16)$$

$$\|\underline{x}\|^2 = \sum_{i=1}^n \frac{c_i^2}{(\alpha_i + \sigma \|\underline{x}\|^{p-2})^2}.$$

Define  $\underline{t}^* = \|\underline{x}\|^{p-2}$ .  $h(\underline{t}^*) = 0$  and

$$t^* \in \left( \max \left\{ -\frac{\alpha_2}{\sigma}, 0 \right\}, -\frac{\alpha_1}{\sigma} \right).$$

and  $\underline{x} = -(H + \sigma \underline{t}^* I)^{-1} \underline{c}$ .

$$h'(t) = - \sum_{i=1}^n \frac{2\sigma c_i^2}{(\alpha_i + \sigma t)^3} - \frac{2}{p-2} t^{\frac{4-p}{p-2}}.$$

necessary optimality condition is equivalent to

$$\text{Diag}(-1, 1, \dots, 1) + \sigma(p-2)\|\underline{x}\|^{p-4}(\Gamma \underline{x})(\Gamma \underline{x})^T \succeq 0,$$

where

$$\Gamma = \text{Diag} \left( \frac{1}{\sqrt{-\alpha_1 - \sigma\|\underline{x}\|^{p-2}}}, \frac{1}{\sqrt{\alpha_2 + \sigma\|\underline{x}\|^{p-2}}}, \dots, \frac{1}{\sqrt{\alpha_n + \sigma\|\underline{x}\|^{p-2}}} \right).$$

Then,

$$\begin{aligned} 0 &\leq \det \left( \text{Diag}(-1, 1, \dots, 1) + \sigma(p-2)\|\underline{x}\|^{p-4}(\Gamma \underline{x})(\Gamma \underline{x})^T \right) \\ &= \left( \frac{p}{2} - 1 \right) \|\underline{x}\|^{p-4} h'(\|\underline{x}\|^{p-2}) = \left( \frac{p}{2} - 1 \right) \|\underline{x}\|^{p-4} h'(\underline{t}^*). \end{aligned}$$

Thus,  $h'(\underline{t}^*) \geq 0$

Prove  $h'(t^*) > 0$  by contradiction.

If  $h'(t^*) = 0$ , There exist  $u = (u_1, \dots, u_n)^T \neq 0$  such that

$$\left( H + \sigma \|\underline{x}\|^{p-2} I \right) u + \sigma(p-2) \|\underline{x}\|^{p-4} \underline{x} \underline{x}^T u = 0,$$

Define  $q(\beta) := g(\underline{x} + \beta u)$ . We can verify that

$$\begin{aligned} q'(\beta) &= \nabla g(\underline{x} + \beta u) u, \\ q''(\beta) &= u^T \nabla^2 g(\underline{x} + \beta u) u, \\ q'''(\beta) &= 3\sigma(p-2) \|\underline{x} + \beta u\|^{p-4} (u^T \underline{x} + \beta u^T u) u^T u \\ &\quad + \sigma(p-2)(p-4) \|\underline{x} + \beta u\|^{p-6} (u^T \underline{x} + \beta u^T u)^3. \end{aligned}$$

$$q'(0) = q''(0) = 0. \text{ and } (q'''(0))^2 > 0.$$

Contradiction! Necessary part is proved.

# Sufficient Part

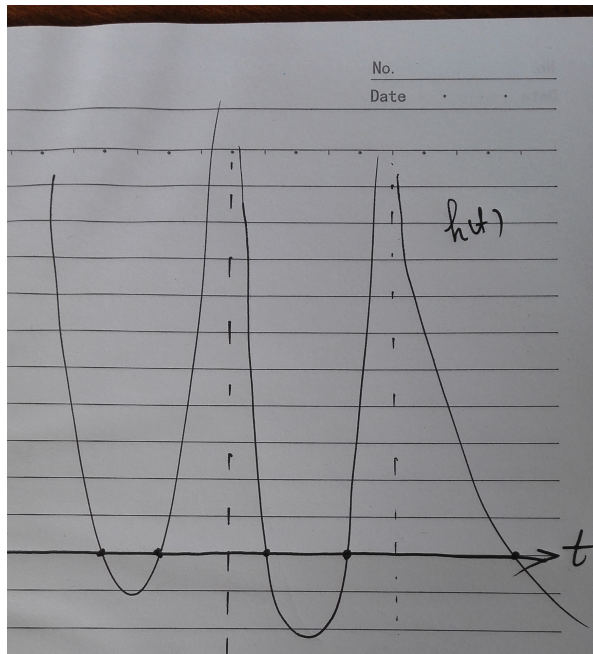
## Main Idea

$$\begin{aligned}
 \lambda_i \left( \nabla^2 g(\underline{x}) \right) &= \lambda_i \left( H + \sigma \|\underline{x}\|^{p-2} I + \sigma(p-2) \|\underline{x}\|^{p-4} \underline{x} \underline{x}^T \right) \\
 &\geq \lambda_i \left( H + \sigma \|\underline{x}\|^{p-2} I \right) + \lambda_1 \left( \sigma(p-2) \|\underline{x}\|^{p-4} \underline{x} \underline{x}^T \right) \\
 &\geq \lambda_i \left( H + \sigma \|\underline{x}\|^{p-2} I \right) > 0, \text{ for } i = 2, 3, \dots, n,
 \end{aligned}$$

$$\prod_{i=1}^n \lambda_i \left( \nabla^2 g(\underline{x}) \right) = \det \left( \nabla^2 g(\underline{x}) \right) = \frac{\left(\frac{p}{2} - 1\right) \|\underline{x}\|^{p-4} h'(t^*)}{\det^2(\Gamma)} > 0,$$

$$\nabla^2 g(\underline{x}) > 0$$





# Only 1 Local Non-Global Minimizer

## Theorem

*(p-RS) with  $p > 2$  has at most one local non-global minimizer.*

## Idea of Proof

- Define the function

$$p(t) = \log \left( \| (H + \sigma t I)^{-1} c \|^2 \right) - \frac{2}{p-2} \log(t),$$

$$t \in \left( \max \left\{ -\frac{\alpha_2}{\sigma}, 0 \right\}, -\frac{\alpha_1}{\sigma} \right).$$

- $p(t) = 0$  and  $h(t) = 0$  equivalent
- $p(t)$  convex

## Remark

*It is indeed surprising that we obtain*

- *the necessary and sufficient conditions for the local non-global minimizers for general  $p > 2$ ,*
- *the number of local non-global minimizer is at most one.*

*It was previously known to be true for  $p = 4$  in the double well potential function but the technique to generalize the result is non-trivial as we do not have a convex secular function for  $2 < p < 4$ .*

# Application to Linear Inequality Constraints

linearly constrained  $p$ -regularized problem:

$$\begin{aligned} (p - \text{RS}_m) \quad & \min \quad \frac{1}{2} x^T H x + c^T x + \frac{\sigma}{p} \|x\|^p \\ & \text{s.t.} \quad l_i \leq a_i^T x \leq u_i, \quad i = 1, \dots, m, \end{aligned}$$

where  $l_i \leq u_i \in \mathbb{R}$  for  $i = 1, \dots, m$ .

# Partition Problem

*Example:* Given numbers:

1, 2, 3, 6, 8.

Partition them into

1, 3, 6

2, 8

## Partition Problem

Given  $r = (r_1, r_2, \dots, r_n) \in \mathbb{R}_+^n$ , Solve

$$r^T x = 0, \quad x \in \{-1, 1\}^n$$

# Relation between Partition Problem and $(p - RS_n)$

Partition Problem can be formulated into:

Special  $(p - RS_n)$  problem:

$$\begin{aligned} \min \phi(x) &= x^T \left( \frac{1}{nr^T r} rr^T - \frac{4}{n} I \right) x + \frac{4}{p(p-1)n^{p/2}} \|x\|^p \\ \text{s.t.} \quad &-1 \leq x_i \leq 1, \quad i = 1, 2, \dots, n. \end{aligned}$$

**because**  $\phi(x)$  is concave in  $[-1, 1]^n$

# NP hardness of $(p - \text{RS}_m)$

Partition Problem is NP-hard

## Theorem

For any  $p > 2$ ,

$$(p - \text{RS}_n),$$

$$\bigcup_{m \geq n} (p - \text{RS}_m),$$

$$\bigcup_{m \in \mathcal{N}} (p - \text{RS}_m)$$

are all NP-hard.

# Binary Quadratic Optimization

$$\begin{array}{ll} \min & x^T Q x \\ \text{s. t.} & e^T x = k, Ax \leq b, x \in \{0, 1\}^n \end{array}$$

where  $Q \in \mathbb{R}^{n \times n}$  is a symmetric matrix,  $k$  is an integer,  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$  have integer entries.

**reduced to a special (PS<sub>m+n+1</sub>) with p=4:**

$$\begin{array}{ll} \min d(x) = & x^T (Q - \theta_1 I - 2\theta_2 k I) x + \theta_2 \|x\|^4 + \theta_1 k + \theta_2 k^2 \\ \text{s.t.} & e^T x = k, \quad Ax \leq b, \quad x \in [0, 1]^n \end{array}$$



# Special Cases of Binary Quadratic Optimization

## $k$ -dispersion-sum problem

$$\begin{aligned} & \max x^T D x \\ \text{s.t. } & e^T x = k, \quad x \in \{0, 1\}^n. \end{aligned}$$

## Quadratic Assignment Problem

$$\begin{aligned} & \min \text{trace}(F X D X^T) \\ \text{s.t. } & X e = X^T e, \quad X \in \{0, 1\}^{n \times n} \end{aligned}$$

both **KDSP** and **QAP** are NP-hard.

# Polynomial Solvable for Problems with fixed $m$

## Theorem

*For each fixed  $m$ ,  $(p - RS_m)$  with  $p = 4$  is polynomially solvable.*

## Idea of Proof

- Reducing  $(p - RS_k)$  to  $(p - RS_{k-1})$
- based on the following result:

## Lemma (Xia and Sheu)

*Let  $A \in R^{m \times q}$  and  $b \in R^m$ , where  $m$  is fixed and  $q$  is arbitrary. For any given  $r > 0$ , it is polynomially checkable whether  $\{u \in R^q \mid Au \leq b, \|u\|^2 = r\}$  is empty. Moreover, if the set is nonempty, a feasible point can be found in polynomial time.*

# Conclusions

## What we have done:

- ① complete analysis to the  $p$ -regularized subproblems for general  $p > 2$  gives the most detailed comparison between the  $p$ -regularized subproblems and trust region subproblems, including
  - necessary and sufficient conditions for minimizers
  - conditions for local non-global minimizers
  - number of local non-global minimizers
- ② For  $p = 4$ , (p-RS) can be extended to solve the  $p$ -regularized subproblems subject to additional linear constraints.

# Thanks very much!