## **Optimality and Calmness Conditions**

Xiaoqi Yang

Department of Applied Mathematics The Hong Kong Polytechnic University

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This talk is based on joint work with Z.Q. Meng.

Outline of the talk:

- 1. Review of exact penalty functions.
- 2. Optimality condition: inequality constraint case.
- 3. Optimality condition: equality constraint case.
- 4. Conclusions

### **1. Review of exact penalty functions**

(NP) min 
$$f(x)$$
 s.t.  $x \in X_0 := \{x \in \mathbb{R}^n : g_i(x) \le 0, i \in I = \{1, \cdots, m\}, h_j(x) = 0, j \in J = \{1, \cdots, q\}\},\$ 

where f and  $g_i (i \in I)$  and  $h_j (j \in J)$  are continuously differentiable,

(P<sub>p</sub>) 
$$\min_{x \in R^n} F_p(x) := f(x) + \rho \left( \sum_{i \in I} g_i^+(x)^p + \sum_{j \in J} |h_j(x)|^p \right),$$

where  $\rho > 0$  is the penalty parameter,  $g_i^+(x) = \max\{g_i(x), 0\}$  and  $0 \le p \le 1$ .

 $F_p(x)$  is an exact penalty function, if any local optimal solution of (NP) is one of the penalty problem  $(P_p)$ .

For  $0 < p_1 < p_2$ , if  $F_{p_2}(x)$  is an exact penalty function, so is  $F_{p_1}(x)$ .

The study of exact penalty functions was originated by the work of Eremin (1966) and Zangwill (1967).

$$F_p(x) = f(x) + \rho \left( \sum_{i \in I} g_i^+(x)^p + \sum_{j \in J} |h_j(x)|^p \right).$$

 $F_p(x)$  is an exact penalty function if and only if

$$\liminf_{u \to 0} \frac{\beta(u) - \beta(0)}{\|u\|^p} > -\infty,$$

where  $\beta(u)$  is the optimal value of the perturbed problem

$$\min f(x) \text{ s.t. } x \in X_u := \{ x \in \mathbb{R}^n : g_i(x) \le u_i, i \in I, \\ h_j(x) = u_{m+j}, j \in J \}.$$

See

Clarke (1983), Burke (1991a), .... for p = 1,

Rubinov and Yang (2003), for 0 .

When p = 0, use the convention  $0^0 = 0$ .

$$\begin{split} F(x) &= f(x) + \rho \left( \sum_{i \in I} \left( g_i^+(x) \right)^0 + \sum_{j \in J} |h_j(x)|^0 \right) \\ & \left\{ \begin{array}{l} = f(x), & \text{if } x \in X_0 \\ \geq f(x) + \rho, & \text{if } x \notin X_0. \end{array} \right. \end{split}$$

• If f is lsc, then F(x) is an exact penalty function.

$$\liminf_{u \to 0} \frac{\beta(u) - \beta(0)}{\|u\|^0} > -\infty \iff \liminf_{u \to 0} \beta(u) \ge \beta(0) \Longleftrightarrow \beta \text{ is lsc at } 0.$$

• If f and  $g_i(i \in I)$  are lsc,  $h_j(j \in J)$  are continuous,  $u \Rightarrow \{x \in \mathbb{R}^n : g_i(x) \leq u_i, i \in I, h_j(x) = u_{m+j}, j \in J\}$  is use at 0 and  $X_0$  is compact, then  $\beta$  is lsc at u = 0, See Rubinov, Huang and Yang (2002).

The result on the existence of lower order exact penalty functions is as follows:

Assume that X is a compact subanalytic set, f is Lipschitz and  $g_j(j = 1, \dots, m$  are continuous subanalytic. (NP) is feasible. Then there exist  $\bar{\rho} > 0$  and a positive integer  $N^*$  such that, if  $x^*$  solves (NP), then  $x^*$  is an optimal solution of the problem

$$\min_{x \in X} f(x) + \rho \left( \sum_{i \in I} g_i^+(x) + \sum_{j \in J} |h_j(x)| \right)^{\frac{1}{N^*}}, \quad \rho > \bar{\rho}.$$

See Warga (1992), Dedieu (1992) and Luo, Pang and Ralph (1996).

The existence of exact penalty functions can also be viewed as a consequence of so-called error bounds and metric regularity. See Borwein (1986), Burke (1991b), Bonnans and Shapiro (2000), Dontchev and Lewis (2005), Pang (1997), ....

Let f be Lipschitz continuous on  $W := X_0 \cap X$  and  $\psi(x)$  be a residual function of the set W (that is,  $\psi(x) \ge 0$ ,  $\forall x \in W$  and  $\psi(x) = 0$  if and only if  $x \in X_0$ ) such that

$$\operatorname{dist}(x,W) \leq c\psi(x), \ \forall x \in X.$$

If (NP) has an optimal solution, then there exists a scalar  $\bar{\rho} > 0$  such that for all  $\rho \geq \bar{\rho}$ ,

 $\mathrm{argmin}\{f(x)|x\in W\}=\mathrm{argmin}\{f(x)+\rho\psi(x)|x\in X\}.$ 

The exact penalty function  $F_1(x)$  allows one to derive first-order and secondorder necessary optimality conditions by employing first-order or second-order calculus rules, see:

Fletcher (1987), Burke (1991b), Bonnans and Shapiro (2000) ....

**Question**: Does lower order exact penalty function  $F_p(x)$  ( $0 \le p < 1$ ) guarantee the existence of a Lagrange multiplier?

#### **Counter Example**.

min x s.t.  $x^2 \le 0$ .

 $x^{\ast}=0$  is a local minimum and  $F_{.5}(x)$  is exact, but there exists no Lagrange multiplier.

Under additional assumptions ? Yes !

## 2. Optimality condition: inequality constraint case $J = \emptyset$

Let  $x^*$  be a local minimum of (NP) and  $F_p(x)$  ( $0 \le p \le 1$ ) be an exact penalty function. So,  $x^*$  is a local minimum of the function

$$F_p(x) := f(x) + \rho \sum_{i \in I} \bar{g}_i(x),$$

where  $\bar{g}_i(x) = [\max\{g_i(x), 0\}]^p$ . Hence the Dini upper directional derivative of  $F_p$  at  $x^*$ :

$$D_+F_p(x^*;u) \ge 0, \quad \forall u \in \mathbb{R}^n,$$

So

$$\nabla f(x^*)^\top u + \rho \sum_{i \in I} D_+ \bar{g}_i(x^*; u) \ge 0, \quad \forall u \in R^n,$$

where  $I = \{1, 2, \cdots, m\}.$ 

For  $x \in \mathbb{R}^n$ , let

$$I(x) = \{ i \in I \mid g_i(x) = 0 \}.$$

If 
$$g_i(x^*) < 0$$
, then  $D_+ \bar{g}_i(x^*; u) = 0$ .  
If  $g_i(x^*) = 0$ ,  $\nabla g_i(x^*)^\top u > 0$ , then  $D_+ \bar{g}_i(x^*; u) = +\infty$ .  
If  $g_i(x^*) = 0$ ,  $\nabla g_i(x^*)^\top u < 0$ , then  $D_+ \bar{g}_i(x^*; u) = 0$ .

Thus the following first-order necessary condition of  $(P_p)$ 

$$\nabla f(x^*)^\top u + \rho \sum_{i \in I} D_+ \bar{g}_i(x^*; u) \ge 0, \quad \forall u \in R^n,$$

becomes

$$\nabla f(x^*)^\top u + \rho \sum_{g_i(x^*)=0, \nabla g_i(x^*)^\top u=0} D_+ \bar{g}_i(x^*; u) \ge 0, \quad \forall u : \nabla g_i(x^*)^\top u \le 0.$$

Farkas Lemma says that exactly one of the following two systems has a solution:

System 1 
$$Au \le 0, c^{\top}u > 0$$
, for some  $u$ ,  
System 2  $A^{\top}\mu = c, \ \mu \ge 0$ , for some  $\mu$ .

If we can show

$$\nabla g_i(x^*)^\top u \le 0, \forall i \in I(x^*) \Longrightarrow -\nabla f(x^*)^\top u \le 0,$$

then it means that System 1 has no solution. Thus System 2 has a solution. So there exists  $\mu^* \ge 0$  such that

$$\sum_{i\in I(x^*)} \mu_i^* \nabla g_i(x^*) = -\nabla f(x^*).$$

Therefore

$$\nabla f(x^*) + \sum_{i \in I(x^*)} \mu_i^* \nabla g_i(x^*) = 0.$$

The first-order necessary condition of  $(P_p)$  is:

$$\nabla f(x^*)^\top u + \rho \sum_{g_i(x^*)=0, \nabla g_i(x^*)^\top u=0} D_+ \bar{g}_i(x^*; u) \ge 0, \quad \forall u : \nabla g_i(x^*)^\top u \le 0.$$

To guarantee

$$^{\prime\prime}\nabla g_{i}(x^{*})^{\top}u \leq 0, \forall i \in I(x^{*}) \Longrightarrow -\nabla f(x^{*})^{\top}u \leq 0, ^{\prime\prime}u \leq 0, \forall i \in I(x^{*}) \geq 0, \forall i$$

we need the following constraint qualification

$$\sum_{g_i(x^*)=0, \nabla g_i(x^*)^\top u=0} D_+ \bar{g}_i(x^*; u) \le 0, \quad \forall u : \nabla g_i(x^*)^\top u \le 0,$$

where  $\bar{g}_i(x) = [\max\{g_i(x), 0\}]^p$ .

Question: Under what conditions, this constraint qualification is verified?

Three cases are considered:

Case 1: p = .5;

Case 2:  $0 \le p < .5;$ 

Case 3: .5 .

Case 1: p = .5

**Theorem 2.1** Let  $x^*$  be a local minimum of (NP) and  $F_{.5}(x)$  be an exact penalty function. Assume that

$$g_i(x^*) = 0, \nabla g_i(x^*)^\top u \le 0 \Longrightarrow g^{\circ \circ}(x^*; u) \le 0,$$

where  $g^{\circ\circ}(x^*; u)$  is the Clarke generalized second-order directional derivative. Then  $\exists \mu^* \ge 0$  such that

$$\nabla f(x^*) + \mu^* \nabla g(x^*) = 0, \quad \mu^* g(x^*) = 0.$$

#### Example.

$$\min x^2 \text{ s.t. } x^4 \le 0.$$

 $x^* = 0$  is a local minimum,  $F_{.5}(x)$  is exact and

$$u^{\top} \nabla^2 g_i(x^*) u = 0.$$

There exists a Lagrange multiplier.

### Why condition

$$g_i(x^*) = 0, \nabla g_i(x^*)^{\top} u \le 0 \Longrightarrow g_i^{\circ \circ}(x^*; u) \le 0,$$

is needed?

$$\begin{aligned} & \text{For } g_i(x^*) = 0, \nabla g_i(x^*)^\top u = 0, \text{ we have} \\ & D_+ \bar{g}_i(x^*; u) = \limsup_{t \to 0^+} \frac{(\max\{g_i(x^* + tu), 0\})^{\frac{1}{2}} - (\max\{g_i(x^*), 0\})^{\frac{1}{2}}}{t} \\ & = \limsup_{t \to 0^+} \frac{\left(\max\{\frac{t^2}{2}u^\top \nabla^2 g_i(x^* + \beta tu)u, 0\}\right)^{\frac{1}{2}}}{t} \quad (0 < \beta < 1) \\ & = \limsup_{t \to 0^+} \left(\max\{\frac{1}{2}u^\top \nabla^2 g_i(x^* + \beta tu)u, 0\}\right)^{\frac{1}{2}} \\ & = \left(\max\{\frac{1}{2}u^\top \nabla^2 g_i(x^*)u, 0\}\right)^{\frac{1}{2}}. \end{aligned}$$

If we assume

$$g_i(x^*) = 0, \nabla g_i(x^*)^\top u \le 0 \Longrightarrow u^\top \nabla^2 g(x^*) u \le 0,$$

then

$$\sum_{g_i(x^*)=0, \nabla g_i(x^*)^\top u=0} D_+ \bar{g}_i(x^*; u) \le 0, \quad \forall u : \nabla g_i(x^*)^\top u \le 0.$$

Case 2:  $0 \le p < .5$ .

**Theorem 2.2** Let  $0 \le p < .5$ , in addition to the  $F_p(x)$  being an exact penalty function condition, assume

$$g_i(x^*) = 0, \nabla g_i(x^*)^\top u \le 0 \Longrightarrow g_i^{\circ \circ}(x^*; u) < 0.$$

Then  $\exists \ \mu^* \ge 0$  such that

$$\nabla f(x^*) + \mu^* \nabla g(x^*) = 0, \quad \mu^* g(x^*) = 0.$$

Case 3: .5 .

**Theorem 2.3** Let  $.5 , <math>F_p(x)$  be an exact penalty function condition and  $g_i(i \in I)$  be  $C^{1,1}$ .

*Then*  $\exists \mu^* \geq 0$  *such that* 

$$\nabla f(x^*) + \mu^* \nabla g(x^*) = 0, \quad \mu^* g(x^*) = 0.$$

The assumption that  $g_i (i \in I)$  are  $C^{1,1}$  is crucial:

min x s.t.  $x^{4/3} \le 0$ .

 $F_{3/4}$  is an exact penalty function, but a Lagrange multiplier doesn't exist. Note that  $g(x) = x^{4/3}$  is not  $C^{1,1}$ .

#### 2.1. Comparisons with known constraint qualifications

Guignard CQ is said to hold at  $x^* \in X_0$  if

$$T^{**}(X_0, x^*) = A(x^*),$$

where

$$A(x^*) = \{ u \in R^n \mid \nabla g_i(x^*)^\top u \le 0, \forall i \in I(x^*) \},\$$

is the set of feasible directions for the linearized constraint set,

$$T(X_0, x^*) = \{ u : u = \lim_{k \to +\infty} \lambda_k (x_k - x^*), \lambda_k > 0, x_k \in X_0, x_k \to x^* \}$$

is the contingent cone of set  $X_0$  at  $x^*$  and  $T^{**}(X_0, x^*)$  is the bipolar cone of  $T(X_0, x^*)$ .

#### Guignard CQ doesn't hold, but Theorem 2.1 holds.

$$\min x^3 \text{ s.t. } x^6 \le 0.$$

 $x^* = 0$  is the local minimum,  $F_{.5}(x)$  is exact and  $u^{\top} \nabla^2 g(x^*) u = 0$ . Theorem 2.1 is applicable.

However,  $T(X_0, x^*) = T^{**}(X_0, x^*) = \{0\}$  and  $A(x^*) = R$ . Hence,  $T^{**}(X_0, x^*) \neq A(x^*) \cup \{0\}$ . The Guignard CQ is not satisfied.

#### Theorem 2.1 doesn't hold, but Guignard CQ holds.

$$\min x \text{ s.t. } x^2 - x \le 0.$$

 $u^{\top} \nabla^2 g(x^* = 0) u = 2u^2 > 0$ . Theorem 2.1 is not applicable.

The Guignard CQ, implied by (LICQ), holds at  $x^* = 0$ .

# **3.** Optimality condition: equality constraint case $I = \emptyset$

**Theorem 3.1** Let  $F_p(x)$  be an exact penalty function condition. Assume that  $x^*$  is a local minimum of (NP). If one of the following two conditions is satisfied:

(i) p = .5 and assume further that

$$j \in J, \nabla h_j(x^*)^\top u = 0 \Longrightarrow h_j^{\circ \circ}(x^*; u) = 0;$$

(ii)  $.5 and <math>h_j (j \in J)$  are  $C^{1,1}$ ,

then there exists a Lagrange multiplier  $\lambda^*$  such that

$$\nabla f(x^*) + \lambda^* \nabla h(x^*) = 0.$$

## 4. Conclusions

• Lower order exact penalty functions are useful in the establishment of optimality conditions.

## References

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