

Geometric and topological characterizations of strong duality in nonconvex optimization with a single equality and geometric constraints

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Terry Fest 2015, Université de Limoges
18 – 22 May, 2015, Limoges - France.

Talk based on a joint work with G. Cárcamo



Contents

- 1 Strong duality (SD of order zero)
- 2 Characterizing KKT optimality conditions (SD or order one)



Constrained Optimization

X real loc. conv. top. vec. sp., and $\emptyset \neq C \subseteq X$. Given $f : C \rightarrow \mathbb{R}$ and $g : C \rightarrow \mathbb{R}$, consider the constrained minimization problem

$$\mu \doteq \inf\{f(x) : g(x) = 0, x \in C\}. \quad (P)$$

The Lagrangian dual problem associated to (P) is

$$\nu \doteq \sup_{\lambda^* \in \mathbb{R}} \inf_{x \in C} [f(x) + \lambda^* g(x)]. \quad (D)$$

We say: (P) has a (Lagrangian) *zero duality gap* if $\mu = \nu$; (P) has *strong duality* if it has a zero duality gap and Problem (D) admits a solution.



A continuous-version of SQP

$$\mu_q \doteq \min \left\{ f(x) \doteq \frac{1}{2} \int_0^1 x^\top(t) A x(t) dt : g(x) \doteq \int_0^1 e^\top(t) x(t) dt - 1 = 0, \right. \\ \left. x \in C \doteq L_+^2([0, 1[; \mathbb{R}^n) \right\}.$$

Here, $A = (a_{ij})$ is a real symmetric copositive matrix, i. e., $x^\top A x \geq 0$ for all $x \in \mathbb{R}_+^n$; $e \in \text{qi } L_+^2([0, 1[; \mathbb{R}^n) = L_{++}^2([0, 1[; \mathbb{R}^n)$. It is known $\{x \in L_+^2([0, 1[; \mathbb{R}^n) : \langle e, x \rangle = 1\}$ is a weakly compact base of $L_+^2([0, 1[; \mathbb{R}^n)$. Thus, the dual is

$$\sup_{\lambda \in \mathbb{R}} \inf_{x \in L_+^2} L(\lambda, x) = \frac{1}{2} \int_0^1 x(t)^\top A x(t) + \lambda \left(\int_0^1 e(t)^\top x(t) dt - 1 \right). \quad (1)$$



Introduce, as usual, **the Lagrangian**

$$L(\gamma, \lambda, x) = \gamma f(x) + \lambda g(x), \quad \gamma \geq 0, \quad \lambda \in \mathbb{R}.$$

By setting $K \doteq \{x \in C : g(x) = 0\}$, we obtain (**weak duality**)

$$\inf_{x \in C} L(\gamma, \lambda, x) \leq \inf_{x \in K} L(\gamma, \lambda, x) \leq \gamma \inf_{x \in K} f(x), \quad \forall \gamma \geq 0, \quad \forall \lambda \in \mathbb{R}.$$

In order to get the equality, we need to find conditions under which the reverse inequality holds, that is, we must have:

$$\gamma(f(x) - \mu) + \lambda g(x) \geq 0 \quad \forall x \in C. \quad (2)$$

This will imply strong duality once we get $\gamma > 0$. Denote $F \doteq (f, g)$, the sets

$$\mathcal{F} \doteq F(C) + \mathbb{R}_+(1, 0), \quad \mathcal{F}_\mu \doteq \mathcal{F} - \mu(1, 0), \quad (3)$$

will play an important role in our analysis.



Then,

$$(\gamma, \lambda) \in [\overline{\text{cone } \mathcal{F}_\mu}]^* = [\overline{\text{cone } \mathcal{F}_\mu}]^* = [\text{cone } \mathcal{F}_\mu]^* = [\mathcal{F}_\mu]^*. \quad (4)$$

Set

$$\mathcal{L}_{SD} \doteq \left\{ \lambda \in \mathbb{R} : (1, \lambda) \in [\text{cone } \mathcal{F}_\mu]^* \right\}. \quad (5)$$

Then, (P) has **SD** property if, and only if $\mathcal{L}_{SD} \neq \emptyset$. Hence

$$\mathcal{L}_{SD} \subseteq \mathcal{S}_D,$$

where \mathcal{S}_D is the solution set to the dual problem (D) .



Furthermore, we need the following numbers:

- if $\Omega_+^- \doteq S_f^-(\mu) \cap S_g^+(0) \neq \emptyset$,

$$s \doteq \sup_{x \in \Omega_+^-} \frac{g(x)}{f(x) - \mu} \in]-\infty, 0];$$

- if $\Omega_-^- \doteq S_f^-(\mu) \cap S_g^-(0) \neq \emptyset$,

$$l \doteq \inf_{x \in \Omega_-^-} \frac{g(x)}{f(x) - \mu} \in [0, +\infty[;$$



The geometric and topological characterizations of SD:

Theorem: [Cárcamo-FB, 2015]

Consider problem (P) with $\mu \in \mathbb{R}$. Then, (a), (b) and (c) are equivalent:

(a) Strong Duality holds for (P) , that is

$$\exists \lambda_0^* \in \mathbb{R} : f(x) + \lambda_0^* g(x) \geq \mu, \forall x \in C; \quad (6)$$

(b) $\overline{\text{cone}(\mathcal{F}_\mu)} \cap (-\mathbb{R}_{++} \times \{0\}) = \emptyset$ and $\overline{\text{cone}(\mathcal{F}_\mu)}$ is convex;

(c) $\text{cone}(\mathcal{F}_\mu)$ is convex and exactly one of the following assertions holds:

(c1) $S_f^-(\mu) = \emptyset$, in which case $0 \in \mathcal{L}_{SD}$;

(c2) $\Omega_+^- \neq \emptyset$, $s < 0$, in which case $\min \mathcal{L}_{SD} = -\frac{1}{s}$;

(c3) $\Omega_-^- \neq \emptyset$, $l > 0$, in which case $\max \mathcal{L}_{SD} = -\frac{1}{l}$.



Theorem (continued ...)

Consequently, under condition (a), one obtains

$$\inf_{x \in K} f(x) = \inf_{\substack{\lambda_0^* g(x) \leq 0 \\ x \in C}} f(x); \quad (7)$$

$$\bar{x} \text{ is a solution to } (P) \iff \begin{cases} \bar{x} \in C, & g(\bar{x}) = 0, \\ f(\bar{x}) = \inf_{x \in C} [f(x) + \lambda_0^* g(x)] \end{cases} \quad (8)$$

and $\mathcal{L}_{SD} = \mathcal{S}_D$.



Remark

We point out that the convexity of $\overline{\text{cone}}(\mathcal{F}_\mu)$ does imply the convexity of $\text{cone}(\mathcal{F}_\mu)$ **without SD**. This is illustrated by the functions $f(x_1, x_2) = 2x_1x_2$, $g(x_1, x_2) = x_1$ and $C = \mathbb{R}^2$. Then, $\mu = 0$, $F(\mathbb{R}^2) = \{(0, 0)\} \cup (\mathbb{R}^2 \setminus \mathbb{R} \times \{0\})$, and so

$$\text{cone}(\mathcal{F}_\mu) = \mathbb{R}^2 \setminus (-\mathbb{R}_{++} \times \{0\}),$$

which is nonconvex, but $\overline{\text{cone}}(\mathcal{F}_\mu) = \mathbb{R}^2$.

The following result, which is new in the literature, provides a characterization of strong duality under a Slater-type condition.

Corollary: [Cárcamo-FB, 2015]

Let $\mu \in \mathbb{R}$ and assume that there exist $x_1, x_2 \in C$ such that $g(x_1) < 0 < g(x_2)$. Then, $\text{cone}(\mathcal{F}_\mu)$ is convex if, and only if strong duality holds for (P) .



The case f and g quadratic: $C = \mathbb{R}^n$; $F = (f, g)$:

Corollary [Opazo-FB, 2014]: Let $\mu \in \mathbb{R}$

Assume that there exist $x_1, x_2 \in \mathbb{R}^n$ st $g(x_1) < 0 < g(x_2)$. Then, $F(\mathbb{R}^n) + \mathbb{R}_+(1, 0)$ is convex if, and only if SD holds.

Lemma [Opazo-FB, 2014]:

$F(\mathbb{R}^n) + \mathbb{R}_+(1, 0)$ is convex if, and only if any of the following conditions is satisfied:

- (C1) $F_L(\ker A \cap \ker B) \neq \{0\}$; $F_L(u) = (\langle a, u \rangle, \langle b, u \rangle)$;
- (C2) $B \neq 0$;
- (C3) $u \in \mathbb{R}^n$, $\langle Bu, u \rangle = 0 \implies \langle Au, u \rangle \geq 0$;
- (C4) $\exists u \in \mathbb{R}^n$, $\langle Au, u \rangle < 0$, $\langle Bu, u \rangle = 0$, $\langle b, u \rangle = 0$.

This characterization encompasses the case when the Hessian of g is non-null, or when g is strictly concave (or convex)



Corollary [Opazo-FB, 2014]:

$F(\mathbb{R}^n) + P$ is convex for all convex cone $P \subseteq \mathbb{R}^2$ with $\text{int } P \neq \emptyset$.

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KKT optimality conditions

This section deals with some characterizations of the validity of the KKT optimality conditions for the problem (P) . For simplicity, take $X = \mathbb{R}^n$, and f and g to be Gâteaux differentiable on \mathbb{R}^n . Such characterizations will be derived as a consequence of our main theorem on SD applied to the linearized approximation problem defined, given $\bar{x} \in C$, by

$$\mu_L \doteq \inf_{v \in G'(\bar{x})} \nabla f(\bar{x})^\top v, \quad (9)$$

where

$$G'(\bar{x}) \doteq \left\{ v \in T(C; \bar{x}) : \nabla g(\bar{x})^\top v = 0 \right\}.$$

Here, $T(C; \bar{x})$ stands for the contingent cone of C (or tangent cone of Bouligand) at \bar{x} , which is always a closed cone. Set

$F_L(v) \doteq (\nabla f(\bar{x})^\top v, \nabla g(\bar{x})^\top v)$. It is obvious that $\mu_L \in \{-\infty, 0\}$.



In view of Theorem 8, we introduce the following sets:

$$\widehat{S}_f^-(0) \doteq \{v \in T(C; \bar{x}) : \nabla f(\bar{x})^\top v < 0\},$$

$$\widehat{S}_g^+(0) \doteq \{v \in T(C; \bar{x}) : \nabla g(\bar{x})^\top v > 0\},$$

$$\widehat{\Omega}_+^- \doteq \widehat{S}_f^-(0) \cap \widehat{S}_g^+(0), \quad \widehat{\Omega}_-^- \doteq \widehat{S}_f^-(0) \cap \widehat{S}_g^-(0).$$

Furthermore, whenever $\widehat{\Omega}_+^- \neq \emptyset \neq \widehat{\Omega}_-^-$, we put

$$\widehat{s} \doteq \sup_{v \in \widehat{\Omega}_+^-} \frac{\nabla g(\bar{x})^\top v}{\nabla f(\bar{x})^\top v}, \quad \widehat{t} \doteq \inf_{v \in \widehat{\Omega}_-^-} \frac{\nabla g(\bar{x})^\top v}{\nabla f(\bar{x})^\top v}.$$

Denote by $\mathcal{L}(\bar{x})$ the set of Lagrange multipliers to (P) associated to a (not necessarily feasible) point $\bar{x} \in C$, i. e., the set of $\lambda^* \in \mathbb{R}$ satisfying (10). When $\mathcal{L}(\bar{x}) \neq \emptyset$, we say that \bar{x} is a **KKT point**.



Let $\bar{x} \in C$. In case $\nabla g(\bar{x}) = 0$, it is not difficult to check that:

- $\mu_L = 0$ if, and only if $\mathcal{L}(\bar{x}) = \mathbb{R}$.
- $\mu_L = -\infty$ if, and only if $\mathcal{L}(\bar{x}) = \emptyset$.

Theorem: [Cárcamo-FB, 2015]

Assume that $\bar{x} \in C$. The following assertions are equivalent:

(a) $\exists \lambda^* \in \mathbb{R}$ such that

$$\nabla f(\bar{x}) + \lambda^* \nabla g(\bar{x}) \in [T(C; \bar{x})]^*. \quad (10)$$

(b) $\mu_L = 0$ and strong duality holds for the problem (9).

(c) $\overline{F_L(T(C; \bar{x})) + \mathbb{R}_+(1, 0)}$ is convex and

$$\overline{[F_L(T(C; \bar{x})) + \mathbb{R}_+(1, 0)]} \cap (-\mathbb{R}_{++} \times \{0\}) = \emptyset. \quad (11)$$



Theorem (continued ...)

(d) $F_L(T(C; \bar{x})) + \mathbb{R}_+(1, 0)$ is convex and exactly one of the following assertions holds:

(d1) $\widehat{S}_f^-(0) = \emptyset$, in which case $0 \in \mathcal{L}(\bar{x})$;

(d2) $\widehat{\Omega}_+^- \neq \emptyset$, $\widehat{s} < 0$, in which case $\min \mathcal{L}(\bar{x}) = -\frac{1}{\widehat{s}}$;

(d3) $\widehat{\Omega}_-^- \neq \emptyset$, $\widehat{l} > 0$, in which case $\max \mathcal{L}(\bar{x}) = -\frac{1}{\widehat{l}}$.

(e) $\overline{F_L(T(C; \bar{x})) + \mathbb{R}_+(1, 0)}$ is convex, $\mu_L = 0$ and

$$\left. \begin{array}{l} v_k \in T(C; \bar{x}), \|v_k\| \rightarrow +\infty, \\ \nabla g(\bar{x})^\top v_k \rightarrow 0, \nabla f(\bar{x})^\top v_k < 0 \end{array} \right\} \implies \overline{\lim}_k \nabla f(\bar{x})^\top v_k = 0. \quad (12)$$



A simple sufficient condition for a minimum to be a KKT point, under strong duality is expressed in the following result.

Proposition [Cárcamo-FB, 2015]:

Assume that strong duality holds for (P) . Then, every solution to (P) is a KKT point, that is, $\mathcal{L}_{SD} \subseteq \mathcal{L}(\bar{x})$ for all $\bar{x} \in \underset{K}{\operatorname{argmin}} f$.

It may applied to situations where results based either on **exact penalization techniques** ([Yang-Peng, MOR 2007]) or where **Abadie's constraint qualification fail**. In addition, there are instances where no minimizer is a KKT point, if strong duality is not satisfied. For **1st case**:

$$0 = \mu \doteq \min\{f(x_1, x_2) \doteq x_2 : g(x_1, x_2) \doteq x_2 - x_1^2 = 0, (x_1, x_2) \in \mathbb{R}^2\}.$$

For **2nd case**: $f(x_1, x_2) = x_2$, $g(x_1, x_2) = (x_1 - 1)^2 + (x_2 - 1)^2 - 1$ and $C \doteq \{(x_1, x_2) \in \mathbb{R}^2 : g_0(x_1, x_2) \leq 0\}$ with $g_0(x_1, x_2) \doteq (x_1 - 1)^2 + (x_2 + 1)^2 - 1$.



Nonconvex QP with two quadratic equality constraints

We now discuss the problem:

$$\mu \doteq \min\{f(x) : g_1(x) = 0, g_2(x) = 0\}, \quad (13)$$

where we specialize the functions $f, g_i, i = 1, 2$ to be (non necessarily homogeneous) quadratic. Here,

$$C \doteq \{x \in \mathbb{R}^n : g_2(x) = 0\}, K \doteq \{x \in C : g_1(x) = 0\},$$

$$f(x) \doteq \frac{1}{2}x^\top Ax + a^\top x + \alpha, \quad g_i(x) \doteq \frac{1}{2}x^\top B_i x + b_i^\top x + \beta_i, \quad i = 1, 2,$$

with $A = A^\top, B_i = B_i^\top; a, b_i \in \mathbb{R}^n$ and α, β_i being real numbers.

In addition to the dual problem

$$\nu \doteq \sup_{\lambda_1 \in \mathbb{R}} \inf_{x \in C} \{f(x) + \lambda_1 g_1(x)\}, \quad (14)$$



consider also the standard (Lagrangian) dual problem to (13):

$$\nu_0 \doteq \sup_{\lambda_1, \lambda_2 \in \mathbb{R}} \inf_{x \in \mathbb{R}^n} \{f(x) + \lambda_1 g_1(x) + \lambda_2 g_2(x)\}. \quad (15)$$

We say that problem (13) has **standard strong duality** (SSD) if $\mu = \nu_0$ and problem (15) **admits solution**. It is easy to check that

$$\nu_0 \leq \nu \leq \mu.$$

One the other hand, given a feasible point \bar{x} , it is said that \bar{x} is a **standard KKT point** to problem (13), if for some $\lambda_1, \lambda_2 \in \mathbb{R}$, one has

$$\nabla f(\bar{x}) + \lambda_1 \nabla g_1(\bar{x}) + \lambda_2 \nabla g_2(\bar{x}) = 0.$$



Set

$$Z(\bar{x}) \doteq \{v \in \mathbb{R}^n : \nabla g_i(\bar{x})^\top v + \frac{1}{2} v^\top B_i v = 0, \quad i = 1, 2\}.$$

It is known that

$$T(C; \bar{x}) = \left\{ v \in \mathbb{R}^n : \nabla g_2(\bar{x})^\top v = 0 \right\} = \nabla g_2(\bar{x})^\perp \text{ if } \nabla g_2(\bar{x}) \neq 0,$$

and so $[T(C; \bar{x})]^* = \mathbb{R} \nabla g_2(\bar{x})$; whereas

$$T(C; \bar{x}) = \left\{ v \in \mathbb{R}^n : v^\top B_2 v = 0 \right\} \text{ if } \nabla g_2(\bar{x}) = 0.$$

The latter set is, in general, nonconvex. However, in case B_2 is positive semidefinite, or equivalently, g_2 is convex (for instance, when such an equality constraint corresponds to a component of x taking the value either 0 or 1), with $\nabla g_2(\bar{x}) = 0$, we obtain $T(C; \bar{x}) = \ker B_2$, and so $[T(C; \bar{x})]^* = (\ker B_2)^\perp = B_2(\mathbb{R}^n)$.



Next theorem, which is new, provides 1st and 2nd order necessary optimality conditions under additional assumptions besides SD. It proves that every optimal solution is a **standard KKT point**.

Theorem [Cárcamo-FB, 2015]: Let $\mu \in \mathbb{R}$

Let f, g_1, g_2 be quadratic, \bar{x} feasible satisfying $\nabla g_2(\bar{x}) \neq 0$. Set $C = \{x \in \mathbb{R}^n : g_2(x) = 0\}$. Then (a) \implies (b), where

(a) \bar{x} is a solution to (13) and SD holds;

(b) $\exists \lambda_1, \lambda_2 \in \mathbb{R}$ such that $\nabla f(\bar{x}) + \lambda_1 \nabla g_1(\bar{x}) + \lambda_2 \nabla g_2(\bar{x}) = 0$,
 $A + \lambda_1 B_1 + \lambda_2 B_2 \succcurlyeq 0$ on $Z_2(\bar{x}) \cup \nabla g_2(\bar{x})^\perp$.

It may be applied to instances without satisfying Abadie's CQ.

$$Z_2(\bar{x}) \doteq \{v \in \mathbb{R}^n : \nabla g_2(\bar{x})^\top v + \frac{1}{2} v^\top B_2 v = 0\}.$$



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A concrete application

$$\mu_q \doteq \min \left\{ f(x) \doteq \frac{1}{2} \int_0^1 x^\top(t) A x(t) dt : g(x) \doteq \int_0^1 e^\top(t) x(t) dt - 1 = 0, \right. \\ \left. x \in C \doteq L_+^2([0, 1[; \mathbb{R}^n) \right\}.$$

Here, $e \in \text{qi } L_+^2([0, 1[; \mathbb{R}^n) = L_{++}^2([0, 1[; \mathbb{R}^n)$. $F = (f, g)$.

Proposition: Assume $\mu_q > 0$,

- (a) $\Omega_+^- = \Omega_+^{\bar{}} = \emptyset$, and therefore $S_g^+(0) = \Omega_+^+ \neq \emptyset$;
- (b) $\emptyset \neq S_f^-(\mu_q) = \Omega_-^-$;
- (c) $m = l = \frac{1}{2\mu_q}$, so $l > 0$ and $\mathcal{L}_{SD} = \mathcal{S}_D = \{-2\mu_q\}$, and so $\text{cone}(F(C) + \mathbb{R}_+(1, 0) - \mu_q(1, 0)) = \left\{ (u, v) : v \leq \frac{1}{2\mu_q} u \right\}$;
- (d) strong duality holds.







By Lyapunov theorem $F(C) + \mathbb{R}_+(1, 0)$ is convex.

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