

Abstract Convex Analysis

J.E. Martínez-Legaz

Universitat Autònoma de Barcelona, Spain

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Introduction to Theory and Applications

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KAOHSIUNG - TAIWAN

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$$f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}} = [-\infty, +\infty]$$

$$f^* : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$$

$$f^*(x^*) = \sup \{ \langle x, x^* \rangle - f(x) \}$$

f^* is convex, l.s.c. and proper.

f^{**} is the largest l.s.c. proper convex minorant of f .

$x^* \in \mathbb{R}^n$ is a subgradient of f at $x_0 \in f^{-1}(\mathbb{R})$ if

$$f(x) - f(x_0) \geq \langle x - x_0, x^* \rangle \quad (x \in \mathbb{R}^n).$$

$$\partial f(x_0) = \{ x^* \in \mathbb{R}^n : \text{is a subgradient of } f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}} \text{ at } x_0 \}$$

$x^* \in \partial f(x_0)$ if and only if $f(x_0) + f^*(x^*) = \langle x_0, x^* \rangle$

$x^* \in \partial f^{**}(x_0)$ if and only if $x_0 \in \partial f^*(x^*)$

$$\partial f(x_0) \neq \emptyset \implies f^{**}(x_0) = f(x_0)$$

$$f^{**}(x_0) = f(x_0) \implies \partial f^{**}(x_0) = \partial f(x_0)$$

$\langle x_1 - x_0, x_0^* \rangle + \langle x_2 - x_1, x_1^* \rangle + \dots + \langle x_0 - x_m, x_m^* \rangle \leq 0$
 for any set of pairs (x_i, x_i^*) , $i = 0, 1, \dots, m$ (m arbitrary)
 such that $x_i^* \in \partial f(x_i)$.

$$\varphi : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \bar{\mathbb{R}}$$

$$(\mathcal{P}_u) \quad \text{minimize } \varphi(x, u)$$

$$(\mathcal{P}) \quad \text{minimize } \varphi(x, 0)$$

$$p : \mathbb{R}^m \rightarrow \bar{\mathbb{R}}$$

$$p(u) = \inf_{x \in \mathbb{R}^n} \varphi(x, u)$$

$$(\mathcal{D}) \quad \text{maximize } -\varphi^*(0, u^*)$$

$$-\varphi^*(0, u^*) = -p^*(u^*)$$

The optimal value is $p^{**}(0)$.

The set of optimal dual solutions is $\partial p^{**}(0)$.

$$(\mathcal{D}_{x^*}) \quad \text{maximize } -\varphi^*(x^*, u^*)$$

$$\psi : \mathbb{R}^m \times \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$$

$$\psi(u^*, x^*) = \varphi^*(x^*, u^*)$$

$$(\mathcal{D}_{x^*}) \quad \text{minimize } \psi(u^*, x^*)$$

$$\text{maximize } -\psi^*(0, x)$$

$$f : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}, g : \mathbb{R}^n \rightarrow \mathbb{R}^m$$

$$\begin{array}{ll} \text{minimize} & f(x) \\ \text{subject to} & g(x) \leq 0 \end{array}$$

$$\varphi : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \bar{\mathbb{R}}$$

$$\varphi(x, u) = \begin{cases} f(x) & \text{if } g(x) + u \leq 0 \\ +\infty & \text{otherwise} \end{cases}$$

$$L : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \bar{\mathbb{R}}$$

$$L(x, u^*) = f(x) + \langle g(x), u^* \rangle$$

$$\begin{array}{ll} \text{maximize} & \inf_{x \in \mathbb{R}^n} L(x, u^*) \\ \text{subject to} & u^* \geq 0 \end{array}$$

$$f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}, \quad g : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{-\infty\}$$

$$\text{minimize } f(x) - g(x)$$

$$\varphi : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$$

$$\varphi(x, u) = f(x + u) - g(x)$$

$$g_* : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$$

$$g_*(u^*) = -(-g)^*(-u^*) = \inf \{ \langle x, u^* \rangle - g(x) \}$$

$$\text{maximize } g_*(u^*) - f^*(u^*)$$

$f, g : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$ l.s.c. proper convex functions

$$\begin{aligned} \inf_{x \in \mathbb{R}^n} \{f(x) - g(x)\} &= \inf_{x \in \mathbb{R}^n} \{f(x) - g^{**}(x)\} \\ &= \inf_{x \in \mathbb{R}^n} \{f(x) - \sup_{x^* \in \mathbb{R}^n} \{ \langle x, x^* \rangle - g^*(x^*) \}\} \\ &= \inf_{x, x^* \in \mathbb{R}^n} \{f(x) - \langle x, x^* \rangle + g^*(x^*)\} \\ &= \inf_{x^* \in \mathbb{R}^n} \{g^*(x^*) + \inf_{x \in \mathbb{R}^n} \{f(x) - \langle x, x^* \rangle\}\} \\ &= \inf_{x^* \in \mathbb{R}^n} \{g^*(x^*) - f^*(x^*)\} \end{aligned}$$

GENERALIZED CONVEX CONJUGATION

X, Y arbitrary sets, $c : X \times Y \rightarrow \overline{\mathbb{R}}$

$$f : X \rightarrow \overline{\mathbb{R}}$$

$$f^c : Y \rightarrow \overline{\mathbb{R}}$$

$$f^c(y) = \sup_{x \in X} \{c(x, y) - f(x)\}$$

$$\begin{aligned} +\infty + (-\infty) &= -\infty + (+\infty) = +\infty - (+\infty) \\ &= -\infty - (-\infty) = -\infty \end{aligned}$$

$$c' : Y \times X \rightarrow \overline{\mathbb{R}}$$

$$c'(y, x) = c(x, y)$$

$$g : Y \rightarrow \overline{\mathbb{R}}$$

$$g^{c'} : X \rightarrow \overline{\mathbb{R}}$$

$$g^{c'}(x) = \sup_{y \in Y} \{c(x, y) - g(y)\}$$

c -elementary functions: $x \in X \rightarrow c(x, y) - \beta \in \overline{\mathbb{R}}$

c' -elementary functions: $y \in Y \rightarrow c(x, y) - \beta \in \overline{\mathbb{R}}$

Φ_c the set of c -elementary functions

$\Phi_{c'}$ the set of c' -elementary functions

Φ set of extended real-valued functions on X

$f : X \rightarrow \overline{\mathbb{R}}$ is Φ -convex if it is the pointwise supremum of a subset of Φ .

The Φ -convex hull of $f : X \rightarrow \overline{\mathbb{R}}$: the largest Φ -convex minorant of f .

PROPOSITION. Let $f : X \rightarrow \overline{\mathbb{R}}$, $g : Y \rightarrow \overline{\mathbb{R}}$,

$x \in X$ and $y \in Y$. Then

(i) $f^c(y) \geq c(x, y) - f(x)$, $g^{c'}(x) \geq c(x, y) - g(y)$.

(ii) $f^{cc'c} = f^c$, $g^{c'cc'} = g^{c'}$.

(iii) f^c and $g^{c'}$ are $\Phi_{c'}$ -convex and Φ_c -convex, respectively.

PROPOSITION. The Φ_c -convex hull of $f : X \rightarrow \overline{\mathbb{R}}$ coincides with $f^{cc'}$.

The $\Phi_{c'}$ -convex hull of $g : Y \rightarrow \overline{\mathbb{R}}$ coincides with $g^{c'c}$.

COROLLARY. A function $f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if it coincides with $f^{cc'}$.

A function $g : Y \rightarrow \overline{\mathbb{R}}$ is $\Phi_{c'}$ -convex if and only if it coincides with $g^{c'c}$.

$f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex at $x_0 \in X$ if $f^{cc'}(x_0) = f(x_0)$.

$g : Y \rightarrow \overline{\mathbb{R}}$ is $\Phi_{c'}$ -convex at $y_0 \in Y$ if $g^{c'c}(y_0) = g(y_0)$.

EXAMPLE. X, Y dual pair of vector spaces

$\langle \cdot, \cdot \rangle : X \times Y \rightarrow \mathbb{R}$ the duality pairing

$$c : X \times Y \rightarrow \overline{\mathbb{R}}$$

$$c(x, y) = \log \langle x, y \rangle$$

$f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if e^f is sublinear

EXAMPLE. $X = Y = [0, +\infty]$

$$c : X \times Y \rightarrow \overline{\mathbb{R}}$$

$$c(x, y) = xy$$

$f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if f is convex and nondecreasing.

EXAMPLE. X topological space, Y arbitrary set

$c : X \times Y \rightarrow \mathbb{R}$ s.t. $\forall (x_0, y, \eta) \in X \times Y \times \mathbb{R}$ and

$\forall N$ neighborhood of x_0

$\exists y' \in Y$ and $\exists N' \subseteq N$, neighborhood of x_0 , s.t.

$$c(x, y') - c(x_0, y') \leq c(x, y) + \eta \quad (x \in X \setminus N')$$

$$c(x, y') - c(x_0, y') \leq 0 \quad (x \in X).$$

$f : X \rightarrow \mathbb{R} \cup \{+\infty\}$ is Φ_c -convex if and only if

f is l.s.c. and has a finite-valued c -elementary minorant.

If X is a Hilbert space and $Y = \mathbb{R}_+ \times X$, one can take

$$c : X \times Y \rightarrow \mathbb{R}$$

$$c(x, (\rho, y)) = -\rho \|x - y\|^2 .$$

EXAMPLE. $X = Y = \mathbb{R}^n$, $0 < \alpha \leq 1$, $N > 0$

$$c : X \times Y \rightarrow \mathbb{R}$$

$$c(x, y) = -N \|x - y\|^\alpha$$

$f : X \rightarrow \mathbb{R}$ is Φ_c -convex if and only if
 f is α -Hölder continuous with constant N .

EXAMPLE. X normed space with dual X^* , $0 < \alpha \leq 1$
 $Y = \mathcal{B}^*(0, N) \times \mathbb{R}$, $\mathcal{B}^*(0, N)$ the closed ball in X^*
with radius $N > 0$

$$c : X \times Y \rightarrow \mathbb{R}$$

$$c(x, (\omega, k)) = \min \{-(k - \omega(x))^\alpha, 0\} + k$$

($t^\alpha = -\infty$ if $t < 0$ and $\alpha \neq 1$)

$f : X \rightarrow \mathbb{R}$ is Φ_c -convex if and only if
 f is quasiconvex and α -Hölder with constant N^α .

EXAMPLE. $X = \{0, 1\}^n$, $Y = C_1 \times C_2 \times \cdots \times C_n$,
with $C_i \subseteq \mathbb{R}$ unbounded from above and from below
 $c : X \times Y \rightarrow \mathbb{R}$ the restriction of the scalar product
 $f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if
either f does not take the value $-\infty$ or $f \equiv -\infty$.

EXAMPLE. $X = \mathbb{R}^n$

$$Y = \bigcup_{k=0}^n \left(\mathcal{L}(\mathbb{R}^n, \mathbb{R}^k) \times \mathbb{R}^k \right) \times \mathbb{R}^n$$

$$c : X \times Y \rightarrow \overline{\mathbb{R}}$$

$$c(x, (u, z, x^*)) = \begin{cases} -\infty & \text{if } u(x) <_L z \\ \langle x, x^* \rangle & \text{if } u(x) = z \\ +\infty & \text{if } u(x) >_L z \end{cases}$$

$f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if it is convex.

EXAMPLE. $X = Y = \mathbb{R}_+^n$

$$c : X \times Y \rightarrow \mathbb{R}$$

$$c(x, y) = \begin{cases} \min_{i \text{ s.t. } y_i > 0} x_i y_i & \text{if } y \neq 0 \\ 0 & \text{if } y = 0 \end{cases}$$

$f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if it is ICAR

EXAMPLE. $X = Y = \mathbb{R}_{++}^n \cup \{0\}$

$$c : X \times Y \rightarrow \mathbb{R}$$

$$c(x, y) = -\max_{i=1, \dots, n} x_i y_i$$

$f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if it is DCAR.

THEOREM. For any $h : X \rightarrow \overline{\mathbb{R}}$, the following statements are equivalent:

(i) h is Φ_c -convex.

$$(ii) \inf_{x \in X} \{f(x) - h(x)\} = \inf_{x \in X} \{f(x) - h^{cc'}(x)\} \quad \forall f$$

$$(iii) \inf_{x \in X} \{f(x) - h(x)\} = \inf_{y \in Y} \{h^c(y) - f^c(y)\} \quad \forall f$$

$$(iv) \inf_{x \in X} \{f(x) - h(x)\} = \inf_{x \in X} \{f^{cc'}(x) - h^{cc'}(x)\} \quad \forall f$$

$$(v) \inf_{x \in X} \{f(x) - h(x)\} = \inf_{x \in X} \{f^{cc'}(x) - h(x)\} \quad \forall f$$

$f : X \rightarrow \overline{\mathbb{R}}$ is c -subdifferentiable at $x_0 \in X$ if

$f(x_0) \in \mathbb{R}$ and

there exists $y_0 \in Y$ such that $c(x_0, y_0) \in \mathbb{R}$ and

$$f(x) - f(x_0) \geq c(x, y_0) - c(x_0, y_0) \quad (x \in X).$$

y_0 is a c -subgradient of f at x_0 .

$\partial_c f(x_0) = \{y_0 \in Y : y_0 \text{ is a } c\text{-subgradient of } f \text{ at } x_0\}$

$\partial_c f(x_0) = \emptyset$ if $f(x_0) \notin \mathbb{R}$

PROPOSITION. Let $f : X \rightarrow \overline{\mathbb{R}}$, $x_0 \in X$ and $y_0 \in Y$.

If $c(x_0, y_0) \in \mathbb{R}$ then

$y_0 \in \partial_c f(x_0)$ if and only if $f(x_0) + f^c(y_0) = c(x_0, y_0)$,

$y_0 \in \partial_c f^{cc'}(x_0)$ if and only if $x_0 \in \partial_{c'} f^c(y_0)$,

$\partial_c f(x_0) \neq \emptyset$ implies that f is Φ_c -convex at x_0 ,

f is Φ_c -convex at x_0 implies $\partial_c f^{cc'}(x_0) = \partial_c f(x_0)$.

$\rho : X \rightrightarrows Y$ is c -cyclically monotone if

$$(c(x_1, y_0) - c(x_0, y_0)) + (c(x_2, y_1) - c(x_1, y_1)) + \cdots + (c(x_0, y_m) - c(x_m, y_m))$$

is nonpositive for any set of pairs (x_i, y_i) , $i = 0, 1, \dots, m$

(m arbitrary) such that $y_i \in \rho(x_i)$.

THEOREM. $\rho : X \rightrightarrows Y$ is c -cyclically monotone if and only if

there exists a Φ_c -convex function $f : X \rightarrow \mathbb{R} \cup \{+\infty\}$ such that $\rho(x) \subseteq \partial_c f(x)$ for every $x \in X$.

EXAMPLE. $X = Y = \{1, 2\}$

$$c : X \times Y \rightarrow \mathbb{R}$$

$$c(i, j) = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

$$f_1, f_2, f_3 : X \rightarrow \mathbb{R}$$

$$f_1(1) = f_1(2) = 1$$

$$f_2(1) = 1, f_2(2) = 0$$

$$f_3(1) = 1, f_3(2) = \frac{3}{2}$$

$$f_1(x) = \max \{c(x, 1), c(x, 2)\}$$

$$f_2(x) = \max \{c(x, 1), c(x, 2) - 1\}$$

$$f_3(x) = \max \left\{ c(x, 1), c(x, 2) + \frac{1}{2} \right\}$$

$$\partial_c f_1(x) = \{x\} \quad (x \in X)$$

$$\partial_c f_2(1) = \{1\}, \quad \partial_c f_2(2) = Y$$

$$\partial_c f_3(x) = \{x\} \quad (x \in X)$$

THEOREM. For a mapping $\Delta : \overline{\mathbb{R}}^X \rightarrow \overline{\mathbb{R}}^Y$,
the following statements are equivalent:

(i) There exists a coupling function $c : X \times Y \rightarrow \overline{\mathbb{R}}$ s.t.

$$\Delta(f) = f^c \quad (f \in \overline{\mathbb{R}}^X).$$

(ii) One has

$$\Delta(\inf_{i \in I} f_i) = \sup_{i \in I} \Delta(f_i) \quad (\{f_i\}_{i \in I} \subseteq \overline{\mathbb{R}}^X)$$

and

$$\Delta(f + c) = \Delta(f) - c \quad (f \in \overline{\mathbb{R}}^X, c \in \mathbb{R}).$$

Moreover, in this case c is uniquely determined by Δ :

$$c(x, y) = \Delta(\delta_{\{x\}})(y) \quad (x \in X, y \in Y),$$

$\delta_{\{x\}}$ denoting the indicator function of $\{x\}$.

GENERALIZED CONVEX DUALITY

X, U arbitrary sets, $\varphi : X \times U \rightarrow \overline{\mathbb{R}}$

$$(\mathcal{P}_u) \quad \text{minimize } \varphi(x, u)$$

$$u_0 \in U$$

$$(\mathcal{P}) \quad \text{minimize } \varphi(x, u_0)$$

$$p : U \rightarrow \overline{\mathbb{R}}$$

$$p(u) = \inf_{x \in X} \varphi(x, u)$$

V arbitrary set, $c : U \times V \rightarrow \overline{\mathbb{R}}$

$$(\mathcal{D}) \quad \text{maximize } c(u_0, v) - p^c(v)$$

PROPOSITION. The optimal value of (\mathcal{D}) is $p^{cc'}(u_0)$.
If it is finite, the optimal solution set is $\partial_c p^{cc'}(u_0)$.

THEOREM. The optimal value of (\mathcal{D}) is not greater than the optimal value of (\mathcal{P}) .

They coincide if and only if p is Φ_c -convex at u_0 .

In this case, if the optimal value is finite

then the optimal solution set to (\mathcal{D}) is $\partial_c p(u_0)$.

COROLLARY. If $x \in X$ and $v \in V$ satisfy

$$\varphi(x, u_0) = c(u_0, v) - p^c(v)$$

then they are optimal solutions to (\mathcal{P}) and (\mathcal{D}) , respectively.

$$\varphi_x : U \rightarrow \overline{\mathbb{R}}$$

$$\varphi_x(u) = \varphi(x, u)$$

$$L : X \times V \rightarrow \overline{\mathbb{R}}$$

$$L(x, v) = c(u_0, v) - \varphi_x^c(v)$$

If φ_x is Φ_c -convex at u_0 for every $x \in X$,

$$\begin{aligned} \sup_{v \in V} L(x, v) &= \sup_{v \in V} \{c(u_0, v) - \varphi_x^c(v)\} = \varphi_x^{cc}(u_0) \\ &= \varphi_x(u_0) = \varphi(x, u_0). \end{aligned}$$

If c does not take the value $+\infty$,

$$\begin{aligned}\inf_{x \in X} L(x, v) &= \inf_{x \in X} \{c(u_0, v) - \varphi_x^c(v)\} \\ &= \inf_{x \in X} \left\{ c(u_0, v) - \sup_{u \in U} \{c(u, v) - \varphi_x(u)\} \right\} \\ &= c(u_0, v) - \sup_{u \in U} \left\{ c(u, v) - \inf_{x \in X} \varphi(x, u) \right\} \\ &= c(u_0, v) - \sup_{u \in U} \{c(u, v) - p(u)\} \\ &= c(u_0, v) - p^c(v).\end{aligned}$$

EXAMPLE. $f : \Omega \subseteq \mathbb{R}^n \rightarrow \bar{\mathbb{R}}, g : \Omega \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$

$$(\mathcal{P}) \quad \begin{array}{ll} \text{minimize} & f(x) \\ \text{subject to} & g(x) \leq 0 \end{array}$$

$$\begin{aligned} \varphi & : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \bar{\mathbb{R}} \\ \varphi(x, u) & = \begin{cases} f(x) & \text{if } x \in \Omega \text{ and } g(x) + u \leq 0 \\ +\infty & \text{otherwise} \end{cases} \end{aligned}$$

$$\begin{aligned} c & : \mathbb{R}^m \times (\mathbb{R}_+ \times \mathbb{R}^m) \rightarrow \mathbb{R} \\ c(u, (\rho, y)) & = -\rho \|u - y\|^2 \end{aligned}$$

$$L : \mathbb{R}^n \times \mathbb{R}_+ \times \mathbb{R}^m \rightarrow \bar{\mathbb{R}}$$

$$\begin{aligned} L(x, \rho, y) & = f(x) + \rho \sum_{i=1}^m \left(2y_i \max\{g_i(x), -y_i\} + (\max\{g_i(x), -y_i\})^2 \right) \\ & \quad \text{if } x \in \Omega \\ & = +\infty \quad \text{if } x \notin \Omega \end{aligned}$$

QUASICONVEX CONJUGATION

THEOREM. For any function $f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$,
the following statements are equivalent:

- (i) f is evenly quasilinear.
- (ii) Every nonempty level set of f is either an (open or closed) halfspace or the whole space.
- (iii) There exists $x^* \in \mathbb{R}^n$ and a nondecreasing function $h : \mathbb{R} \rightarrow \overline{\mathbb{R}}$ such that $f = h \circ \langle \cdot, x^* \rangle$.

X, Y arbitrary sets, $G \subseteq X \times Y$

$$c : X \times Y \rightarrow \overline{\mathbb{R}}$$
$$c(x, y) = \begin{cases} 0 & \text{if } (x, y) \in G \\ -\infty & \text{otherwise} \end{cases}$$

$$F : X \rightrightarrows Y$$

$$F(x) = \{y \in Y : (x, y) \in G\}$$

$$\text{For } f : X \rightarrow \overline{\mathbb{R}}, \quad f^c(y) = - \inf_{x \in F^{-1}(y)} f(x)$$

$$\text{For } g : Y \rightarrow \overline{\mathbb{R}}, \quad g^{c'}(x) = - \inf_{y \in F(x)} g(y)$$

$$f^{cc'}(x_0) = \sup_{y \in F(x_0)} \inf_{x \in F^{-1}(y)} f(x) \quad (x_0 \in X)$$

$$f : X \rightarrow \overline{\mathbb{R}}, x_0 \in f^{-1}(\mathbb{R}), y_0 \in Y$$

$$y_0 \in \partial_c f(x_0) \iff y_0 \in F(x_0), f(x_0) = \inf_{x \in F^{-1}(y_0)} f(x)$$

THEOREM. Let $f : X \rightarrow \overline{\mathbb{R}}$ and $x_0 \in X$.

Then f is Φ_c -convex at x_0 if and only if

$$\forall \lambda < f(x_0) \exists y_\lambda \in F(x_0) \text{ s.t. } S_\lambda(f) \cap F^{-1}(y_\lambda) = \emptyset.$$

COROLLARY. A function $f : X \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if

each level set of f is of the form $\bigcap_{y \in Y_\lambda} (X \setminus F^{-1}(y))$ with

$$Y_\lambda \subseteq Y.$$

THEOREM. For any $h : X \rightarrow \overline{\mathbb{R}}$, the following statements are equivalent:

(i) h is Φ_c -convex.

$$(ii) \inf_{x \in X} \max \{f(x), -h(x)\} = \inf_{x \in X} \max \{f(x), -h^{cc'}(x)\} \\ \forall f : X \rightarrow \overline{\mathbb{R}}.$$

$$(iii) \inf_{x \in X} \max \{f(x), -h(x)\} = \inf_{y \in Y} \max \{h^c(y), -f^c(y)\} \\ \forall f : X \rightarrow \overline{\mathbb{R}}.$$

$$(iv) \inf_{x \in X} \max \{f(x), -h(x)\} = \inf_{x \in X} \max \{f^{cc'}(x), -h^{cc'}(x)\} \\ \forall f : X \rightarrow \overline{\mathbb{R}}.$$

$$(v) \inf_{x \in X} \max \{f(x), -h(x)\} = \inf_{x \in X} \max \{f^{cc'}(x), -h(x)\} \\ \forall f : X \rightarrow \overline{\mathbb{R}}.$$

$$X = \mathbb{R}^n, Y = \mathbb{R}^n \times \mathbb{R}$$

$$G = \{(x, x^*, t) \in \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R} : \langle x, x^* \rangle \geq t\}$$

$$f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$$

$$f^c(x^*, t) = -\inf \{f(x) : \langle x, x^* \rangle \geq t\}$$

$$g : \mathbb{R}^n \times \mathbb{R} \rightarrow \overline{\mathbb{R}}$$

$$g^{c'}(x) = -\inf \{g(x^*, t) : \langle x, x^* \rangle \geq t\}$$

$$f^{cc'}(x_0) = \sup_{x^* \in \mathbb{R}^n} \inf \{f(x) : \langle x, x^* \rangle \geq \langle x_0, x^* \rangle\}$$

THEOREM. A function $f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$ is Φ_c -convex if and only if it is evenly quasiconvex.

COROLLARY. The second c -conjugate $f^{cc'}$ of any function $f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$ coincides with the evenly quasiconvex hull of f .

COROLLARY. Every evenly quasiconvex function is the pointwise supremum of a collection of evenly quasilinear functions.

If f is evenly quasiconvex,

$$f = \sup_{x^* \in \mathbb{R}^n} \varphi_{x^*}, \text{ with } \varphi_{x^*} = \inf \{f(x) : \langle x, x^* \rangle \geq \langle \cdot, x^* \rangle\}.$$

THEOREM. Let $f : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$, $x_0 \in \mathbb{R}^n$ be such that $f(x_0) \in \mathbb{R}$, and let

$$\partial^{GP} f(x_0) = \{x^* \in \mathbb{R}^n : \langle x, x^* \rangle < \langle x_0, x^* \rangle \\ \forall x \in \mathbb{R}^n \text{ s. t. } f(x) < f(x_0)\}.$$

Then

$$\partial_c f(x_0) = \{(x^*, t) \in \mathbb{R}^n \times \mathbb{R} : x^* \in \partial^{GP} f(x_0), t \leq \langle x_0, x^* \rangle, \\ \inf \{f(x) : \langle x, x^* \rangle \geq t\} = f(x_0)\}.$$

COROLLARY. Let f and x_0 be as above. Then

$$\partial^{GP} f(x_0) = \{x^* \in \mathbb{R}^n : (x^*, \langle x_0, x^* \rangle) \in \partial_c f(x_0)\}.$$

COROLLARY. Let f and x_0 be as above. Then $\partial^{GP} f(x_0)$ coincides with the projection of $\partial_c f(x_0)$ onto \mathbb{R}^n .

X real vector space, ρ order relation on X

ρ is compatible with the linear structure of X if

$$x_1 \rho y_1 \quad , \quad x_2 \rho y_2 \quad \implies \quad x_1 + x_2 \rho y_1 + y_2 \\ \text{and} \\ x \rho y \quad , \quad \lambda \geq 0 \quad \implies \quad \lambda x \rho \lambda y.$$

THEOREM. Let X be a real vector space.

A function $f : X \rightarrow \overline{\mathbb{R}}$ is quasiconvex if and only if there is a family $\{\rho_i\}_{i \in I}$ of total order relations on X that are compatible with its linear structure and a corresponding family $\{f_i\}_{i \in I}$ of isotonic functions $f_i : (X, \rho_i) \rightarrow (\overline{\mathbb{R}}, \leq)$ such that

$$f(x) = \max_{i \in I} f_i(x) \quad (x \in X).$$

QUASICONVEX DUALITY

X, U arbitrary sets, $\varphi : X \times U \rightarrow \overline{\mathbb{R}}$

$$(\mathcal{P}_u) \quad \text{minimize } \varphi(x, u)$$

$$p \quad : \quad U \rightarrow \overline{\mathbb{R}}$$

$$p(u) = \inf_{x \in X} \varphi(x, u)$$

$$u_0 \in U$$

$$(\mathcal{P}) \quad \text{minimize } \varphi(x, u_0)$$

V arbitrary set, $G \subseteq U \times V$

$$F : U \rightrightarrows V$$

$$F(u) = \{v \in V : (u, v) \in G\}$$

$$c(u, v) = \begin{cases} 0 & \text{if } (u, v) \in G \\ -\infty & \text{otherwise} \end{cases}$$

$$(\mathcal{D}) \quad \text{maximize } c(u_0, v) - p^c(v)$$

$$(\mathcal{D}) \quad \text{maximize } \inf_{x \in X, u \in F^{-1}(v)} \varphi(x, u) \\ \text{subject to } v \in F(u_0)$$

$$L : X \times V \rightarrow \overline{\mathbb{R}}$$

$$L(x, v) = c(u_0, v) - \varphi_x^c(v) = c(u_0, v) + \inf_{u \in F^{-1}(v)} \varphi(x, u) \\ = \begin{cases} \inf_{u \in F^{-1}(v)} \varphi(x, u) & \text{if } v \in F(u_0) \\ -\infty & \text{otherwise} \end{cases}$$

$$U = \mathbb{R}^m, \quad V = \mathbb{R}^m \times \mathbb{R},$$

$$G = \{(u, u^*, t) \in \mathbb{R}^m \times \mathbb{R}^m \times \mathbb{R} : \langle u, u^* \rangle \geq t\}, \quad u_0 = 0$$

$$(\mathcal{D}) \quad \text{maximize } \inf_{x \in X, \langle u, u^* \rangle \geq t} \varphi(x, u) \\ \text{subject to } t \leq 0$$

$$(\mathcal{D}) \quad \text{maximize} \quad \inf_{x \in X, \langle u, u^* \rangle \geq 0} \varphi(x, u)$$

$$L(x, u^*, t) = \begin{cases} \inf \{ \varphi(x, u) : \langle u, u^* \rangle \geq t \} & \text{if } t \leq 0 \\ -\infty & \text{otherwise} \end{cases}$$

PROPOSITION. The optimal value of (\mathcal{D}) coincides with the value of the evenly quasiconvex hull of p at 0.

THEOREM. The optimal value of (\mathcal{D}) is not greater than the optimal value of (\mathcal{P}) . They coincide if and only if p is evenly quasiconvex at 0.

COROLLARY. Let $x_0 \in X$ be an optimal solution to (\mathcal{P}) . Then $u^* \in \mathbb{R}^n$ is an optimal solution to (\mathcal{D}) if $(x_0, 0) \in X \times \mathbb{R}^m$ minimizes $\varphi(x, u)$ subject to the constraint $\langle u, u^* \rangle \geq 0$.

$$f : \Omega \subseteq \mathbb{R}^n \rightarrow \bar{\mathbb{R}}, \quad g : \Omega \rightarrow \mathbb{R}^m$$

$$\varphi(x, u) = \begin{cases} f(x) & \text{if } x \in \Omega, \quad g(x) + u \leq 0 \\ +\infty & \text{otherwise} \end{cases}$$

$$\inf_{x \in X, \langle u, u^* \rangle \geq 0} \varphi(x, u)$$

$$= \inf \{ f(x) : g(x) + u \leq 0, \quad \langle u, u^* \rangle \geq 0 \}$$

$$= \begin{cases} \inf \{ f(x) : \langle g(x), u^* \rangle \leq 0 \} & \text{if } u^* \geq 0 \\ \inf f(\Omega) & \text{if } u^* \not\geq 0 \end{cases}$$

$$(\mathcal{P}) \quad \begin{array}{ll} \text{minimize} & f(x) \\ \text{subject to} & g(x) \leq 0 \end{array}$$

$$(\mathcal{D}) \quad \begin{array}{ll} \text{maximize} & \inf \{ f(x) : \langle g(x), u^* \rangle \leq 0 \} \\ \text{subject to} & u^* \geq 0 \end{array}$$

$$L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R} \rightarrow \bar{\mathbb{R}}$$

$$L(x, u^*, t) = \begin{cases} \inf \{ f(x) : \langle g(x), u^* \rangle + t \leq 0 \} & \text{if } u^* \geq 0 \text{ and } t \leq 0 \\ \inf f(\Omega) & \text{if } u^* \not\geq 0 \text{ and } t \leq 0 \\ -\infty & \text{if } t > 0 \end{cases}$$

THEOREM. If f is quasiconvex and u.s.c. along lines, the component functions of g are convex and there is an $x \in \Omega$ such that $g(x) < 0$ (componentwise) then

$$\inf \{f(x) : g(x) \leq 0\} = \max_{u^* \geq 0} \inf \{f(x) : \langle g(x), u^* \rangle \leq 0\}.$$

Hence, $u^* \geq 0$ is an optimal solution to (\mathcal{D}) if and only if the optimal value of (\mathcal{P}) coincides with that of

$$\begin{aligned} (\mathcal{S}_{u^*}) \quad & \text{minimize} && f(x) \\ & \text{subject to} && \langle g(x), u^* \rangle \leq 0. \end{aligned}$$

In this case, any optimal solution $x_0 \in \Omega$ to (\mathcal{P}) is also an optimal solution to (\mathcal{S}_{u^*}) .