

A NEW APPROACH FOR THE CONVEX FEASIBILITY PROBLEM VIA MONOTROPIC PROGRAMMING

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With Regina and an Aussie friend

December 2013, Adelaide, Australia

Convex Feasibility Problem

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- Numerous problems in mathematics and physical sciences can be recast as **Convex Feasibility Problem**:

$\{C_i\}_{i=1}^m$ nonempty closed convex subsets of H Hilbert

$$\text{find } x \in \bigcap_{i=1}^m C_i$$

(CFP)

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- broad applicability in different disciplines:
 - *image and signal reconstruction* (computerized tomography)
Combettes (1996)



Combettes, The Convex Feasibility Problem in Image Recovery, Advances in Imaging and Electron Physics 95, Academic Press, New York, 1996

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- widely studied from diverse frameworks:
 - iterative projection methods provided the intersection is nonempty,
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What if $\bigcap_{i=1}^m C_i = \emptyset$?

Translation to the product space

$\mathbf{H} = \underbrace{H \times \cdots \times H}_{m \text{ times}}$ Hilbert space endowed with the scalar product

$$\langle\langle \mathbf{x}, \mathbf{y} \rangle\rangle = \sum_{i=1}^m w_i \langle x_i, y_i \rangle, \quad \mathbf{x}, \mathbf{y} \in \mathbf{H}$$

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Let $\mathbf{C} = C_1 \times \cdots \times C_m = \{\mathbf{x} \in \mathbf{H} : x_i \in C_i\}$, cartesian product of the sets
and $\mathbf{D} = \{(x, \cdots, x) \in \mathbf{H} : x \in H\}$, closed diagonal subspace of \mathbf{H}

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Thus $\mathbf{C} \cap \mathbf{D} = \{(x, \cdots, x) \in \mathbf{H} : x \in \bigcap_{i=1}^m C_i\}$

and in the product space the CFP can be reformulated as finding

find $\mathbf{x} \in \mathbf{C} \cap \mathbf{D}$

(CFP)

Monotropic Programming Problem

Monotropic Programming Problem

Extended monotropic programming problem:

$$\inf_{(x_1, \dots, x_m) \in S} f_1(x_1) + f_2(x_2) + \dots + f_m(x_m)$$

(P)

where $f_i : X_i \rightarrow \mathbb{R}$ **proper convex function**, $i = 1, \dots, m$

X_i **separately locally convex spaces**, $i = 1, \dots, m$

$S \subseteq \prod_{i=1}^m X_i$ **linear closed subspace** such that $S \cap \prod_{i=1}^m \text{dom} f_i \neq \emptyset$

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The dual problem is

$$\sup_{(x_1^*, \dots, x_m^*) \in S^\perp} -f_1^*(x_1^*) - f_2^*(x_2^*) - \dots - f_m^*(x_m^*) \quad (\text{D})$$

where $f^*(x^*) := \sup_{x \in X} \{\langle x^*, x \rangle - f(x)\}$ is the **Fenchel conjugate function** of f
 $S^\perp = \{x^* : \langle x^*, x \rangle = 0, \forall x \in S\}$ is the **orthogonal subspace** of S .

Monotropic Programming Problem

Extended monotropic programming problem:

$$\inf_{(x_1, \dots, x_m) \in S} f_1(x_1) + f_2(x_2) + \dots + f_m(x_m) = v(P) \quad (P)$$

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the situation $v(P) = v(D)$ is called *zero duality gap*

Important results in Monotropic Programming Problems

Rockafellar was the first to prove a **zero duality gap result** for the original class of monotropic programs when each space X_i is \mathbb{R} .



Rockafellar, Network Flows and Monotropic Optimization. Wiley, New York, **1984**

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Bertsekas generalized Rockafellar's result to *extended monotropic programs* in which the X_i 's are finite-dimensional spaces, assuming:

- f_i **lower semicontinuous** in $\text{dom} f_i$, for all $i = 1, \dots, m$,
- $S^\perp + \prod_{i=1}^m \partial_\varepsilon f_i(x_i)$ **closed**, $\forall \varepsilon > 0$, $\forall (x_1, \dots, x_m) \in \prod_{i=1}^m \text{dom} f_i \cap S$

where $\partial_\varepsilon f_i$ denotes the ε -subdifferential of f_i :

$$\partial_\varepsilon f(x) := \begin{cases} \{v \in H \mid \langle v, y - x \rangle - \varepsilon \leq f(y) - f(x), \text{ for all } y \in H\} & \text{if } f(x) \in \mathbb{R} \\ \emptyset & \text{otherwise} \end{cases}$$



Bertsekas, Extended monotropic programming and duality. JOTA. 139, 209–225, **2008**

Important results in Monotropic Programming Problems

Boţ and Csetnek extended Bertsekas' result to the general case:

Zero Duality Gap Theorem (**Boţ et al.**, 2010)

X_i **separately locally convex spaces**, $i = 1, \dots, m$

$f_i : X_i \rightarrow \overline{\mathbb{R}} := (-\infty, +\infty]$ **proper convex functions**, $i = 1, \dots, m$

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$g : \prod_{i=1}^m X_i \rightarrow \mathbb{R}$ defined by $g(x_1, \dots, x_m) = \sum_{i=1}^m f_i(x_i)$,

$\text{cl} f_i$ proper functions and $g(x) = \text{cl } g(x)$ for all $x \in \text{dom } \text{cl } g \cap S$

$S^\perp + \prod_{i=1}^m \partial_\varepsilon f_i(x_i)$ **closed**, $\forall \varepsilon > 0$, $\forall (x_1, \dots, x_m) \in \prod_{i=1}^m \text{dom} f_i \cap S$

then $v(P) = v(D)$.



Boţ et al., On a zero duality gap result in extended monotropic programming. JOTA 147, 473–482, 2010

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C_1, C_2 closed convex sets in $X = H$, Hilbert space, $C_1 \cap C_2$ possibly empty

find $x \in C_1 \cap C_2$

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To find a **best approximation solution** to (CFP) we consider:

$$\inf_{x \in H} d_{C_1}(x) + d_{C_2}(x)$$

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equivalent to the **monotropic optimization problem**

$$\inf_{(x,y) \in S} d_{C_1}(x) + d_{C_2}(y)$$

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where $S = \{(x,y) \in H^2 : x = y\}$

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$f_1 := d_{C_1}(\cdot)$ and $f_2 := d_{C_2}(\cdot)$ are **convex and continuous everywhere**

Convex Feasibility Problem

monotropic optimization problem

$$\inf_{(x,y) \in S} d_{C_1}(x) + d_{C_2}(y) \quad (\text{P})$$

Then the dual problem of (P) is

$$\sup_{(v,w) \in S^\perp} -d_{C_1}^*(v) - d_{C_2}^*(w) \quad (\text{D})$$

where $S^\perp = \{(v, w) \in H^2 : v + w = 0\}$ and $d_C^*(v) = \sigma_C(v) + \iota_B(v)$

$$\sigma_C(v) := \sup_{y \in C} \langle v, y \rangle, \quad \text{support function of } C$$

$$\iota_B(x) := \begin{cases} 0 & \text{if } x \in B \\ +\infty & \text{if } x \notin B \end{cases} \quad \text{indicator function of the unit ball in } H$$

(P) and (D) satisfy the **zero duality gap** property

Consequence of Bot and Csetnek's result:

- C_i closed and convex $\Rightarrow f_i = d_{C_i}$ convex and continuous.
 \Rightarrow Thus functions f_i **satisfy the assumptions of Theorem**
- f_i real-valued $\Rightarrow \partial_\varepsilon f_i(x_i) \ (x_i \in H)$ nonempty and weakly compact
 $\Rightarrow S^\perp + \prod_{i=1}^m \partial_\varepsilon f_i(x_i)$ is **weakly closed**
(every weakly closed convex set is closed for the strong topology)

Strong duality and optimality conditions

To derive **strong duality** (existence of a dual solution)
and **first order optimality conditions** for primal-dual problems (P) and (D)
we use these classical primal-dual problems in Fenchel duality

$$\inf_{(x,y) \in H^2} f(x,y) + g(x,y) \quad (P_0)$$

$$\sup_{(v,w) \in H^2} -f^*(v,w) - g^*(-v,-w) \quad (D_0)$$

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Proposition (Strong duality)

$f, g : H^2 \rightarrow \overline{\mathbb{R}}$ **proper and lsc functions** such that $0 \in \text{core}(\text{dom } g - \text{dom } f)$

Then
$$\inf_{x \in H^2} f(x) + g(x) = -\min_{v \in H^2} f^*(v) + g^*(-v)$$

$$\text{core}(C) := \{x \in C : \text{cone}(C - x) = H\}$$

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Theorem (First order optimality conditions)

$f, g : H^2 \rightarrow \overline{\mathbb{R}}$ **proper and lsc functions** such that $\text{dom } g \cap \text{dom } f \neq \emptyset$

Then the following are equivalent:

- (i) (x_1, x_2) solves (P_0) , and (v_1, v_2) solves (D_0)
- (ii) $(v_1, v_2) \in \partial f(x_1, x_2)$ and $-(v_1, v_2) \in \partial g(x_1, x_2)$

Strong duality and optimality conditions

$$\inf_{(x,y) \in S} d_{C_1}(x) + d_{C_2}(y)$$

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$$\sup_{(v,w) \in S^\perp} -d_{C_1}^*(v) - d_{C_2}^*(w)$$

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Lemma

Defining $f(x,y) := d_{C_1}(x) + \iota_S(x,y)$ and $g(x,y) := d_{C_2}(y)$:

- (a) $\inf_{(x,y) \in S} d_{C_1}(x) + d_{C_2}(y) = \inf_{(x,y) \in H^2} f(x,y) + g(x,y)$
- (b) $(z_1, z_2) \in S$ solves (P) if and only if (z_1, z_2) solves (P_0)
- (c) $\sup_{(v,w) \in S^\perp} -d_{C_1}^*(v) - d_{C_2}^*(w) = \sup_{(v,w) \in H^2} -f^*(v,w) - g^*(-v, -w)$
- (d) $(u, -u) \in H^2$ solves (D) if and only if $(0, u)$ solves (D_0) .

Strong duality and optimality conditions

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(P)

$$\sup_{(v,w) \in S^\perp} -d_{C_1}^*(v) - d_{C_2}^*(w)$$

(D)

Proposition

Problems (P) and (D) satisfy **strong duality**:

the dual problem always has a solution.

$$\begin{cases} (x,y) \text{ primal solution to (P)} \\ (u,v) \text{ dual solution to (D)} \end{cases} \iff \begin{cases} (x,y) \in S \\ (u,v) \in S^\perp \\ u \in \partial d_{C_1}(x), v \in \partial d_{C_2}(y) \end{cases}$$

Separation of sets

C_1, C_2 are *separated* if there exist $v \in H$, $\|v\| = 1$, and $\delta \in \mathbb{R}$ such that

$$C_1 \subseteq H_{v,\delta}^{\leq} := \{x \in H : \langle v, x \rangle \leq \delta\}$$

$$C_2 \subseteq H_{v,\delta}^{\geq} := \{y \in H : \langle v, y \rangle \geq \delta\}.$$

The separating hyperplane is $H = H_{v,\delta} := \{x \in H : \langle v, x \rangle = \delta\}$.

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The separating hyperplane is $H = H_{v,\delta} := \{x \in H : \langle v, x \rangle = \delta\}$. This separation is said to be:

- *proper* if C_1 and C_2 are not contained in H ;
- *nice* if the hyperplane H is disjoint from C_1 or C_2 ;
- *strict* if the hyperplane H is disjoint from both C_1 and C_2 ;
- *strong* if there exist $\varepsilon > 0$ such that $C_1 + \varepsilon B$ is contained in one of the open half-spaces bounded by H and $C_2 + \varepsilon B$ is contained in the other;

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Standard Separation Theorem

C_1 and C_2 nonempty convex sets such that $\text{int } C_1 \neq \emptyset$

$$\text{properly separated} \quad \Leftrightarrow \quad (\text{int } C_1) \cap C_2 = \emptyset$$

Consistency of CFP and the optimal dual values

The dual problem (D):

$$\begin{aligned}\sup_{v \in H} -d_{C_1}^*(v) - d_{C_2}^*(-v) &= \sup_{v \in H} -[\sigma_{C_1}(v) + \iota_B(v)] - [\sigma_{C_2}(-v) + \iota_B(-v)] \\ &= \sup_{\|v\| \leq 1} -\sigma_{C_1}(v) - \sigma_{C_2}(-v) \\ &= \max_{t \in [0,1]} \sup_{\|v\|=t} -\sigma_{C_1}(v) - \sigma_{C_2}(-v) \\ &= -\min_{t \in [0,1]} \underbrace{\inf_{\|v\| \leq t} \sigma_{C_1}(v) + \sigma_{C_2}(-v)}_{\Phi(t)} \\ &= -\min_{t \in [0,1]} \{t\Phi(1)\} \\ &= \begin{cases} -\Phi(1) (> 0) & \text{if } \Phi(1) < 0, \\ 0 & \text{if } \Phi(1) = 0. \end{cases}\end{aligned}$$

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By studying the values of $\Phi(1)$, we can obtain information about $C_1 \cap C_2$.

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The key point is the relation between Φ and the **infimal convolution of the support functions**

Consistency of CFP and the optimal dual values

$$\begin{aligned}(\sigma_{C_1} \square \sigma_{C_2})(0) &= \inf_{v \in H} \{ \sigma_{C_1}(v) + \sigma_{C_2}(-v) \} \\ &= \inf_{t > 0} \inf_{\|v\| \leq t} \{ \sigma_{C_1}(v) + \sigma_{C_2}(-v) \} \\ &= \inf_{t > 0} t\Phi(1).\end{aligned}$$

Consistency of CFP and the optimal dual values

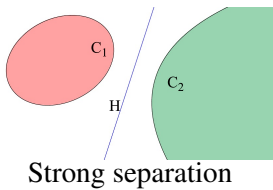
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Theorem

1. If $\Phi(1) < 0$, then $C_1 \cap C_2 = \emptyset$.
 C_1 and C_2 are strongly separated
2. If $\Phi(1) = 0$:
 - 2.1 If $(\sigma_{C_1} \square \sigma_{C_2})(\cdot)$ is not lower-semicontinuous at 0 then $C_1 \cap C_2 = \emptyset$.
 C_1 and C_2 are separated but not strongly
 - 2.2 If $(\sigma_{C_1} \square \sigma_{C_2})(\cdot)$ is lower-semicontinuous at 0 then $C_1 \cap C_2 \neq \emptyset$.

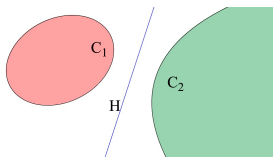
Separation of sets

- $\Phi(1) < 0$:



Separation of sets

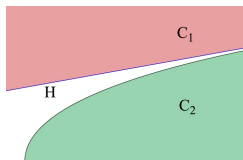
- $\Phi(1) < 0$:



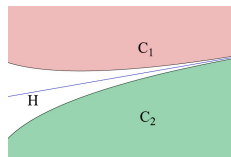
Strong separation

- $\Phi(1) = 0$:

- $(\sigma_{C_1} \square \sigma_{C_2})(0)$ not lsc



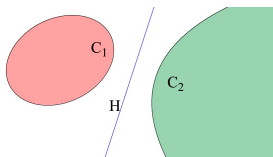
Nice separation



Strict separation

Separation of sets

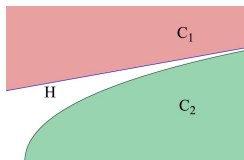
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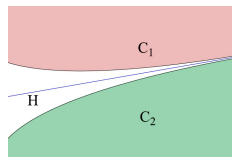
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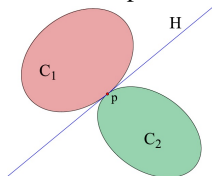


Nice separation

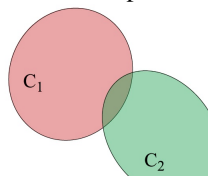


Strict separation

- $(\sigma_{C_1} \square \sigma_{C_2})(0)$ lsc



No nice separation



No separation

Characterization of $C_2 - C_1$

The value of $\Phi(1)$ in the dual problem (D) characterizes also the Minkowski difference set

$$C_2 - C_1 := \{x - y \in H : x \in C_2, y \in C_1\}.$$

Theorem

- (i) $\Phi(1) < 0$ if and only if $0 \notin \overline{C_2 - C_1}$ the closure of $C_2 - C_1$.
- (ii) $\Phi(1) = 0$ and $(\sigma_{C_1} \square \sigma_{C_2})(0)$ not lsc if and only if $0 \in \text{Bd}(C_2 - C_1)$, the boundary of $C_2 - C_1$.
- (iii) $\Phi(1) = 0$ and $(\sigma_{C_1} \square \sigma_{C_2})(0)$ lsc if and only if $0 \in \text{int}(C_2 - C_1)$, the interior of $C_2 - C_1$.

Lower semicontinuity of infimal convolution

Lower semicontinuity of infimal convolution

Geometric Condition for the lower semicontinuity of the infimal convolution:

Corollary

If $(\sigma_{C_1} \square \sigma_{C_2})(0) > -\infty$ then $(\sigma_{C_1} \square \sigma_{C_2})$ is proper, and the following statements are equivalent and satisfied:

- (i) $C_1 \cap C_2 \neq \emptyset$,
- (ii) $(\sigma_{C_1} \square \sigma_{C_2})$ is lsc at 0,
- (iii) $\{0\} \times \mathbb{R} \cap \text{epi} (\sigma_{C_1} \square \sigma_{C_2}) = \{0\} \times \mathbb{R}_+$

Consequently, if $\text{epi } \sigma_{C_1} + \text{epi } \sigma_{C_2}$ is closed, then $C_1 \cap C_2 \neq \emptyset$.

Consistency of CFP and dual solutions

We have seen that

- (D) always has a solution.
- If $v(D)$ is positive then CFP has no solution (strong separation).
- If $v(D) = 0$, CFP may or may not have solution.

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The following result gives us information about consistency of the CFP when $v(D) = 0$.

Corollary

Assume that $v(D) = 0$

- (a) $v = 0$ unique solution to the dual problem $(D) \Leftrightarrow C_1 \cap C_2 \neq \emptyset$.
- (b) The dual problem (D) has multiple solutions $\Leftrightarrow C_1 \cap C_2 = \emptyset$.
In this situation, every nonzero dual solution induces a separation of the sets.

Consistency of CFP and primal solutions

Assume that problem (P) has a solution

we study the set $C_1 \cap C_2$ in terms of the location of the solutions.

For that the subdifferential of the distance function d_C is given by

$$\partial d_C(x) = \begin{cases} 0 & \text{if } x \in \text{int } C, \\ N_C(x) \cap B & \text{if } x \in \text{Bd } C, \\ \frac{x - P_C(x)}{\|x - P_C(x)\|} & \text{if } x \notin C, \end{cases}$$

where $P_C(x)$ is the metric projection of x onto C .

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Theorem

- (a) $\inf_{x \in H} \|P_{C_1}(x) - P_{C_2}(x)\| = d(C_1, C_2)$.
- (b) The set of solutions of (P) is the set

$$\text{sol}(P) = \{x \in H : d(C_1, C_2) = \|P_{C_1}(x) - P_{C_2}(x)\|\}.$$

Corollary

Assume that $d(C_1, C_2) = 0$. In this situation, the following statements are equivalent.

- (i) (P) has no solutions.
- (ii) $0 \in \text{cl}(C_1 - C_2) \setminus (C_1 - C_2)$.
- (iii) $\sigma_{C_1} \square \sigma_{C_1}$ is not lsc at 0.
- (iv) $C_1 \cap C_2 = \emptyset$
- (v) $\{0\} \times \mathbb{R}_{--} \cap \text{epi}(\sigma_{C_1} \square \sigma_{C_2}) \neq \emptyset$.

THANK YOU! - ¡MUCHAS GRACIAS!