

Projections alternées pour des contraintes de convexité généralisées

Xavier Dupuis

LUISS University - Rome

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travail en collaboration avec Guillaume Carlier (Paris-Dauphine)

Outline

Motivation and assumptions

Projection problems over b -convex functions

Dykstra's algorithm and numerical results

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An example

The following problem arises in economics [Rochet, Choné '98]:

$$\min_{\substack{u \text{ convex} \\ u \geq 0}} \int [c(\nabla u(x)) - x \cdot \nabla u(x) + u(x)] d\mu(x)$$

Convexity constraint

- ▶ arises in various contexts (e.g. Newton's least resistance)
- ▶ no tractable Euler-Lagrange equation
- ▶ challenging for numerical methods:
[Carlier et al. '01], . . . , [Ekeland, Moreno-Bromberg '10],
[Oberman '13], [Mérigot, Oudet '14], [Mirebeau '15]

A generalization

Definition (*b*-convexity)

A function u is *b*-convex if for some function v and for all x

$$u(x) = \sup_{y \in Y} \{b(x, y) - v(y)\}$$

This notion is crucial in optimal transport [Gangbo, McCann '96].
For $b(x, y) = x \cdot y$, we recover the notion of convexity.

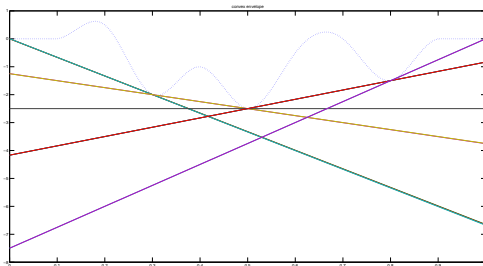


Figure: Convex vs *b*-convex envelope

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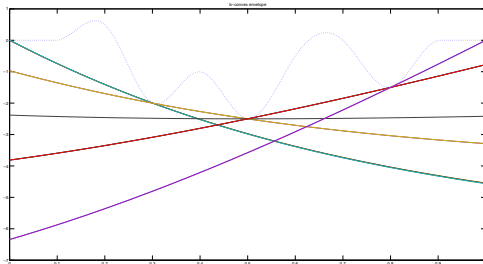


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b-convexity constraints

- ▶ arise in economics [Carlier '01]
- ▶ the *convexity of $\{u \text{ } b\text{-convex}\}$* requires assumptions on b [Figalli, Kim, McCann '11]
- ▶ no numerical method so far

The principal-agent problem

A **principal** (e.g. monopolist) faces

- ▶ a population of **agents**: agents of **type** $x \in X$ are present according to a **distribution** $d\mu(x)$;
- ▶ a range of **products**: products of **type** $y \in Y$ have **value** $b(x, y)$ for agents of type x and **cost** $c(y)$ for the principal.

She is looking for

- ▶ a **contract menu** $(y, p): X \rightarrow Y \times \mathbb{R} \cup \{+\infty\}$

which specifies that

- ▶ agents x buy the product $y(x)$ at the price $p(x)$

and which maximizes her profit $\int_X [p(x) - c(y(x))] d\mu(x)$.

Incentive compatibility constraint

The utility (to be maximized) of agents of type x is

- ▶ $b(x, y) - p$ for buying the product y at the price p , or
- ▶ zero for not buying anything (outside option).

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Adverse selection

Agents actually behave according to a contract menu (y, p) if it is **incentive compatible** and provide non-negative utility:

$$b(x, y(x)) - p(x) \geq b(x, y(x')) - p(x') \quad \forall (x, x'), \quad (\text{IC})$$

$$b(x, y(x)) - p(x) \geq 0 \quad \forall x. \quad (\text{IR})$$

The principal's problem is then the following optimization problem:

$$\min_{(y, p)} \int_X [c(y(x)) - p(x)] d\mu(x) \quad \text{subject to (IC)-(IR).}$$

Change of variables

Given (y, p) , we define u by $u(x) := b(x, y(x)) - p(x)$ for all x .
The incentive compatibility constraint (IC) becomes

$$u(x') - u(x) \geq b(x', y(x)) - b(x, y(x)) \quad \forall (x, x') \quad (\text{IC}')$$

If (y, u) satisfies (IC'), then

- ▶ $u(x) = \sup_y \{b(x, y) - v(y)\}$ for $v(y(x)) := p(x)$,
- ▶ u is b -convex, $\nabla u(x) = \frac{\partial b}{\partial x}(x, y(x))$ if u is differentiable at x .

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Assumption 1 The b -exponential map y_b is well defined by

$$y = y_b(x, q) \Leftrightarrow q = \frac{\partial b}{\partial x}(x, y).$$

Given (y, u) , we define q by $q(x) := \frac{\partial b}{\partial x}(x, y(x))$ for all x ,
we replace $y(x)$ by $y_b(x, q(x))$ in (IC') and we introduce

$$\Gamma_b(x', x, q) := b(x', y_b(x, q)) - b(x, y_b(x, q)).$$

The convexity issue

We therefore consider, more generally, the following problem:

$$\begin{aligned} \min_{(u,q)} \int_X L(x, u(x), q(x)) dx \quad \text{subject to} \\ u(x') - u(x) \geq \Gamma_b(x', x, q(x)) \quad \forall (x, x') \end{aligned} \quad (\text{IC''})$$

It is convex if $L(x, \cdot, \cdot)$ is convex for all x and if b satisfies **Assumption 2** The function $\Gamma_b(x', x, \cdot)$ is convex for all x, x' .
 [Figalli, Kim, McCann '11], [Carlier, D. '15]

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[Figalli, Kim, McCann '11], [Carlier, D. '15]

Remarks

- ▶ If (u, q) is feasible, then u is b -convex and $q = \nabla u$ a.e.
- ▶ For $b(x, y) = x \cdot y$, $\Gamma_b(x', x, q) = (x' - x) \cdot q$ and the convexity constraint (IC'') is as in [Ekeland, Moreno-Bromberg '10].

A tractable class of b

We consider perturbations of the scalar product

$$b(x, y) = x \cdot y + f(x)g(y) \quad \text{on } X \times \mathbb{R}^d$$

with f, g convex and C^1 , $g \geq 0$, $\inf_{x, y} \nabla f(x) \cdot \nabla g(y) > -1$;

- ▶ $\Gamma_b(x', x, q) = (x' - x) \cdot q + D_f(x', x)g(y_b(x, q))$ where
- ▶ $D_f \geq 0$ is the Bregman divergence associated to f ,
- ▶ $g(y_b(x, q))$ is the solution to the scalar equation

$$\lambda = g(q - \lambda \nabla f(x))$$

and can be shown to be convex w.r.t. q .

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Numerical implementation (to come)

- ▶ $f(x) = \sqrt{1 + |x|^2}$, $g(y) = \sqrt{1 + |y|^2}$
- ▶ closed form for $g(y_b(x, q))$

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Quadratic integrands

We consider a projection problem over b -convex functions, that we discretize for any $\{x_k\}_{1 \leq k \leq N} \subset X$ as follows:

$$\begin{aligned} \min_{((u_k)_k, (q_k)_k)} \sum_{k=1}^N \left[\frac{\alpha_k}{2} |q_k - \bar{q}_k|^2 + \frac{\beta_k}{2} |u_k - \bar{u}_k|^2 \right] \\ \text{subject to } u_i - u_j \geq \Gamma_b(x_i, x_j, q_j) \quad \forall (i, j) \quad (\text{IC''}) \end{aligned}$$

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subject to $u_i - u_j \geq \Gamma_b(x_i, x_j, q_j) \quad \forall (i, j) \quad (\text{IC}''')$

Solving these convex optimization problems, we get **interior and convergent approximations** of the continuous solution by setting

$$u^N(x) := \max_{1 \leq k \leq N} \{u_k + \Gamma_b(x, x_k, q_k)\}, \quad q^N(x) := \nabla u^N(x).$$

[Ekeland, Moreno-Bromberg '10] (convex case), [Carlier, D. '15]

Formulation as a projection problem

Introducing the **convex sets**, for all (i, j) , in $\mathbb{R}^N \times \mathbb{R}^{dN}$

$$C_{i,j} := \{(u, q) : u_i - u_j \geq \Gamma_b(x_i, x_j, q_j)\},$$

the discrete problem can be seen as a projection problem

- ▶ onto their intersection $C := \bigcap_{(i,j)} C_{i,j}$
- ▶ for the weighted Euclidean distance $D_{\alpha,\beta}$

where is to be found $P_C(\bar{u}, \bar{q})$, solution in $\mathbb{R}^N \times \mathbb{R}^{dN}$ to

$$\min_{(u,q) \in C} D_{\alpha,\beta}((u, q), (\bar{u}, \bar{q})).$$

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We solve it iteratively by **Dijkstra's algorithm** [Boyle, Dijkstra '86]: at each step we compute an **elementary projection** $P_{C_{i,j}}$ and then **cycle over the N^2 convex sets**; the sequence that we get converges.

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Elementary projections

Any elementary projection $P_{C_{i,j}}(\hat{u}, \hat{q},)$ coincides with (\hat{q}, \hat{u}) up to (u_i, u_j, q_j) , solution to

$$\min_{(u_i, u_j, q_j)} \frac{\alpha_j}{2} |q_j - \hat{q}_j|^2 + \frac{\beta_i}{2} |u_i - \hat{u}_i|^2 + \frac{\beta_j}{2} |u_j - \hat{u}_j|^2$$

subject to $u_i - u_j \geq \Gamma_b(x_i, x_j, q_j)$

- ▶ optimization problem in $\mathbb{R}^2 \times \mathbb{R}^d$ (instead of $\mathbb{R}^N \times \mathbb{R}^{dN}$)
- ▶ single scalar inequality constraint (instead of N^2)

We solve this problem by determining a primal-dual solution to

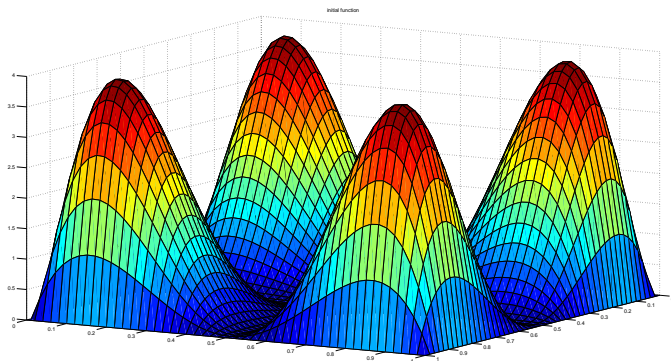
- ▶ the necessary and sufficient (KKT) optimality conditions
- ▶ by a Newton method when the constraint is active.

The projections are explicit in the convex case $b(x, y) = x \cdot y$.

H^1 projection on b -convex functions

$$\min_{(u,q)} \int_X \left[\frac{1}{2} |q(x) - \nabla \bar{u}(x)|^2 + \frac{1}{2} |u(x) - \bar{u}(x)|^2 \right] dx$$

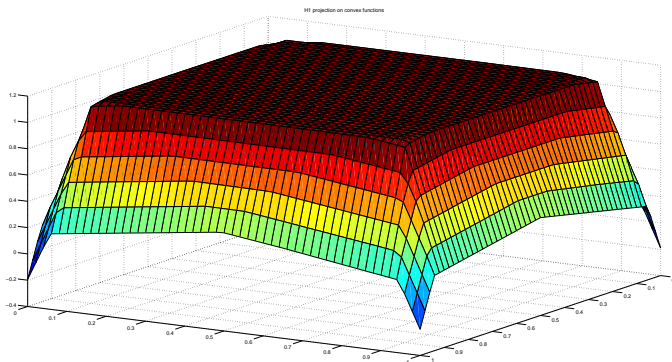
subject to (IC'')



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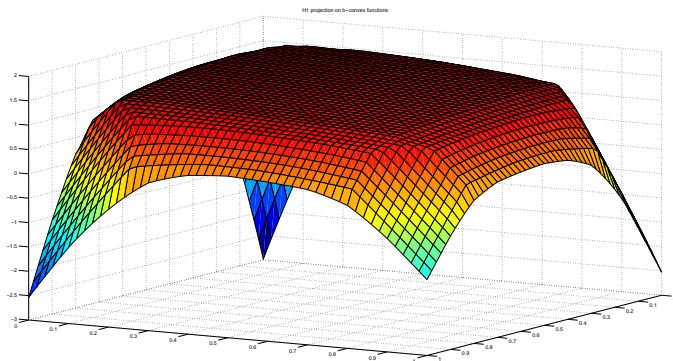
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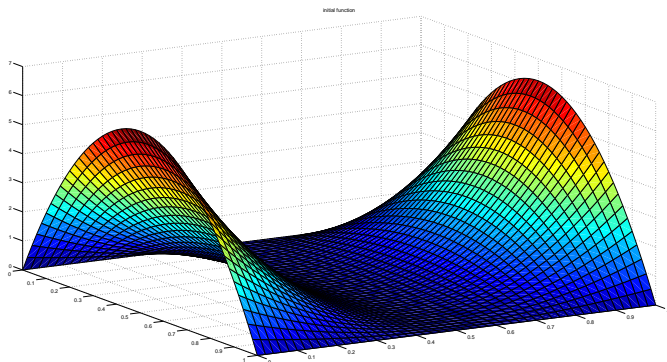
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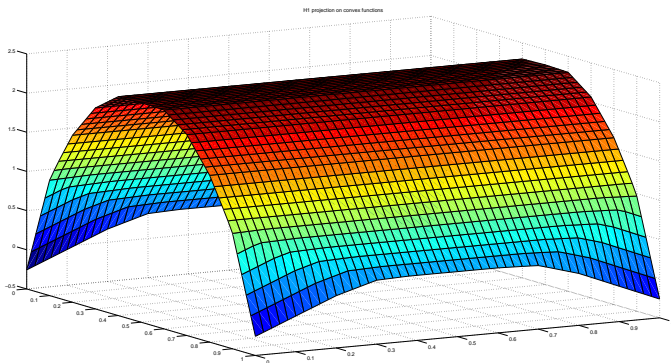
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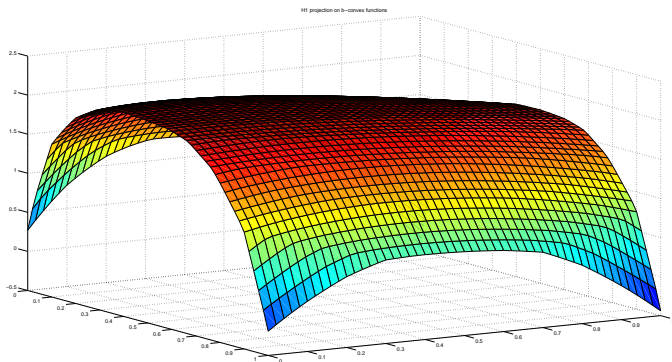
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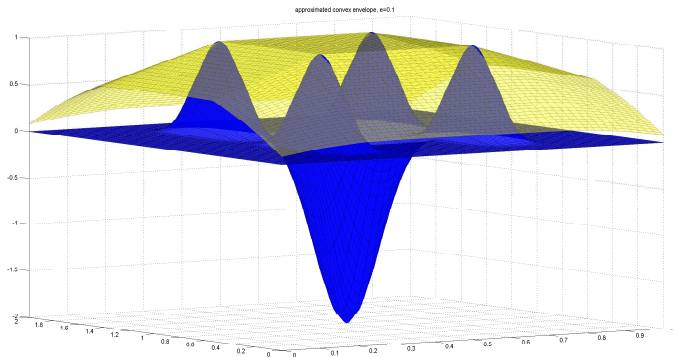
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Approximated b -convex envelope

$$\min_{(u,q)} \int_X \left[\frac{\varepsilon}{2} |q(x)|^2 + \frac{1}{2} |u(x) - \bar{u}(x)|^2 \right] dx$$

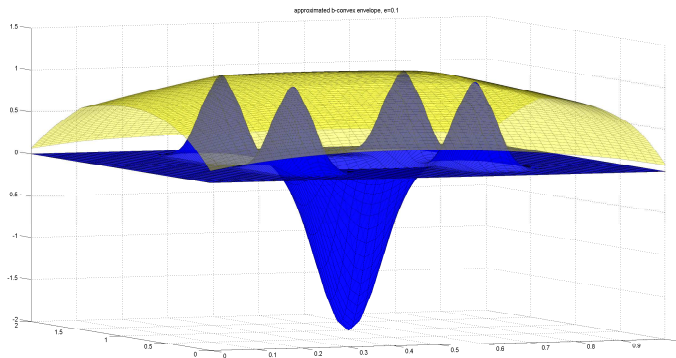
subject to (IC''), $u(x) \leq \bar{u}(x) \quad \forall x$



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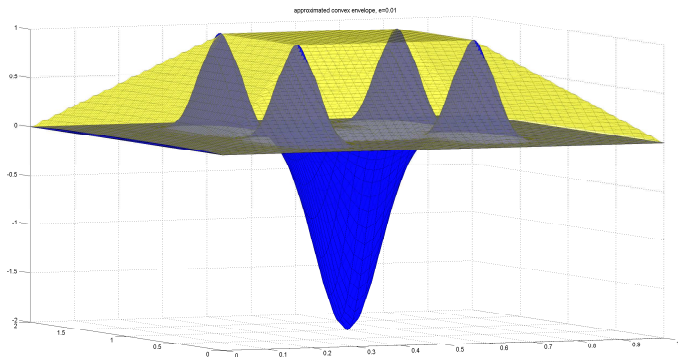
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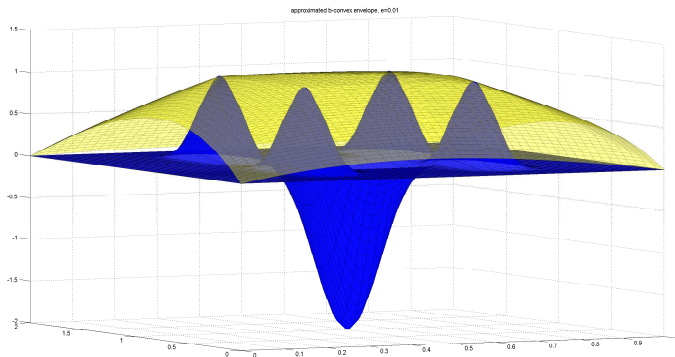
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Principal-agent problem

In the convex case $b(x, y) = x \cdot y$ and $c(y) = \frac{1}{2}|y|^2$,

$$\int_X \left[\frac{1}{2}|q(x)|^2 - x \cdot q(x) + u(x) \right] d\mu(x)$$

can be regularized to fit into the projections framework as

$$\int_X \left[\frac{1}{2}|q(x) - x|^2 + \frac{\varepsilon}{2}|u(x) + \frac{1}{\varepsilon}|^2 \right] d\mu(x).$$

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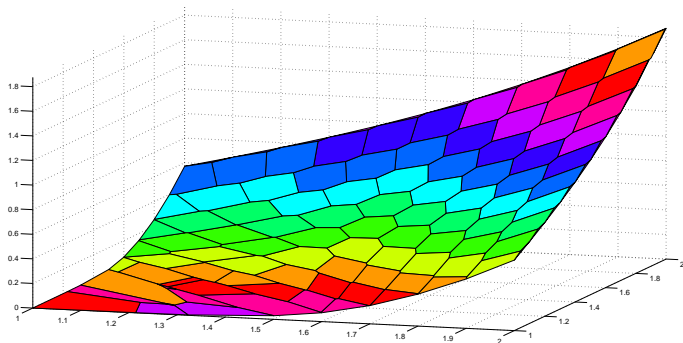
For more general $b(x, y) = x \cdot y + f(x)g(y)$, when the objective

$$\int_X \left[\frac{1}{2}|y_b(x, q(x))|^2 - b(x, y_b(x, q(x))) + \frac{\varepsilon}{2}|u(x) + \frac{1}{\varepsilon}|^2 \right] d\mu(x)$$

is a **Bregman distance** (in particular strictly convex) in (q, u) , an extension of Dijkstra's algorithm is available [[Baushcke, Lewis '98](#)].

Principal-agent problem

Indirect utility of the agents in the convex case
(μ uniform distribution)



Principal-agent problem

Distribution of the types of products sold in the convex case
(μ uniform distribution)

