

Perspectives of Capra-convexity in sparse optimization

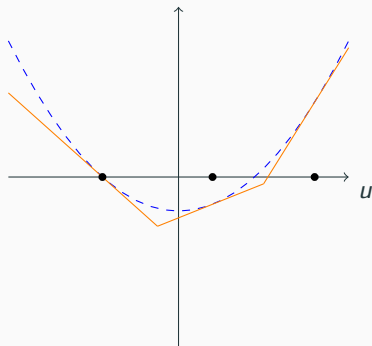
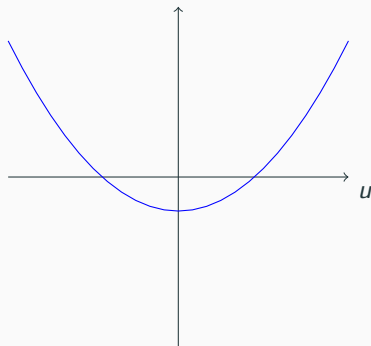
BrainPOP seminar - 14th February 2021

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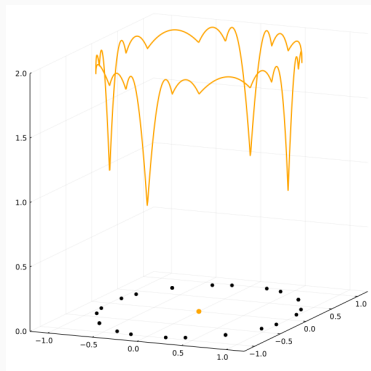
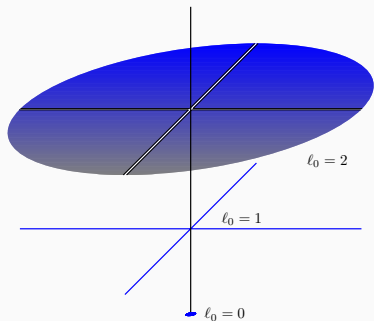


Fenchel conjugate, subdifferential, and polyhedral approximate of a convex lower semicontinuous function



$$f(u) \geq \max_{\substack{v_i \in \partial f(u_i) \\ i \in I}} (\langle u, v_i \rangle + (-f^*(v_i)))$$

Beyond convex lower semicontinuous functions...



$$l_0(u) \geq \max_{\substack{v_i \in \partial_{\dot{C}} l_0(u_i) \\ i \in I}} \left(\dot{C}(u, v_i) + (-l_0^{\dot{C}}(v_i)) \right)$$

Outline of the presentation

1. Background notions on generalized convexity
2. The Capra coupling and the ℓ_0 pseudonorm
3. Perspectives in sparse optimization
4. Conclusion

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1. **Background notions on generalized convexity**
2. The Capra coupling and the ℓ_0 pseudonorm
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Couplings and generalized Fenchel-Moreau conjugacies

$$\overline{\mathbb{R}} = \mathbb{R} \cup \{-\infty, +\infty\} \quad \text{and} \quad (+\infty) \dot{+} (-\infty) = (-\infty) \dot{+} (+\infty) = -\infty$$

Definition

Two sets \mathbb{U} ("Primal") and \mathbb{V} ("Dual") paired by

a **coupling function** $c : \mathbb{U} \times \mathbb{V} \rightarrow \overline{\mathbb{R}}$

give rise to the **c -Fenchel-Moreau conjugacy**

$$f \in \overline{\mathbb{R}}^{\mathbb{U}} \mapsto f^c \in \overline{\mathbb{R}}^{\mathbb{V}}$$

$$f^c(v) = \sup_{u \in \mathbb{U}} \left(c(u, v) \dot{+} (-f(u)) \right), \quad \forall v \in \mathbb{V}$$

Example: two vector spaces \mathbb{U} and \mathbb{V} paired with a bilinear form $\langle \cdot, \cdot \rangle$

give rise to the classic Fenchel conjugacy $f \in \overline{\mathbb{R}}^{\mathbb{U}} \mapsto f^* \in \overline{\mathbb{R}}^{\mathbb{V}}$

Generalized c -biconjugate and c -convexity

- We also introduce the **c' -Fenchel-Moreau conjugacy**

$$g \in \overline{\mathbb{R}}^{\mathbb{V}} \mapsto g^{c'} \in \overline{\mathbb{R}}^{\mathbb{U}}, \quad g^{c'}(u) = \sup_{v \in \mathbb{V}} \left(\underbrace{c(u, v)}_{=c'(v, u)} \dot{+} (-g(v)) \right), \quad \forall u \in \mathbb{U}$$

- This gives rise to the **c -Fenchel-Moreau biconjugate**

$$f \in \overline{\mathbb{R}}^{\mathbb{U}} \mapsto f^{cc'} \in \overline{\mathbb{R}}^{\mathbb{U}}, \quad f^{cc'}(u) = (f^c)^{c'}(u), \quad \forall u \in \mathbb{U}$$

Definition

A function $f \in \overline{\mathbb{R}}^{\mathbb{U}}$ is **c -convex** if $f = f^{cc'}$, that is

$$f(u) = \sup_{v \in \mathbb{V}} \left(c(u, v) \dot{+} (-f^c(v)) \right), \quad \forall u \in \mathbb{U}$$

Example: a proper function $f \in \overline{\mathbb{R}}^{\mathbb{U}}$ is $\langle \cdot, \cdot \rangle$ -convex iff f is convex and lsc

Generalized c -subdifferential

Definition

The **c -subdifferential** of a function $f \in \overline{\mathbb{R}}^{\mathbb{U}}$ at $u \in \mathbb{U}$ with respect to the coupling c is the subset $\partial_c f(u) \subseteq \mathbb{V}$ defined equivalently either by

$$v \in \partial_c f(u) \iff f^c(v) = c(u, v) \dot{+} (-f(u))$$

or by

$$v \in \partial_c f(u) \iff c(u, v) \dot{+} (-f(u)) \geq c(u', v) \dot{+} (-f(u')), \quad \forall u' \in \mathbb{U}$$

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 - Capra-convexity of ℓ_0
 - Capra-subdifferential of the ℓ_0 pseudonorm
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The Capra coupling

Definition (Chancelier and De Lara [2020])

Let $\|\cdot\|$ be a norm on \mathbb{R}^d called the **source norm**

we define the **Capra coupling** $\mathbb{R}^d \overset{\zeta}{\longleftrightarrow} \mathbb{R}^d$ by

$$\forall v \in \mathbb{R}^d, \zeta(u, v) = \begin{cases} \frac{\langle u, v \rangle}{\|u\|} & \text{if } u \neq 0 \\ 0 & \text{if } u = 0 \end{cases}$$

The coupling Capra is **Constant Along Primal Rays (Capra)**

The ℓ_0 pseudonorm

$$\ell_0(u) = |\{j \in \{1, \dots, d\} \mid u_j \neq 0\}|, \quad \forall u \in \mathbb{R}^d$$

Proposition (Chancelier and De Lara [2021])

If both the source norm $\|\cdot\|$ and the dual norm $\|\cdot\|_*$ are **orthant-strictly monotonic**, we have that

$$\begin{aligned} \ell_0 &= \ell_0^{\dot{C}\dot{C}'} \\ \partial_{\dot{C}} \ell_0(u) &\neq \emptyset, \quad \forall u \in \mathbb{R}^d \end{aligned}$$

that is, the pseudonorm ℓ_0 is **Capra-convex** and **Capra-subdifferentiable** everywhere on \mathbb{R}^d

Examples: $\begin{cases} \|(0, 1)\|_\infty = \|(1, 1)\|_\infty = 1 \text{ hence } \ell_\infty \text{ is not OSM} \\ \ell_2 \text{ is OSM} \end{cases}$

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Explicit formulations for the Capra-subdifferential of ℓ_0

Proposition (Le Franc et al. [2021])

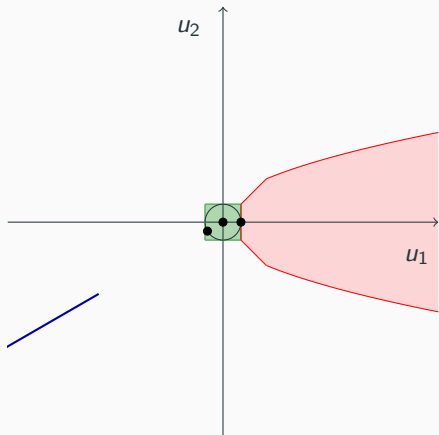
For the source norms $\|\cdot\| = \ell_p, p \in]1, \infty[$, we have that

$$\partial_{\dot{\zeta}} \ell_0(0) = \mathbb{B}_{\ell_\infty}$$

and if $u \neq 0, I = \ell_0(u), L = \text{supp}(u)$, for $v \in \mathbb{R}^d, |v_{\nu(1)}| \geq \dots \geq |v_{\nu(d)}|$, $\|v\|_{(k,q)}^{\text{tn}} = (|v_{\nu(1)}|^q + \dots + |v_{\nu(k)}|^q)^{\frac{1}{q}}$ and $\frac{1}{p} + \frac{1}{q} = 1$

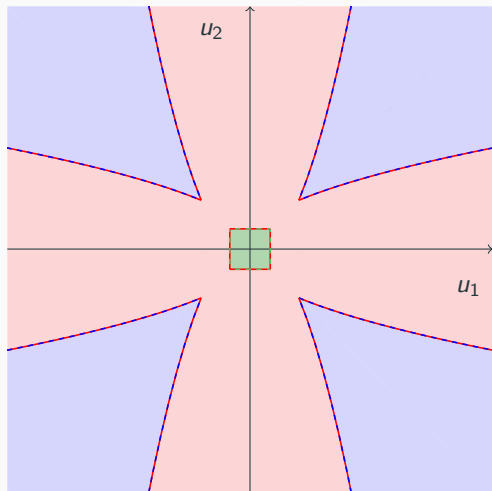
$$v \in \partial_{\dot{\zeta}} \ell_0(u) \iff \begin{cases} v_L \in \mathcal{N}_{\mathbb{B}_{\|\cdot\|_p}}\left(\frac{u}{\|u\|_p}\right) \\ |v_j| \leq \min_{i \in L} |v_i|, \quad \forall j \notin L \\ |v_{\nu(k+1)}|^q \geq (\|v\|_{(k,q)}^{\text{tn}} + 1)^q - (\|v\|_{(k,q)}^{\text{tn}})^q, \quad \forall k < I \\ |v_{\nu(I+1)}|^q \leq (\|v\|_{(I,q)}^{\text{tn}} + 1)^q - (\|v\|_{(I,q)}^{\text{tn}})^q \end{cases}$$

Examples of sets $\partial_{\zeta} \ell_0(u)$ in \mathbb{R}^2 with the source norm $\|\cdot\| = \ell_2$



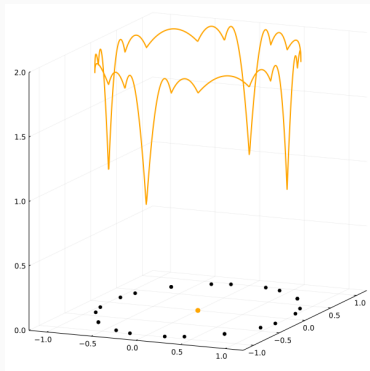
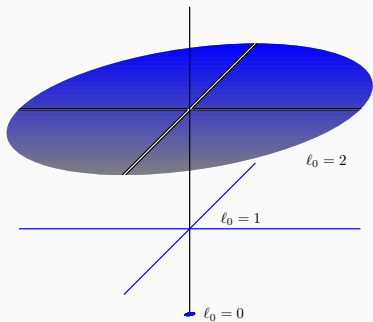
$$\partial_{\zeta} \ell_0(\mathbf{0}, \mathbf{0}), \partial_{\zeta} \ell_0(\mathbf{1}, \mathbf{0}), \partial_{\zeta} \ell_0\left(-\frac{\sqrt{3}}{2}, -\frac{1}{2}\right)$$

Visualisation of $\partial_{\zeta} \ell_0$ in \mathbb{R}^2 with the source norm $\|\cdot\| = \ell_2$



$$\partial_{\zeta} \ell_0(0) \cup \left\{ \bigcup_{\ell_0(u)=1} \partial_{\zeta} \ell_0(u) \right\} \cup \left\{ \bigcup_{\ell_0(u)=2} \partial_{\zeta} \ell_0(u) \right\}$$

Polyhedral-like approximation of ℓ_0



$$\ell_0(u) \geq \max_{\substack{v_i \in \partial_{\dot{\zeta}} \ell_0(u_i) \\ i \in I}} \left(\dot{\zeta}(u, v_i) + (-\ell_0^{\dot{\zeta}}(v_i)) \right)$$

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A key property

we see that if we introduce

$$\mathbb{S}^{(0)} = \mathbb{S} \cup \{0\}$$

and the **normalization mapping**

$$n : \mathbb{R}^d \rightarrow \mathbb{S}^{(0)}, \quad n(u) = \begin{cases} \frac{u}{\|u\|} & \text{if } u \neq 0 \\ 0 & \text{if } u = 0 \end{cases}$$

the Capra coupling is **One-sided linear (OSL)**

$$\dot{\langle} (u, v) = \langle n(u), v \rangle, \quad \forall (u, v) \in (\mathbb{R}^d)^2$$

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Capra-convex sparse optimization problems

We consider problems of type

$$\min_{u \in U} \ell_0(u)$$

and we look for constraint sets $U \subseteq \mathbb{U}$ for which we have a **Capra-convex (sparse) optimization problem**

Definition

We say that **the set $U \subseteq \mathbb{U}$ is Capra-convex** if the indicator function **δ_U is a Capra-convex function**

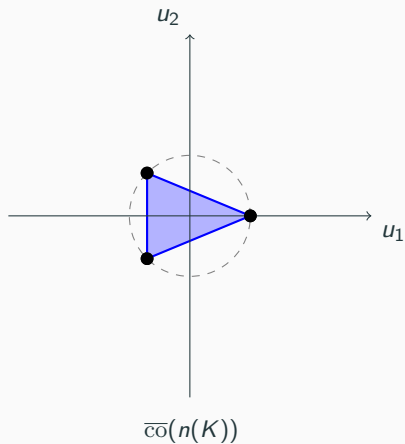
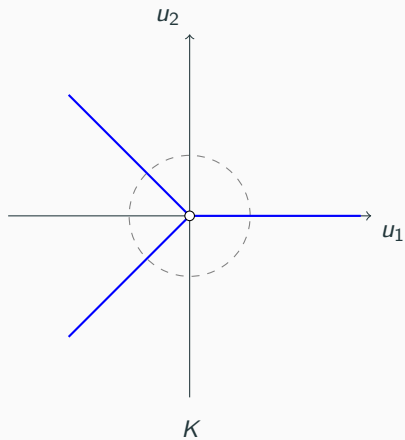
Which sets are Capra-convex ?

Proposition (Le Franc [2021])

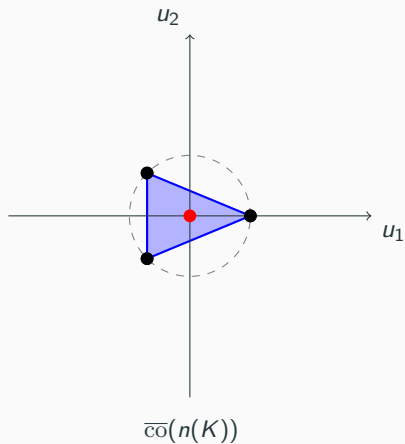
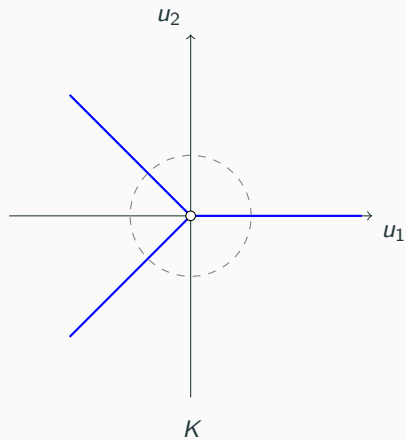
Let the source norm $\|\cdot\| = \|\cdot\|_p$, $p \in]1, \infty[$
and $U \subseteq \mathbb{U}$ be a nonempty set

$$U \text{ is Capra-convex} \iff \begin{cases} U \text{ is a cone} \\ U \cup \{0\} \text{ is closed} \\ U \cap \{0\} = \overline{\text{co}}(n(U)) \cap \{0\} \end{cases}$$

Example with $\|\cdot\| = \ell_2$: a non Capra-convex cone

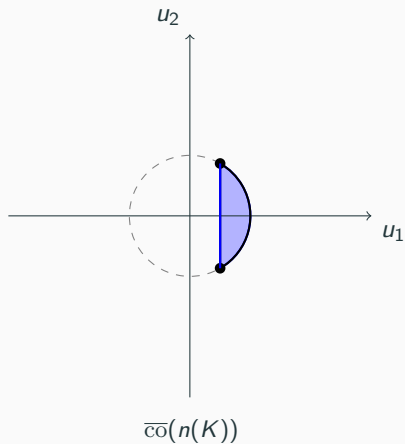
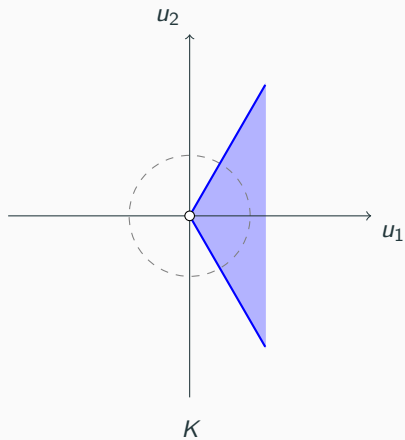


Example with $\|\cdot\| = \ell_2$: a non Capra-convex cone

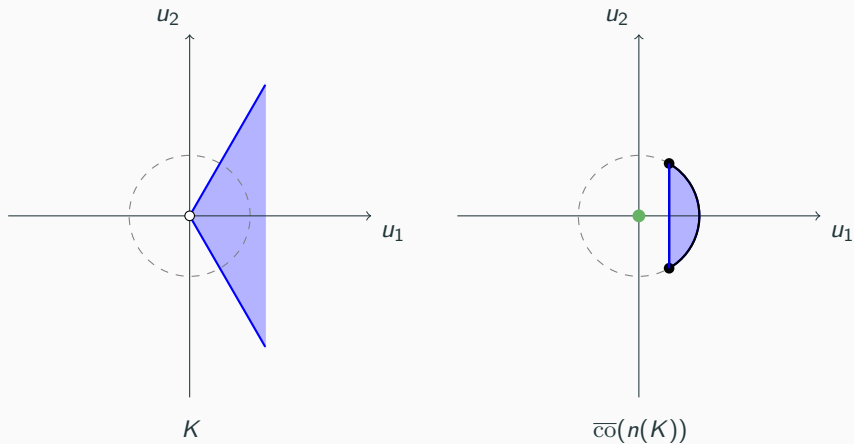


$$K \cap \{0\} \neq \overline{\text{co}}(n(K)) \cap \{0\}$$

Example with $\|\cdot\| = \ell_2$: a Capra-convex cone



Example with $\|\cdot\| = \ell_2$: a Capra-convex cone



$$K \cap \{0\} = \overline{\text{co}}(n(K)) \cap \{0\}$$

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The standard Bregman divergence

Definition

Let \mathbb{U} and \mathbb{V} be two vector spaces paired by a bilinear form $\langle \cdot, \cdot \rangle$
let $\kappa \in \overline{\mathbb{R}}^{\mathbb{U}}$ be a proper, closed, convex and differentiable
(divergence generating) function.

We define the **Bregman divergence associated with κ** by

$$D_{\kappa}(u, u') = \kappa(u) - \kappa(u') - \langle u - u', \nabla \kappa(u') \rangle , \\ \forall (u, u') \in \mathbb{U} \times \text{dom}(\nabla \kappa)$$

D_{κ} is not a distance, but if κ is **strongly convex**

- $D_{\kappa}(u, u') \geq 0$, $\forall (u, u') \in \mathbb{U} \times \text{dom}(\nabla \kappa)$
- $D_{\kappa}(u, u') = 0 \iff u = u'$
- We have a “triangular inequality”
that makes mirror descent work

The Bregman divergence with couplings

Definition

Let \mathbb{U} and \mathbb{V} be two sets and a **finite coupling** $\mathbb{U} \xleftrightarrow{c} \mathbb{V}$
let $\kappa \in \overline{\mathbb{R}}^{\mathbb{U}}$ be a proper c -convex (divergence generating) function.
We define the **c -Bregman divergence associated with κ** by

$$D_{\kappa}^c(u, u', v') = \kappa(u) - \kappa(u') - c(u, v') + c(u', v') , \\ \forall (u, u') \in \mathbb{U} \times \text{dom}(\partial_c \kappa) , \quad \forall v' \in \partial_c \kappa(u')$$

If moreover

- \mathbb{V} is a vector space
- The coupling c is **OSL**
- The function κ is **c -strongly convex**

We retrieve some properties of the original Bregman divergence

The mirror descent algorithm with OSL couplings

We consider the optimization problem

$$\min_{u \in U} f(u)$$

- We initialize three sequences by

$$u_0 \in U$$

$$v_0 \in \partial_c(\kappa + \delta_U)(u_0)$$

$$v_0^f \in \partial_c f(u_0)$$

- We run $N \in \mathbb{N}$ steps with a step size $\alpha_n > 0$ and the update rules

$$u_{n+1} \in \arg \min_{u \in U} \left(\kappa(u) + c(u, \alpha_n v_n^f - v_n) \right)$$

$$v_{n+1} = v_n - \alpha_n v_n^f$$

$$v_{n+1}^f \in \partial_c f(u_{n+1})$$

Theorem (Le Franc [2021])

Under a suitable choice of divergence generating function κ we can bound the optimality gap by

$$\min_{0 \leq n \leq N-1} \left(f(u_n) - \inf_{u \in U} f(u) \right) \leq \frac{R^2 + \frac{G^2}{4} \sum_{n=0}^{N-1} \alpha_n^2}{\sum_{n=0}^{N-1} \alpha_n}$$

- R and G are constant values determined by the problem and by κ
- We retrieve the same convergence rule as in the standard mirror descent algorithm

Solving $\min_{u \in K} \ell_0(u)$?

- We need to identify suitable **divergence generating functions** κ such that $\kappa + \delta_K$ is **Capra-strongly convex**
- We need to make sure that we can **compute efficiently**

$$u_{n+1} \in \arg \min_{u \in K} (\kappa(u) + \zeta(u, \alpha_n v_n^f - v_n))$$

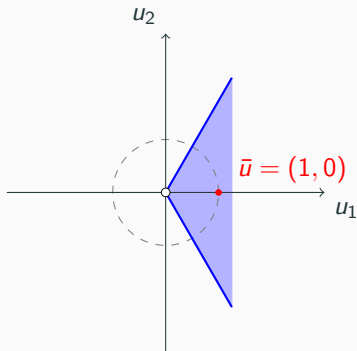
Not that simple...

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An example where the subdifferential of the sum...

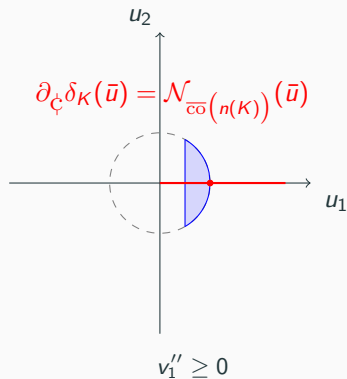
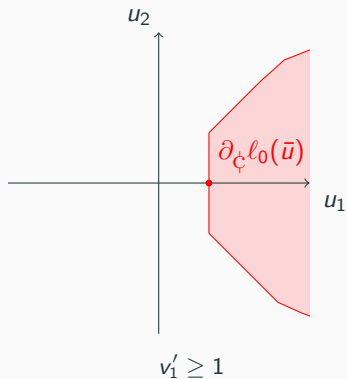
$$\|\cdot\| = \ell_2$$



$$\bar{u} \in \arg \min_{\mathcal{K}} \ell_0 \implies 0 \in \partial_{\dot{\zeta}}(\ell_0 + \delta_{\mathcal{K}})(\bar{u}) \quad (\text{a property of OSL couplings})$$

...is not the sum of the subdifferentials

Let $v' \in \partial_{\zeta} l_0(\bar{u})$ and $v'' \in \partial_{\zeta} \delta_K(\bar{u})$



$0 \notin \partial_{\zeta} l_0(\bar{u}) + \partial_{\zeta} \delta_K(\bar{u})$ hence $\partial_{\zeta} l_0(\bar{u}) + \partial_{\zeta} \delta_K(\bar{u}) \subsetneq \partial_{\zeta} (l_0 + \delta_K)(\bar{u})$

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Conclusion

Background notions:

- Standard tools of convex analysis (Fenchel conjugacies, subdifferentials...) extend well to general couplings
- The Capra coupling is OSL and well suited to handle ℓ_0

Novelties:

- We have explicated **the Capra-subdifferential of ℓ_0**
- We have identified **Capra-convex sets**
- We have introduced an extension of **the mirror descent algorithm with OSL couplings**

Perspectives: still a long way for numerical applications but they could raise from the mirror descent algorithm



Figure 7: [https://en.wikipedia.org/wiki/Capra_\(genus\)](https://en.wikipedia.org/wiki/Capra_(genus))

- Jean-Philippe Chancelier and Michel De Lara. Constant along primal rays conjugacies and the ℓ_0 pseudonorm. *Optimization*, 0(0):1–32, 2020. URL <https://doi.org/10.1080/02331934.2020.1822836>.
- Jean-Philippe Chancelier and Michel De Lara. Capra-convexity, convex factorization and variational formulations for the ℓ_0 pseudonorm. *Set-Valued and Variational Analysis*, pages 1–23, 2021.
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- Adrien Le Franc, Jean-Philippe Chancelier, and Michel De Lara. The Capra-subdifferential of the ℓ_0 pseudonorm. 2021. URL <https://hal.archives-ouvertes.fr/hal-03505168>.