

Gauge optimization: Duality and polar envelope

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April 2019
(Joint work with Michael Friedlander and Ives Macêdo)

Motivating example

Minimum norm solutions:

- In sparse optimization:

$$\begin{aligned} \min \quad & \|x\|_1 \\ \text{s.t.} \quad & \|b - Ax\| \leq \sigma, \end{aligned}$$

where $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$ and $\sigma < \|b\|$.

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- More generally, minimization of **atomic norm** (Chandrasekaran et al. '12)

$$\|x\|_{\mathcal{A}} = \inf\{\lambda \geq 0 : x \in \lambda \text{conv } \mathcal{A}\},$$

where \mathcal{A} is a set of “atoms” characterizing the notion of sparsity:

- ★ $\mathcal{A} = \{\pm e_i : i = 1, \dots, n\} \Rightarrow \|x\|_{\mathcal{A}} = \sum_{i=1}^n |x_i|$.
- ★ $\mathcal{A} = \text{unit norm rank 1 matrices} \Rightarrow \|X\|_{\mathcal{A}} = \sum_{i=1}^n \sigma_i(X)$.

Gauges

- Gauges are **generalizations of norms**: nonnegative convex positively homogeneous functions that are zero at the origin.
- $\kappa(x) = \inf\{\lambda \geq 0 : x \in \lambda U\}$ for some convex set U .

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- $\kappa(x) = \inf\{\lambda \geq 0 : x \in \lambda U\}$ for some convex set U .
- Polar gauge generalizes **dual norm**:

$$\begin{aligned}\kappa^\circ(y) &= \inf\{\lambda > 0 : \langle x, y \rangle \leq \lambda \kappa(x) \forall x\} \\ &= \sup\{\langle x, y \rangle : \kappa(x) \leq 1\}.\end{aligned}$$

- **Generalized Cauchy inequality**: for all $x \in \text{dom } \kappa$ and $y \in \text{dom } \kappa^\circ$,

$$\langle x, y \rangle \leq \kappa(x)\kappa^\circ(y).$$

Gauge optimization

$$\begin{aligned} v_\rho &:= \min && \kappa(x) \\ &\text{s.t.} && \rho(\mathbf{b} - A\mathbf{x}) \leq \sigma. \end{aligned} \quad (\mathbf{P}_\rho)$$

- κ is a gauge.
- ρ is a closed gauge with $\rho^{-1}(0) = \{0\}$, $0 \leq \sigma < \rho(\mathbf{b})$.

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- κ is a **gauge**.
- ρ is a **closed gauge** with $\rho^{-1}(0) = \{0\}$, $0 \leq \sigma < \rho(\mathbf{b})$.
- Lagrange and gauge dual problems:

$$\begin{aligned} v_\ell &:= \max && \langle \mathbf{b}, \mathbf{y} \rangle - \sigma \rho^\circ(\mathbf{y}) \\ &\text{s.t.} && \kappa^\circ(A^* \mathbf{y}) \leq 1. \end{aligned} \quad \begin{aligned} v_g &:= \min && \kappa^\circ(A^* \mathbf{y}) \\ &\text{s.t.} && \langle \mathbf{b}, \mathbf{y} \rangle - \sigma \rho^\circ(\mathbf{y}) \geq 1. \end{aligned}$$

- The role of objective and constraint is **reversed** in the gauge dual.

Outline

- Gauge duality: general framework.
- Gauge duality: structured problem.
- Smoothing technique: polar envelope.
- Projected polar proximal point algorithm.

Gauge duality framework

Let \mathcal{C} be a **nonempty** closed convex set **not containing the origin**, and define its anti-polar

$$\mathcal{C}' = \{u : \langle u, x \rangle \geq 1 \quad \forall x \in \mathcal{C}\}.$$

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Freund ('87) defined the following primal-dual gauge pairs:

$$\begin{aligned} v_p &:= \min && \kappa(x) \\ &\text{s.t.} && x \in \mathcal{C}, \end{aligned} \tag{P}$$

$$\begin{aligned} v_g &:= \min && \kappa^\circ(u) \\ &\text{s.t.} && u \in \mathcal{C}'. \end{aligned} \tag{D}$$

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Theorem 1. [Strong duality] (Freund '87)

Suppose that κ is closed, $\text{ri dom } \kappa^\circ \cap \text{ri } \mathcal{C}' \neq \emptyset$ and $\text{ri dom } \kappa \cap \text{ri } \mathcal{C} \neq \emptyset$. Then $v_p v_g = 1$ and both values are attained.

Anti-polar calculus

Let $\mathcal{D} := \{u : \rho(b - u) \leq \sigma\}$. Then

$$\mathcal{C} = \{x : \rho(b - Ax) \leq \sigma\} = A^{-1}\mathcal{D}.$$

How do we compute \mathcal{C}' ?

Fact 2.

$$\mathcal{D}' = \{y : \langle b, y \rangle - \sigma \rho^\circ(y) \geq 1\}.$$

Proposition 1. (Friedlander, Macêdo, P. '14)

$$(A^{-1}\mathcal{D})' = \text{cl}(A^*\mathcal{D}').$$

If, in addition, $\text{ri } \mathcal{D} \cap \text{Range } A \neq \emptyset$, then

$$(A^{-1}\mathcal{D})' = A^*\mathcal{D}' = \{A^*y : \langle b, y \rangle - \sigma \rho^\circ(y) \geq 1\}.$$

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Let $\mathcal{D} := \{u : \rho(\mathbf{b} - u) \leq \sigma\}$ so that primal feasible set is $\mathbf{A}^{-1}\mathcal{D}$.

Theorem 2. (Friedlander, Macêdo, P. '14)

Suppose that κ is closed, $\text{ri dom } \kappa^\circ \cap \text{ri } \mathbf{A}^*\mathcal{D}' \neq \emptyset$ and $\text{ri dom } \kappa \cap \mathbf{A}^{-1}\text{ri } \mathcal{D} \neq \emptyset$. Then $v_\rho v_g = 1$ and both values are attained.

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Unlike the Lagrange dual, the gauge dual (\mathbf{D}_ρ) has a complicated objective and simple constraint.

Solution method: Smoothing

For proper closed convex functions f_1 and f_2 , with **suitable CQ**:

$$\begin{array}{ccc}
 \underset{x}{\text{minimize}} & f_1(x) + f_2(x) & \xrightarrow{\text{addition}} & \underset{x}{\text{minimize}} & (f_1 + \frac{\alpha}{2} \|\cdot\|_2^2)(x) + f_2(x) \\
 \uparrow \text{Fenchel} & & & & \uparrow \text{Fenchel} \\
 \text{duality} & x \in \partial f_1^*(y) \cap \partial f_2^*(-y) & & & x = \nabla (f_1^* \square \frac{1}{2\alpha} \|\cdot\|_2^2)(y) \\
 \downarrow & & & & \downarrow \\
 \underset{y}{\text{minimize}} & f_1^*(y) + f_2^*(-y) & \xrightarrow{\text{sum convolution}} & \underset{y}{\text{minimize}} & (f_1^* \square \frac{1}{2\alpha} \|\cdot\|_2^2)(y) + f_2^*(-y)
 \end{array}$$

Here, $f_1^* \square \frac{1}{2\alpha} \|\cdot\|^2$ is the **Moreau envelope** of αf_1^* :

$$(f_1^* \square \frac{1}{2\alpha} \|\cdot\|^2)(x) := \inf_{y \in \mathbb{R}^n} \left\{ f_1^*(y) + \frac{1}{2\alpha} \|x - y\|^2 \right\}$$

which is **smooth**.

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which is **smooth**. Does not preserve gauge structure!

Polar envelope

Definition. (Friedlander, Macêdo, P. '18)

Let κ be a gauge, $\alpha > 0$. The polar envelope and polar proximal mapping are

$$\kappa_{\alpha}(x) := \inf_z \max \left\{ \kappa(z), \frac{1}{\alpha} \|x - z\| \right\},$$

$$\text{pprox}_{\alpha\kappa}(x) := \text{Arg min}_z \max \left\{ \kappa(z), \frac{1}{\alpha} \|x - z\| \right\}.$$

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Note:

- For proper convex functions f_1 and f_2 , their **max-convolution** is

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- For **gauges** κ_1 and κ_2 : (Friedlander, Macêdo, P. '18)

$$(\kappa_1 \diamond \kappa_2)^\circ = \kappa_1^\circ + \kappa_2^\circ.$$

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Recall that for proper convex functions f_1 and f_2 , $(f_1 \square f_2)^* = f_1^* + f_2^*$.

Polar envelope: Differential properties

Theorem 3. (Friedlander, Macêdo, P. '18)

Let κ be a gauge and $\alpha > 0$.

- (i) If $\bar{x} \in \text{pprox}_{\alpha\kappa}(x)$, then $\|x - \bar{x}\| \geq \alpha\kappa(\bar{x})$. If in addition κ is continuous, then $\|x - \bar{x}\| = \alpha\kappa(\bar{x})$.
- (ii) If κ is **closed**, then $\text{pprox}_{\alpha\kappa}(x)$ is a singleton for all x , and $\text{pprox}_{\alpha\kappa}$ is continuous and positively homogeneous.
- (iii) Suppose κ is **closed**. Then κ_α is differentiable at all x such that $\kappa_\alpha(x) > 0$. Moreover, at these x , it holds that $\langle x, x - \bar{x} \rangle > 0$ and

$$\nabla \kappa_\alpha(x) = \frac{\|x - \bar{x}\|}{\alpha \langle x, x - \bar{x} \rangle} (x - \bar{x}),$$

where $\bar{x} = \text{pprox}_{\alpha\kappa}(x)$.

Polar envelope: Explicit example

Proposition 2. (Friedlander, Macêdo, P. '18)

Let κ be a **continuous gauge**. Then for any x satisfying $\kappa_\alpha(x) > 0$, it holds that

$$\kappa_\alpha(x) = \bar{r} \text{ and } \text{pprox}_{\alpha\kappa}(x) = \text{Proj}_{[\kappa \leq \bar{r}]}(x),$$

where \bar{r} is the **unique root** satisfying

$$\alpha^2 \bar{r}^2 = \|x - \text{Proj}_{[\kappa \leq \bar{r}]}(x)\|^2. \quad (\clubsuit)$$

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Example: Consider $\kappa = \|\cdot\|_\infty$. For $x \neq 0$, (\clubsuit) becomes

$$\alpha^2 \bar{r}^2 = \sum_{i=1}^n (|x_i| - \bar{r})_+^2 \quad \xleftrightarrow{\bar{r} = \bar{\gamma}^{-1}} \quad \alpha^2 = \sum_{i=1}^n (\bar{\gamma}|x_i| - 1)_+^2.$$

Solved by simple **root-finding** procedure.

Solution method: Smoothing revisited

For **closed gauges** κ, ρ satisfying $\kappa^{-1}(0) = \{0\}$ and $\rho^{-1}(0) = \{0\}$, $\mathcal{C} = \{x : \rho(b - Ax) \leq \sigma\}$ and $\sigma \in [0, \rho(b))$, with **suitable CQ**:

$$\begin{array}{ccc}
 \underset{x \in \mathcal{C}}{\text{minimize}} \kappa(x) & \xrightarrow{\text{addition}} & \underset{x \in \mathcal{C}}{\text{minimize}} (\kappa + \alpha \|\cdot\|_2)(x) \\
 \updownarrow \text{gauge duality} & & \updownarrow \text{gauge duality} \\
 x \in [\text{cl cone } \partial \kappa^\circ(y)] \cap \partial \delta_{\mathcal{C}}^*(-y) & & x = (\text{Theorem 6.2})(y) \\
 \underset{y \in \mathcal{C}'}{\text{minimize}} \kappa^\circ(y) & \xrightarrow{\text{max convolution}} & \underset{y \in \mathcal{C}'}{\text{minimize}} (\kappa^\circ \diamond \frac{1}{\alpha} \|\cdot\|_2)(y)
 \end{array}$$

Here, “ $x = (\text{Theorem 6.2})(y)$ ” refers to (Friedlander, Macêdo, P. '18)

$$\bar{x} = \frac{\bar{r}^{-1}}{\kappa(\text{prox}_{\bar{r}\kappa}(A^*\bar{u})) + \alpha \|\text{prox}_{\bar{r}\kappa}(A^*\bar{u})\|} \text{prox}_{\bar{r}\kappa}(A^*\bar{u}),$$

where $A^*\bar{u}$ solves the **smoothed gauge dual** with optimal value \bar{r} .

Projected polar proximal point algorithm

Let f be **proper closed convex** with $\inf f > 0$ and $\text{Arg min } f \neq \emptyset$. Then

$$\min_x f(x) \text{ if and only if } \min_{\lambda=1,x} f^\pi(x, \lambda),$$

where

$$f^\pi(x, \lambda) := \begin{cases} \lambda f(\lambda^{-1}x) & \text{if } \lambda > 0, \\ f_\infty(x) & \text{if } \lambda = 0, \\ \infty & \text{if } \lambda < 0. \end{cases}$$

It holds that $\text{epi } f^\pi = \text{cl cone}(\text{epi } f \times \{1\})$.

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Definition. (Friedlander, Macêdo, P. '18)

For any $\alpha > 0$, define the **projected polar envelope** and **projected polar proximal map** of f^π by

$$p_{\alpha, f}(x) := (f^\pi)_\alpha(x, 1) \text{ and } \mathfrak{P}_{\alpha, f}(x) := \text{pprox}_{\alpha f^\pi}(x, 1).$$

Projected polar proximal point algorithm

Theorem 4. (Friedlander, Macêdo, P. '18)

- (i) Suppose that $x \in \text{Arg min } p_{\alpha, f}$ and let $(\bar{x}, \bar{\lambda}) = \mathfrak{P}_{\alpha, f}(x)$. Then $\bar{\lambda} > 0$, $\bar{x} = x$ and $\bar{\lambda}^{-1}x \in \text{Arg min } f$.
- (ii) If $x \in \text{Arg min } f$, then $[1 + \alpha f(x)]^{-1}x \in \text{Arg min } p_{\alpha, f}$.

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- (iii) If $(x, \lambda) = \mathfrak{P}_{\alpha, f}(x)$, then $\lambda > 0$ and $\lambda^{-1}x \in \text{Arg min } f$.
- (iv) If $x \in \text{Arg min } f$, then $\exists \lambda > 0$ so that $(\tau x, \lambda) = \mathfrak{P}_{\alpha, f}(\tau x)$, where $\tau = [1 + \alpha f(x)]^{-1}$.

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Idea: Find “fixed point” so that $(x^*, \lambda_*) = \mathfrak{P}_{\alpha, f}(x^*)!$

Projected polar proximal point algorithm

P⁴A: Fix $\alpha > 0$ and any x^0 . For each $k = 0, 1, \dots$,

$$(x^{k+1}, \lambda_{k+1}) = \mathfrak{P}_{\alpha, f}(x^k).$$

Projected polar proximal point algorithm

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Theorem 5. (Friedlander, Macêdo, P. '18)

Let $\{(x^k, \lambda_k)\}$ be generated by **P⁴A**. Then the following statements hold.

- (i) $p_{\alpha, f}(x^{k+1}) \leq p_{\alpha, f}(x^k)$.
- (ii) If $\exists \gamma > 0$ so that $(x, \lambda) \mapsto [f^\pi(x, \lambda)]^2 - (\gamma/2)\|x\|^2$ is convex, then any accumulation point (x^*, λ_*) of $\{(x^k, \lambda_k)\}$ satisfies $\lambda_* > 0$ and $\lambda_*^{-1}x^* \in \text{Arg min } f$.

Future directions

- Efficient implementation of **P⁴A**: proximal gradient versus proximal point?
- Polar analogue of **Moreau identity**: For any proper closed convex f and any x , it holds that

$$\text{prox}_f(x) + \text{prox}_{f^*}(x) = x.$$

What about pprox_{κ} and $\text{pprox}_{\kappa^\circ}$?

- It is known that f is proper closed **strongly convex** if and only if f^* is **Lipschitz differentiable**. Any analogue for polar operation?

Conclusion

- Gauge optimization framework captures many applications.
- Gauge strong duality holds under conditions similar to **standard CQ** in Lagrange duality theory.
- **Polar envelope and polar proximal mapping** appear naturally in **dual smoothing** and **primal solution recovery**.

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Thanks for coming! ☺