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Norges teknisk-naturvitenskapelige universitet

# Nonlinear Fenchel conjugates

Ronny Bergmann

joint work with

Anton Schiela and Roland Herzog

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# The Fenchel Conjugate

The Fenchel conjugate of a function  $f: \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$  is given by

$$f^*(\xi) := \sup_{x \in \mathbb{R}^n} \langle \xi, x \rangle - f(x) = \sup_{x \in \mathbb{R}^n} \begin{pmatrix} \xi \\ -1 \end{pmatrix}^T \begin{pmatrix} x \\ f(x) \end{pmatrix}$$

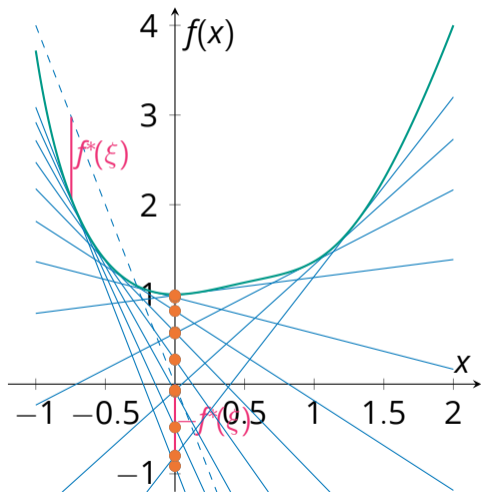
- ▶ given  $\xi \in \mathbb{R}^n$ : maximize the distance between  $\xi^T \cdot$  and  $f$
- ▶ can also be written in the epigraph

The Fenchel biconjugate reads

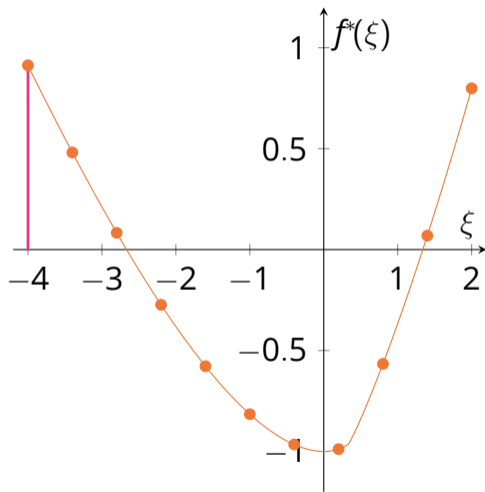
$$f^{**}(x) = (f^*)^*(x) = \sup_{\xi \in \mathbb{R}^n} \langle \xi, x \rangle - f^*(\xi).$$

# Illustration of the Fenchel Conjugate

The function  $f$



The Fenchel conjugate  $f^*$



# The Chambolle–Pock Algorithm

From the pair of primal-dual problems

[Chambolle, Pock, 2011]

$$\begin{aligned} \min_{x \in \mathbb{R}^n} f(x) + g(Kx), \quad K \text{ linear,} \\ \max_{\xi \in \mathbb{R}^m} -f^*(-K^*\xi) - g^*(\xi) \end{aligned}$$

we obtain for  $f, g$  proper convex, lsc the optimality conditions of a solution  $(\hat{x}, \hat{\xi})$  as

$$\begin{aligned} -K^*\hat{\xi} &\in \partial f(\hat{x}) \\ K\hat{x} &\in \partial g^*(\hat{\xi}) \end{aligned}$$

# The Chambolle–Pock Algorithm

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[Chambolle, Pock, 2011]

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we obtain for  $f, g$  proper convex, lsc the

**Chambolle–Pock Algorithm.** with  $\sigma > 0$ ,  $\tau > 0$ ,  $\theta \in \mathbb{R}$  reads

$$\begin{aligned} x^{(k+1)} &= \text{prox}_{\sigma f}(x^{(k)} - \sigma K^* \bar{\xi}^{(k)}) \\ \xi^{(k+1)} &= \text{prox}_{\tau g^*}(\xi^{(k)} + \tau Kx^{(k+1)}) \\ \bar{\xi}^{(k+1)} &= \xi^{(k+1)} + \theta(\xi^{(k+1)} - \xi^{(k)}) \end{aligned}$$

# Applications of the Fenchel conjugate

The Fenchel conjugate is at the core of nonsmooth optimization

$$\arg \min_{x \in \mathbb{R}^n} f(x) + g(Kx)$$

as a so-called **splitting method**

- ▶ primal-dual (PD) algorithms [Esser, Zhang, Chan, 2010; Chambolle, Pock, 2011]
- ▶ PD with non-linear operators  $K$  [Valkonen, 2014; Mom, Langer, Sixou, 2022]
- ▶ several variants: hybrid gradient, primal/dual relaxed, linearized,...

Recently this has been generalised Riemannian manifolds using

- ▶ a tangent space approach [RB, Herzog, Silva Louzeiro, Tenbrinck, Vidal-Núñez, 2021]
- ▶ a tangent bundle approach [Silva Louzeiro, RB, Herzog, 2022]
- ▶ Busemann functions [de Carvalho Bento, Neto, Melo, 2023]

# The Nonlinear Fenchel Conjugate

[Schiela, Herzog, RB, 2024]

In the Fenchel conjugate we use **linear** test functions  $\varphi(x) = \langle \xi, x \rangle$ .

💡 Use use **arbitrary** test functions

Let  $\mathcal{M}$  be a set. We define the domain of the sum (difference) of two extended real-valued functions  $f, g \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  as

$$\mathcal{D}(f \pm g) := \{x \in \mathcal{M} \mid f(x) \pm g(x) \text{ is defined}\}.$$

## Definition

The **nonlinear Fenchel conjugate** of  $f \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  is defined as

$$\begin{aligned} f^* : \mathcal{P}_{\pm\infty}(\mathcal{M}) &\rightarrow \mathbb{R}_{\pm\infty} \\ \varphi &\mapsto f^*(\varphi) := \sup\{\varphi(x) - f(x) \mid x \in \mathcal{D}(\varphi - f)\}. \end{aligned}$$

## A few properties

The following properties carry over to the nonlinear case, just being a bit careful with the domain of the test functions.

Suppose that  $f, g \in \mathcal{P}_{\pm\infty}(\mathcal{M})$ .

[Schiela, Herzog, RB, 2024]

1. For  $\alpha > 0$  and  $\beta \in \mathbb{R}$ ,

$$\alpha f^*(\varphi) + \beta = (\alpha f)^*(\alpha \varphi + \beta) = (\alpha f - \beta)^*(\alpha \varphi).$$

2. If  $\mathcal{D}(f - \psi) = \mathcal{D}(\varphi + \psi) = \mathcal{M}$ , then

$$(f - \psi)^*(\varphi) = f^*(\varphi + \psi).$$

3. If  $\mathcal{D}(f + g) = \mathcal{D}(\varphi + \psi) = \mathcal{M}$  and  $f^*(\varphi) + g^*(\psi)$  is defined, then

$$(f + g)^*(\varphi + \psi) \leq f^*(\varphi) + g^*(\psi).$$

4.  $\varphi \geq \psi$  and  $f \leq g$  implies  $f^*(\varphi) \geq g^*(\psi)$ .
5.  $f^*$  is convex on  $\mathcal{P}_{\infty}(\mathcal{M})$ .



# The Fenchel-Young inequality

An important inequality in the classical case is the Fenchel-Young inequality

$$f(x) + f^*(\xi) \geq \langle \xi, x \rangle$$

This carries over to the nonlinear case, with a bit of carefulness as to when the sum is defined.

## Theorem (Fenchel-Young inequality)

Suppose that  $f, \varphi \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  and  $x \in \mathcal{M}$ .

The Fenchel-Young inequalities

- ▶  $f^*(\varphi) \geq \varphi(x) - f(x)$
- ▶  $f(x) \geq \varphi(x) - f^*(\varphi)$
- ▶  $\varphi(x) \leq f(x) + f^*(\varphi)$

hold, provided that the respective right-hand side is defined in  $\mathbb{R}_{\pm\infty}$ .

# Nonlinear dual map

**Motivation.** In the classical case, we saw  $K^*$  the adjoint or dual map of  $K$ .

## Definition

Suppose  $\mathcal{M}$  and  $\mathcal{N}$  are two non-empty sets and  $A: \mathcal{M} \rightarrow \mathcal{N}$  is some map. The map

$$A^\otimes: \mathcal{P}_{\pm\infty}(\mathcal{N}) \rightarrow \mathcal{P}_{\pm\infty}(\mathcal{M})$$

$$\psi \mapsto A^\otimes(\psi) := \psi \circ A$$

is called the **dual or adjoint map of  $A$** , or the pullback by  $A$ .

- ▶  $A^\otimes(\alpha\psi_1 + \psi_2) = \alpha A^\otimes(\psi_1) + A^\otimes(\psi_2)$  is a homomorphism
- ▶ If  $A$  is bijective, then  $(f \circ A^{-1})^\otimes = f^\otimes \circ A^\otimes$
- ▶ more generally:  
defining  $(f \bullet A^{-1})(y) := \inf_{x \in A^{-1}(y)} f(x)$ , we obtain  $(f \bullet A^{-1})^\otimes = f^\otimes \circ A^\otimes$ .

# Motivation: The biconjugate

- ▶ approximate  $f$  its maximal convex, lsc. minorant
- ▶ linear setting:  $\Gamma$ -regularization, the pointwise supremum of continuous affine functions.

[Ch. I.3 Ekeland, Temam, 1999]

$\Rightarrow f^{**} \in \mathcal{P}_{\pm\infty}(V)$  coincides with  $\Gamma$ -regularization of  $f$ , i. e. the largest convex lsc. minorant of  $f \in \mathcal{P}_{\pm\infty}(V)$

- ▶ **Fenchel-Moreau:**

[Thm. 13.32 Bauschke, Combettes, 2011]

$f \in \mathcal{P}_{\infty}(V)$  is convex, lsc.  $\Leftrightarrow f^{**} = f$ .

## Nonlinear case.

Find a suitable subset  $\mathcal{F} \subset \mathcal{P}_{\pm\infty}(\mathcal{M})$  as a generalization for affine functions.

? Can we state a biconjugation theorem as well?

# $\mathcal{F}$ regularization

[Schiela, Herzog, RB, 2024]

Suppose that  $\emptyset \neq \mathcal{F} \subseteq \mathcal{P}_{\pm\infty}(\mathcal{M})$  and denote by

$$\tilde{\mathcal{F}} := \{\varphi + c \mid \varphi \in \mathcal{F}, c \in \mathbb{R}\}$$

the set of all  $\varphi$  that result from a shift of elements of  $\mathcal{F}$ .

We define the  $\mathcal{F}$ -regularization of  $f \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  as

$$\lfloor f \rfloor_{\mathcal{F}}(x) := \sup\{\varphi(x) \mid \varphi \in \tilde{\mathcal{F}}, \varphi \leq f\}.$$

💡  $\lfloor f \rfloor_{\mathcal{F}}$  is the pointwise supremum of all minorants of  $f$  taken from  $\mathcal{F}$  and its constant shifts.

In short we write:  $\lfloor f \rfloor_{\mathcal{F}} = \sup\{\varphi \mid \varphi \in \tilde{\mathcal{F}}, \varphi \leq f\}$

# Some properties of $\mathcal{F}$ -regularization

[Schiela, Herzog, RB, 2024]

1.  $f \leq g$  and  $\mathcal{F} \subseteq \mathcal{G}$  implies  $[f]_{\mathcal{F}} \leq [g]_{\mathcal{G}}$ .
2. For  $\varphi \in \mathcal{F}$  and  $c \in \mathbb{R}$  we have  $[f + \varphi + c]_{\mathcal{F}} = [f]_{\mathcal{F}} + \varphi + c$ .
3.  $[f]_{\mathcal{F}} \leq f$ , thus  $f \leq [f]_{\mathcal{F}} \Leftrightarrow [f]_{\mathcal{F}} = f$
4.  $f \in \mathcal{F} \Rightarrow [f]_{\mathcal{F}} = f$ .
5.  $\mathcal{F} \subseteq \mathcal{G}$  implies  $[[f]_{\mathcal{G}}]_{\mathcal{F}} = [f]_{\mathcal{F}}$ .
6. if  $\mathcal{F}$  is a convex cone we obtain for  $\alpha_1, \alpha_2 > 0$  and  $f_1, f_2 \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  with  $[f_1]_{\mathcal{F}} \neq -\infty$  and  $[f_2]_{\mathcal{F}} \neq -\infty$  we obtain

$$\alpha_1 [f_1]_{\mathcal{F}} + \alpha_2 [f_2]_{\mathcal{F}} \leq [\alpha_1 f_1 + \alpha_2 f_2]_{\mathcal{F}} \leq \alpha_1 f_1 + \alpha_2 f_2$$

# Examples

1. If  $\mathcal{M}$  is a locally convex linear topological space
  - ▶  $\mathcal{F} = \mathcal{M}^*$  is its topological dual space
  - ▶  $\tilde{\mathcal{F}}$  is the space of all continuous affine functions
  - ▶  $\lfloor f \rfloor_{\mathcal{M}^*}$  is the pointwise supremum over all affine minorants of  $f$ .
2. Suppose that  $\mathcal{M}$  is a metric space.
  - ▶ Then lower semi-continuous functions  $f \in \mathcal{P}_\infty(\mathcal{M})$  can be written as the pointwise supremum of continuous functions
  - ▶ For  $\mathcal{F} = C(\mathcal{M})$  the set  $\text{sup-cl}(\mathcal{F}) := \{ \lfloor f \rfloor_{\mathcal{F}} \mid f \in \mathcal{P}_{\pm\infty}(\mathcal{M}) \}$  consists of the cone of lower semi-continuous functions in  $\mathcal{P}_\infty(\mathcal{M})$
3. alternate generalization: the  $C$ -conjugate [Martínez-Legaz, 2005]

For a coupling function  $c: \mathcal{M} \times \mathcal{N} \rightarrow \mathbb{R}_{\pm\infty}$  defined as

$$f^c(y) := \sup_{x \in \mathcal{M}} c(x, y) - f(x) \quad \text{for } y \in \mathcal{N}.$$

Generalizes duality pairing instead of the set of test functions.

# $\mathcal{F}$ -biconjugates

[Schiela, Herzog, RB, 2024]

- ▶ We denote the restriction of the conjugate  $f^* \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  to  $\mathcal{F}$  by

$$f^*|_{\mathcal{F}}: \mathcal{F} \rightarrow \mathbb{R}_{\pm\infty}$$

- ▶ Let the evaluation (Dirac) functions be given by

$$\delta_x: \mathcal{P}_{\pm\infty}(\mathcal{M}) \rightarrow \mathbb{R}_{\pm\infty}, \quad \varphi \mapsto \delta_x(\varphi) := \varphi(x).$$

- ⊕  $\delta_x|_{\mathcal{F}}, \mathcal{F} \subset \mathcal{P}_{\pm\infty}(\mathcal{M})$  linear, is a linear function and continuous.

## Definition

Suppose that  $\mathcal{F}$  is a linear subspace of  $\mathcal{P}(\mathcal{M})$ .

We define the  $\mathcal{F}$ -biconjugate  $f_{\mathcal{F}}^{**}$  of  $f \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  as

$$f_{\mathcal{F}}^{**}: \mathcal{M} \rightarrow \mathbb{R}_{\pm\infty}, \quad x \mapsto (f^*|_{\mathcal{F}})^*(\delta_x).$$

**Note.** We employ the embedding of  $\mathcal{M}$  into the dual space of  $\mathcal{F}$  via

$$J_{\mathcal{M} \rightarrow \mathcal{F}'}: \mathcal{M} \rightarrow \mathcal{F}', \quad x \mapsto \delta_x.$$

# $\mathcal{F}$ biconjugate theorem

## Remember.

For the classical Fenchel biconjugate the set  $\mathcal{F}$  are all affine functions and  $\lfloor f \rfloor_{\mathcal{F}}$  is largest convex lsc. minorant of  $f \in \mathcal{P}_{\pm\infty}(V)$

## Theorem

Suppose that  $\mathcal{F}$  is a linear subspace of  $\mathcal{P}(\mathcal{M})$ . The  $\mathcal{F}$ -biconjugate satisfies  $f_{\mathcal{F}}^{**} = \lfloor f \rfloor_{\mathcal{F}}$  for all  $f \in \mathcal{P}_{\pm\infty}(\mathcal{M})$ . [Schiela, Herzog, RB, 2024]

➡ If  $f = \lfloor f \rfloor_{\mathcal{F}}$ , or in other words  $f$  agrees with the pointwise supremum of all minorants from  $\mathcal{F}$ , then we recover  $f$  from its  $\mathcal{F}$ -biconjugate.



## Motivation: The subdifferential

With the Fenchel conjugate  $f^*: V^* \rightarrow \mathbb{R}_{\pm\infty}$  of a proper, convex, lsc. function  $f: V \rightarrow \mathbb{R}_{\pm\infty}$  on a vector space  $V$  we have

$$\xi \in \partial f(x) \quad \text{if and only if} \quad x \in \partial f^*(\xi)$$

➡ we can characterize both subdifferentials.

### **Nonlinear case.**

We need “more structure on  $\mathcal{M}$ ” to define a subdifferential of  $f$ .

In practice/numerics we use Riemannian manifolds.

In the following we consider a manifold  $\mathcal{M}$ , that is locally homeomorphic to a Banach space  $\mathcal{X}$ , or a **Banach manifold** for short.

# The viscosity Fréchet Subdifferential

A function  $f \in \mathcal{P}_{\pm\infty}(\mathcal{M})$  is lower semi-continuous at  $x \in \mathcal{M}$  if,  $\forall \varepsilon > 0 \exists$  a neighbourhood  $\mathcal{U}$  of  $x$  s.t. that  $f(y) \geq f(x) - \varepsilon$  for all  $y \in \mathcal{U}$ . We denote by  $\text{lsc}_{\infty}(\mathcal{M})$  the set of all functions that are lower semi-continuous at every  $x \in \mathcal{M}$ .

## Definition

Suppose that  $\mathcal{M}$  is a  $C^1$ -Banach manifold,  $f \in \text{lsc}_{\infty}(\mathcal{M})$ ,  $x \in \mathcal{M}$  and  $f(x) \neq +\infty$ .

The (viscosity) Fréchet subdifferential  $\partial_F f(x)$  of  $f$  is defined as follows:

$$\partial_F f(x) := \{ \varphi'(x) \mid \varphi \in C^1(\mathcal{M}), f - \varphi \text{ attains a local minimum at } x \} \subseteq \mathcal{T}_x^* \mathcal{M},$$

where  $\mathcal{T}_x^* \mathcal{M} := (\mathcal{T}_x \mathcal{M})^*$  denotes the cotangent space at  $x$ .

In case  $f(x) = +\infty$ , we set  $\partial_F f(x) := \emptyset$ .

# Subdifferential Classification

## Theorem

[Schiela, Herzog, RB, 2024]

Suppose that  $\mathcal{M}$  is a  $C^1$ -Banach manifold.

Let  $x \in \mathcal{M}$ ,  $f$  be lower semicontinuous at every  $x \in \mathcal{M}$  and  $\varphi \in C^1(\mathcal{M})$ .

1. If  $f^*(\varphi) = \varphi(x) - f(x)$ , i. e. we have equality in the Fenchel-Young inequality,  
then  $\varphi'(x) \in \partial_E f(x)$  and the Dirac function  $\delta_x \in \partial(f^*|_{C^1(\mathcal{M})})(\varphi)$ .
2. Conversely, if  $\delta_x \in \partial(f^*|_{C^1(\mathcal{M})})(\varphi)$ , then  $f^*(\varphi) = \varphi(x) - f(x)$ .

# Motivation: Infimal convolution

Infimal convolution is defined as

$$(f \star_{\text{inf}} g)(x) := \inf_{y \in \mathcal{M}} \{f(y) + g(x - y)\}.$$

The infimal convolution formula shows that

[Prop. 13.21 Bauschke, Combettes, 2011]

$$(f \star_{\text{inf}} g)^* = f^* + g^*$$

## Nonlinear case.

We need even “slightly more structure” to generalise infimal convolution, a way to define “ $x - y \in \mathcal{M}$ ” to be precise.

? Can we then get the same result for the nonlinear Fenchel conjugate? And what is a suitable restriction of  $\mathcal{P}_{\pm\infty}(\mathcal{M})$  then?

# Using Lie groups

Let

- ▶  $\mathcal{M}$  be a Riemannian manifold
- ▶  $\cdot : \mathcal{M} \times \mathcal{M} \rightarrow \mathcal{M}$  be a group operation
- ⊕  $(\mathcal{M}, \cdot)$  is a Lie group.

We generalize **infimal convolution** to functions  $f, g \in \mathcal{P}_\infty(\mathcal{M})$  as

$$(f \star_{\text{inf}} g)(x) := \inf_{y \in \mathcal{M}} f(x \cdot y^{-1}) + g(y) = \inf_{z \in \mathcal{M}} f(z) + g(z^{-1} \cdot x).$$

Consider the linear space of group homomorphisms

$$\mathcal{H} := \text{Hom}((\mathcal{M}, \cdot), (\mathbb{R}, +))$$

Then we get the relation

$$(f \star_{\text{inf}} g)^{\circledast}(\varphi) = f^{\circledast}(\varphi) + g^{\circledast}(\varphi) \quad \text{for all } \varphi \in \mathcal{H}. \quad [\text{Schiela, Herzog, RB, 2024}]$$

# Chambolle-Pock algorithm

## Special case: Test functions on $\mathcal{T}_x\mathcal{M}$

For a  $x \in \mathcal{M}$  consider a neighbourhood  $V$  of the origin in the tangent space  $\mathcal{T}_x\mathcal{M}$  on which the exponential map  $\exp_x$  is a diffeomorphism to  $\mathcal{V} := \exp_x(V) \subseteq \mathcal{M}$ .

As set of test functions we use [Alcadi, Savandi, Amini, 2010; RB, Herzog, Silva Louzeiro, Tenbrinck, Vidal-Núñez, 2021]

$$\mathcal{F}_x := \{x^* \circ \exp_x^{-1} \in C^\infty(\mathcal{V}, \mathbb{R}) \mid x^* \in \mathcal{T}_x^*\mathcal{M}\}$$

We also consider a **localised** version of the nonlinear conjugate

$$(f + \iota_{\mathcal{V}})^{\circledast}(\varphi) = \sup_{y \in \mathcal{V}} \{\varphi(y) - f(y)\} \quad \text{for } \varphi \in \mathcal{F}_x.$$

This indeed agrees with the classical Fenchel conjugate on the tangent space as  $f_x(x^*) := (f \circ \exp_x + \iota_V)^*(x^*)$

# Saddle Point Formulation on Manifolds

On manifolds, we consider for

$$\min_{p \in \mathcal{M}} f(p) + g(\Lambda p), \quad \Lambda: \mathcal{M} \rightarrow \mathcal{N},$$

where  $f$  is geodesically convex, and  $g \circ \exp_n$  is convex for some  $n \in \mathcal{N}$ .

**Saddle point formulation.** Using the  $n$ -Fenchel conjugate  $g_n^*$  of  $g$ :

$$\min_{p \in \mathcal{C}} \max_{\xi_n \in \mathcal{T}_n^* \mathcal{N}} \langle \xi_n, \log_n \Lambda(p) \rangle + f(p) - g_n^*(\xi_n).$$

**But.**  $\Lambda$  is inherently nonlinear and inside a logarithmic map  $\Rightarrow$  no adjoint.

**Approach.** Linearization: Choose  $m$  such that  $n = \Lambda(m)$  and [\[Valkonen, 2014\]](#)

$$\Lambda(p) \approx \exp_{\Lambda(m)} D\Lambda(m)[\log_m p].$$



# The exact Riemannian Chambolle–Pock Algorithm

[RB, Herzog, Silva Louzeiro, Tenbrinck, Vidal-Núñez, 2021; Chambolle, Pock, 2011]

**Input:**  $m, p^{(0)} \in \mathcal{C} \subset \mathcal{M}$ ,  $n = \Lambda(m)$ ,  $\xi_n^{(0)} \in \mathcal{T}_n^* \mathcal{N}$ , and  $\sigma, \tau, \theta > 0$

1:  $k \leftarrow 0$

2:  $\bar{p}^{(0)} \leftarrow p^{(0)}$

3: **while** not converged **do**

4:  $\xi_n^{(k+1)} \leftarrow \text{prox}_{\tau g_n^*} \left( \xi_n^{(k)} + \tau \left( \log_n \Lambda(\bar{p}^{(k)}) \right)^\flat \right)$

5:  $p^{(k+1)} \leftarrow \text{prox}_{\sigma f} \left( \exp_{p^{(k)}} \left( P_{p^{(k)} \leftarrow m} \left( -\sigma D\Lambda(m)^* [\xi_n^{(k+1)}] \right)^\sharp \right) \right)$

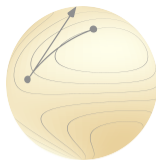
6:  $\bar{p}^{(k+1)} \leftarrow \exp_{p^{(k+1)}} \left( -\theta \log_{p^{(k+1)}} p^{(k)} \right)$

7:  $k \leftarrow k + 1$

8: **end while**

**Output:**  $p^{(k)}$

# Manopt.jl



**Goal.** Provide optimization algorithms on Riemannian manifolds.

**Features.** Given a `Problem p` and a `SolverState s`,  
implement `initialize_solver!(p, s)` and `step_solver!(p, s, i)`  
⇒ an algorithm in the `Manopt.jl` interface

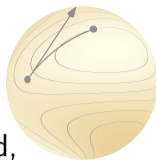
**Highlevel interfaces** like `gradient_descent(M, f, grad_f)`  
on any manifold `M` from `Manifolds.jl`.

All provide `debug` output, `recording`, `cache` & `counting` capabilities,  
as well as a library of `step sizes` and `stopping criteria`.

## Manopt family.



# List of Algorithms in Manopt.jl



**Derivative Free** Nelder-Mead, Particle Swarm, CMA-ES

**Subgradient-based** Subgradient Method, Convex Bundle Method,  
Proximal Bundle Method

**Gradient-based** Gradient Descent, Conjugate Gradient, Stochastic,  
Momentum, Nesterov, Averaged, ...  
Quasi-Newton with (L-)BFGS, DFP, Broyden, SR1,...  
Levenberg-Marquard

**Hessian-based** Trust Regions, Adaptive Regularized Cubics (ARC)

**nonsmooth** Chambolle-Pock, Douglas-Rachford, Cyclic Proximal Point

**constrained** Augmented Lagrangian, Exact Penalty, Frank-Wolfe,  
Interior Point Newton

**nonconvex** Difference of Convex Algorithm, DCPA

# Riemannian Chambolle-Pock in Manopt.jl

To call the exact Riemannian Chambolle-Pock algorithm in `Manopt.jl`:

```
ChambollePock(  
    M, N, F, p, X, m, n, prox_f, prox_g_n, DΛ*; kwargs...  
)
```

- ▶  $M, N$  are the manifolds  $f$  and  $g$ , resp., are defined on
- ▶  $F$  is the objective function  $f + g$
- ▶  $p, n, m$  are the initial, Fenchel conjugate base, and linearization point, resp.
- ▶  $X$  is the initial tangent vector
- ▶  $\text{prox}_f, \text{prox}_g_n$  are the proximal maps of  $f$  and  $g_n^*$ , resp.
- ▶  $D\Lambda^*$  is the adjoint of the linearization of  $\Lambda$

# Summary








The [Nonlinear Fenchel Conjugate](#) generalises the Fenchel conjugate. A lot of properties can be proven more generally as well:

- ▶ Fenchel-Young inequality
- ▶ Biconjugate theorem
- ▶ Subdifferential classification
- ▶ Infimal convolution

➔ Unified framework for the existing generalisations and hence for nonsmooth optimization on Riemannian manifolds.

**Example** Chambolle-Pock algorithm on Riemannian manifolds and its implementation in [Manopt.jl](#).

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