NTNU
Norwegian University of Science and Technology

Nonsmooth, nonconvex Optimization on Riemannian Manifolds

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Workshop
From Modeling and Analysis to Approximation and Fast Algorithms,
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Motivation

The Rayleigh Quotient

When minimizing the Rayleigh quotient for a symmetric $A \in \mathbb{R}^{n\times n}$

$$\operatorname*{arg\,min}_{x\in\mathbb{R}^n\setminus\{0\}} \frac{x^\mathrm{T}Ax}{\|x\|^2}$$

- Any eigenvector x^* to the smallest EV λ is a minimizer
- no isolated minima and Newton's method diverges
- Constrain the problem to unit vectors $\|x\| = 1$!

classic constrained optimization (ALM, EPM,...)

Today Utilize the geometry of the sphere

- unconstrained optimization $\operatorname*{arg\,min}_{p\in\mathbb{S}^{n-1}} p^\mathrm{T}Ap$
- adapt unconstrained optimization to Riemannian manifolds.

The Generalized Rayleigh Quotient

More general. Find a basis for the space of eigenvectors to $\lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_k$:

$$\operatorname*{arg\,min}_{X \in \mathrm{St}(n,k)} \mathrm{tr}(X^\mathsf{T} A X), \qquad \mathrm{St}(n,k) := \left\{ X \in \mathbb{R}^{n \times k} \,\middle|\, X^\mathsf{T} X = I \right\},$$

a problem on the Stiefel manifold $\mathrm{St}(n,k)$

Invariant under rotations within a k-dim subspace.

Find the best subspace!

$$\operatorname*{arg\,min}_{\mathrm{span}(X) \in \mathrm{Gr}(n,k)} \mathrm{tr}(X^\mathsf{T} A X), \qquad \mathrm{Gr}(n,k) := \left\{ \mathrm{span}(X) \,\middle|\, X \in \mathrm{St}(n,k) \right\},$$

a problem on the Grassmann manifold $\mathrm{Gr}(n,k) = \mathrm{St}(n,k)/O(k)$.

Optimization on Riemannian Manifolds

We are looking for numerical algorithms to find

$$\operatorname*{arg\,min}_{p \in \mathcal{M}} f(p)$$

where

- ▶ $\mathcal{M}$ is a Riemannian manifold
- ▶ $f\colon \mathcal{M} \to \overline{\mathbb{R}}$ is a function
- ⚠ f might be nonsmooth and/or nonconvex
- ⚠ $\mathcal{M}$ might be high-dimensional

A Riemannian Manifold $\mathcal{M}$

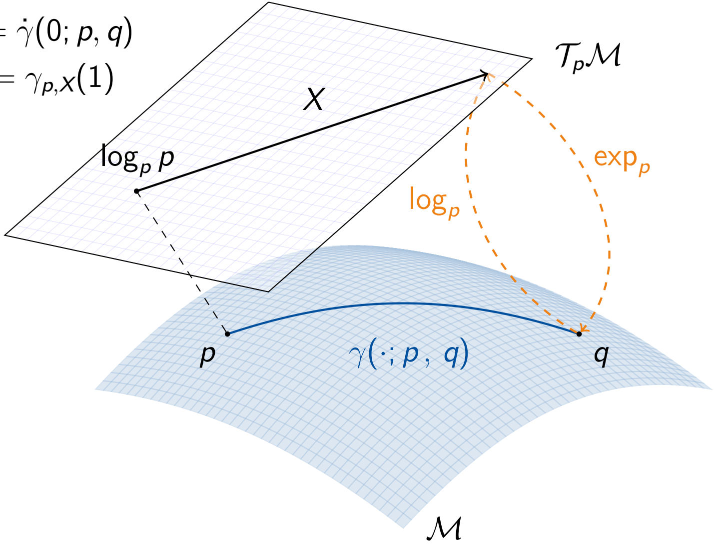
A d-dimensional Riemannian manifold can be informally defined as a set $\mathcal{M}$ covered with a "suitable" collection of charts, that identify subsets of $\mathcal{M}$ with open subsets of $\mathbb{R}^d$ and a continuously varying inner product on the tangent spaces.

[Absil, Mahony, and Sepulchre 2008]

A Riemannian Manifold $\mathcal{M}$

Notation.

- Logarithmic map $\log_p q = \dot\gamma(0; p, q)$
- Exponential map $\exp_p X = \gamma_{p,X}(1)$
- Geodesic $\gamma(\cdot; p, q)$
- Tangent space $\mathcal{T}_p\mathcal{M}$
- inner product $(\cdot, \cdot)_p$



(Geodesic) Convexity

[Sakai 1996; Udriște 1994]

A set $\mathcal{C} \subset \mathcal{M}$ is called (strongly geodesically) convex
if for all $p, q \in \mathcal{C}$ the geodesic $\gamma(\cdot; p, q)$ is unique and lies in $\mathcal{C}$.

A function $F\colon \mathcal{C} \to \overline{\mathbb{R}}$ is called (geodesically) convex
if for all $p, q \in \mathcal{C}$ the composition $F(\gamma(t; p, q)), t \in [0, 1]$, is convex.

The Riemannian Subdifferential

The subdifferential of f at $p \in \mathcal{C}$ is given by [Lee 2003; Udriște 1994]

$$\partial_{\mathcal{M}} f(p) := \bigl\{\xi \in \mathcal{T}_p^*\mathcal{M} \bigm| f(q) \geq f(p) + \langle \xi \,, \log_p q\rangle_p \ \text{ for } q \in \mathcal{C}\bigr\},$$

where

- $\mathcal{T}_p^*\mathcal{M}$ is the dual space of $\mathcal{T}_p\mathcal{M}$,
- $\langle \cdot \,, \cdot \rangle_p$ denotes the duality pairing on $\mathcal{T}_p^*\mathcal{M} \times \mathcal{T}_p\mathcal{M}$

Musical Isomorphisms

Using the tangent space $\mathcal{T}_p\mathcal{M}$ and its dual $\mathcal{T}_p^*\mathcal{M}$,
the inner product $(\cdot\,,\,\cdot)_p$ and the duality pairing $\langle\cdot\,,\cdot\rangle$,

the musical isomorphisms are [Lee 2003]

$$\flat\colon \mathcal{T}_p\mathcal{M} \to \mathcal{T}_p^*\mathcal{M} \quad \text{and} \quad \sharp\colon \mathcal{T}_p^*\mathcal{M} \to \mathcal{T}_p\mathcal{M}$$

such that for any $X, Y \in \mathcal{T}_p\mathcal{M}$ and $\xi \in \mathcal{T}_p^*\mathcal{M}$ we have

$$\langle X^\flat\,, Y\rangle = (X,\, Y)_p \quad \text{and} \quad (\xi^\sharp\,,\, Y)_p = \langle \xi\,, Y\rangle$$

The Proximal Map

For a function $f\colon \mathcal{M} \to \mathbb{R}$ and a $\lambda > 0$ we define the proximal map as

[Moreau 1965; Rockafellar 1970; O. Ferreira and Oliveira 2002]

$$\operatorname{prox}_{\lambda f}(p) := \operatorname*{arg\,min}_{q\in\mathcal{M}} d_{\mathcal{M}}(q,p)^2 + \lambda f(q).$$

Properties.

- Minimizer p^* of $f \Leftrightarrow$ fix point of the prox $\operatorname{prox}_{\lambda f}(p^*) = p^*$
- If f is proper, convex, lsc.: arg min unique.
- proximal point algorithm (PPA): $p^{(k+1)} = \operatorname{prox}_{\lambda f}(p^{(k)})$ converges to p^*

Nonsmooth splittings

Splitting Methods & Algorithms

For $\operatorname*{arg\,min}_{p\in\mathcal{M}} f(p) + g(p)$ we can use

- Cyclic Proximal Point Algorithm (CPPA) [Bačák 2014]
- (parallel) Douglas–Rachford Algorithm (PDRA) [RB, Persch, and Steidl 2016]

which are for $\mathcal{M} = \mathbb{R}^n$ also equivalend to [Setzer 2011; O'Connor and Vandenberghe 2018]

- Primal-Dual Hybrid Gradient Algorithm (PDHGA) [Esser, Zhang, and Chan 2010]
- Chambolle-Pock Algorithm (CPA) [Chambolle and Pock 2011; Pock, Cremers, Bischof, and Chambolle 2009]

Challenge.
These rely on the dual space of $\mathbb{R}^n$, which $\mathcal{M}$ does not have.
More precisely. They employ the Fenchel conjugate.

The Fenchel Conjugate

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

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

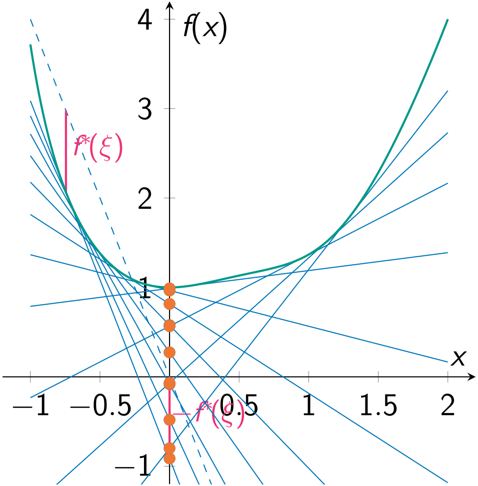
- given $\xi \in \mathbb{R}^n$: maximize the distance between $\xi^{\mathsf{T}}\cdot$ and f
- can also be written in the epigraph

The Fenchel biconjugate reads

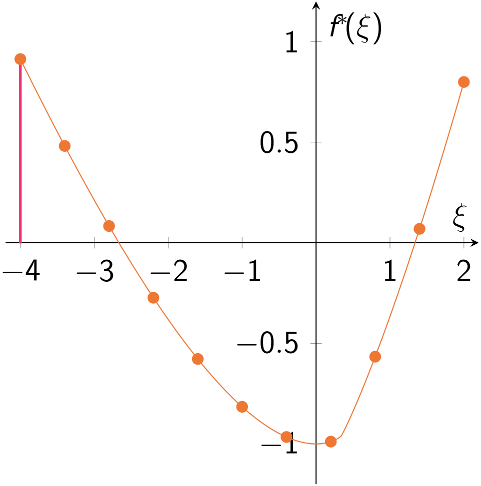
$$f^{**}(x) = (f^*)^*(x) = \sup_{\xi\in\mathbb{R}^n} \langle \xi , x\rangle - f^*(\xi).$$

Illustration of the Fenchel Conjugate

The function f



The Fenchel conjugate f^*



Properties of the Fenchel Conjugate

[Rockafellar 1970]

- The Fenchel conjugate f^* is convex (even if f is not)
- f^{**} is the largest convex, lsc function with $f^{**} \leq f$
- If $f(x) \leq g(x)$ for all $x \in \mathbb{R}^n \Rightarrow f^*(\xi) \geq g^*(\xi)$ for all $\xi \in \mathbb{R}^n$
- Fenchel–Moreau Theorem. f convex, proper, lsc $\Rightarrow f^{**} = f$.
- Fenchel–Young inequality.

$$f(x) + f^*(\xi) \geq \xi^\mathsf{T} x \quad \text{for all} \quad x, \xi \in \mathbb{R}^n$$

- For a proper, convex function f

$$\xi \in \partial f(x) \Leftrightarrow f(x) + f^*(\xi) = \xi^\mathsf{T} x$$

- For a proper, convex, lsc function f, then

$$\xi \in \partial f(x) \Leftrightarrow x \in \partial f^*(\xi)$$

The (Riemannian) m-Fenchel Conjugate

[RB, Herzog, Silva Louzeiro, Tenbrinck, and Vidal-Núñez 2021]

Idea. Localize to $\mathcal{C} \subset \mathcal{M}$ around a point m which "acts as" 0.

The m-Fenchel conjugate of a function $f\colon \mathcal{C} \to \overline{\mathbb{R}}$ is given by

$$f_m^*(\xi_m) := \sup_{X \in \mathcal{L}_{\mathcal{C},m}} \bigl\{ \langle \xi_m , X \rangle - f(\exp_m X) \bigr\},$$

where $\mathcal{L}_{\mathcal{C},m} := \{ X \in \mathcal{T}_m\mathcal{M} \mid q = \exp_m X \in \mathcal{C} \text{ and } \lVert X \rVert_p = d(q,p) \}$.

Let $m' \in \mathcal{C}$. The mm'-Fenchel-biconjugate $F_{mm'}^{**} \colon \mathcal{C} \to \overline{\mathbb{R}}$ is given by

$$F_{mm'}^{**}(p) = \sup_{\xi_{m'} \in \mathcal{T}_{m'}^*\mathcal{M}} \bigl\{ \langle \xi_{m'} , \log_{m'} p \rangle - F_m^*(\mathrm{P}_{m \leftarrow m'} \xi_{m'}) \bigr\},$$

where usually we only use the case $m = m'$.

Properties of the m-Fenchel Conjugate

- f_m^* is convex on $\mathcal{T}_m^*\mathcal{M}$
- If $f(p) \leq g(p)$ for all $p \in \mathcal{C} \Rightarrow f_m^*(\xi_m) \geq g_m^*(\xi_m)$ for all $\xi_m \in \mathcal{T}_m^*\mathcal{M}$
- Fenchel–Moreau Theorem $f \circ \exp_m$ convex (on $\mathcal{T}_m\mathcal{M}$), proper, lsc, $\Rightarrow f_{mm}^{**} = f$ on $\mathcal{C}$.
- Fenchel-Young inequality: For a proper, convex function $f \circ \exp_m$

$$\xi_p \in \partial_{\mathcal{M}} f(p) \Leftrightarrow f(p) + f_m^*(\mathrm{P}_{m\leftarrow p}\xi_p) = \langle \mathrm{P}_{m\leftarrow p}\xi_p\,, \log_m p \rangle.$$

- For a proper, convex, lsc function $f \circ \exp_m$

$$\xi_p \in \partial_{\mathcal{M}} f(p) \Leftrightarrow \log_m p \in \partial f_m^*(\mathrm{P}_{m\leftarrow p}\xi_p).$$

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The Chambolle–Pock Algorithm

From the pair of primal-dual problems [Chambolle and Pock 2011]

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

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

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

The Chambolle–Pock Algorithm

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

$$x^{(k+1)} = \operatorname{prox}_{\sigma f}\big(x^{(k)} - \sigma K^*\bar{\xi}^{(k)}\big)$$
$$\xi^{(k+1)} = \operatorname{prox}_{\tau g,^*}\big(\xi^{(k)} + \tau K x^{(k+1)}\big)$$
$$\bar{\xi}^{(k+1)} = \xi^{(k+1)} + \theta(\xi^{(k+1)} - \xi^{(k)})$$

Saddle Point Formulation on Manifolds

On manifolds, we consider for

$$\min_{p\in\mathcal{M}} f(p) + g(\Lambda p), \qquad \Lambda\colon \mathcal{M} \to \mathcal{N},$$

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. Λ 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, and Vidal-Núñez 2021; Chambolle and 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: $\quad \xi_n^{(k+1)} \leftarrow \operatorname{prox}_{\tau g_n^*}\Bigl(\xi_n^{(k)} + \tau\bigl(\log_n \Lambda(\bar{p}^{(k)})\bigr)^\flat\Bigr)$

5: $\quad p^{(k+1)} \leftarrow \operatorname{prox}_{\sigma f}\Bigl(\exp_{p^{(k)}}\Bigl(\mathrm{P}_{p^{(k)} \leftarrow m}\bigl(-\sigma D\Lambda(m)^*[\xi_n^{(k+1)}]\bigr)^\sharp\Bigr)\Bigr)$

6: $\quad \bar{p}^{(k+1)} \leftarrow \exp_{p^{(k+1)}}\bigl(-\theta \log_{p^{(k+1)}} p^{(k)}\bigr)$

7: $\quad k \leftarrow k + 1$

8: **end while**

Output: $p^{(k)}$

Difference of Convex

Difference of Convex

We aim to solve

$$\operatorname*{arg\,min}_{p\in\mathcal{M}} f(p)$$

where

- $\mathcal{M}$ is a Riemannian manifold
- $f\colon \mathcal{M} \to \mathbb{R}$ is a difference of convex function, i. e. of the form

$$f(p) = g(p) - h(p)$$

- $g, h\colon \mathcal{M} \to \overline{\mathbb{R}}$ are convex, lower semicontinuous, and proper

The Euclidean DCA

Idea 1. At x_k, approximate $h(x)$ by its affine minorization $h_k(x) := h(x^{(k)}) + \langle x - x^{(k)}, y^{(k)} \rangle$ for some $y^{(k)} \in \partial h(x^k)$.

$\Rightarrow$ minimize $g(x) - h_k(x) = g(x) + h(x^{(k)}) - \langle x - x^{(k)}, y^{(k)} \rangle$ instead.

Idea 2. Using duality theory finding a new $y^{(k)} \in \partial h(x^{(k)})$ is equivalent to

$$y^{(k)} \in \operatorname*{arg\,min}_{y \in \mathbb{R}^n} \Bigl\{ h^*(y) - g^*(y^{(k-1)}) - \langle y - y^{(k-1)}, x^{(k)} \rangle \Bigr\}$$

Idea 3. Reformulate 2 using a proximal map $\Rightarrow$ DCPPA

On manifolds: [Almeida, Neto, Oliveira, and Souza 2020; Souza and Oliveira 2015]

In the Euclidean case, all three models are equivalent.

A Fenchel Duality on a Hadamard Manifold

[Silva Louzeiro, RB, and Herzog 2022]

Definition

Let $f\colon \mathcal{M} \to \overline{\mathbb{R}}$. The Fenchel conjugate of f is the function $f^*\colon \mathcal{T}^*\mathcal{M} \to \overline{\mathbb{R}}$ defined by

$$f^*(p,\xi) := \sup_{q\in\mathcal{M}} \Big\{ \langle \xi, \log_p q \rangle - f(q) \Big\}, \qquad (p,\xi) \in \mathcal{T}^*\mathcal{M}.$$

The Dual Difference of Convex Problem

Given the Difference of Convex problem

$$\operatorname*{arg\,min}_{p\in\mathcal{M}} g(p) - h(p)$$

and the Fenchel duals g^* and h^* we can state the dual difference of convex problem as [RB, O. P. Ferreira, Santos, and Souza 2023]

$$\operatorname*{arg\,min}_{(p,\xi)\in T^*\mathcal{M}} \ h^*(p,\xi) - g^*(p,\xi).$$

On $\mathcal{M} = \mathbb{R}^n$ this indeed simplifies to the classical dual problem.

[RB, O. P. Ferreira, Santos, and Souza 2023]

Theorem.

$$\inf_{(q,X)\in\mathcal{T}^*\mathcal{M}} \Big\{ h^*(q,X) - g^*(q,X) \Big\} = \inf_{p\in\mathcal{M}} \{g(p) - h(p)\}\,.$$

The Dual Difference of Convex Problem

The primal and dual Difference of convex problem

$$\operatorname*{arg\,min}_{p\in\mathcal{M}} g(p) - h(p) \qquad \text{and} \qquad \operatorname*{arg\,min}_{(p,\xi)\in T^*\mathcal{M}} h^*(p,\xi) - g^*(p,\xi)$$

are equivalent in the following sense.

Theorem. [RB, O. P. Ferreira, Santos, and Souza 2023]

If p^* is a solution of the primal problem, then $(p^*, \xi^*) \in T^*\mathcal{M}$ is a solution for the dual problem for all $\xi^* \in \partial_{\mathcal{M}} h(p^*) \cap \partial_{\mathcal{M}} g(p^*)$.

If $(p^*, \xi^*) \in T^*\mathcal{M}$ is a solution of the dual problem for some $\xi^* \in \partial_{\mathcal{M}} h(p^*) \cap \partial_{\mathcal{M}} g(p^*)$, then p^* is a solution of the primal problem.

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Derivation of the Riemannian DCA

We consider the linearization of h at some point $p^{(k)}$:
With $\xi \in \partial h(p^{(k)})$ we get

$$h_k(p) = h(p^{(k)}) + \langle \xi\,, \log_{p^{(k)}} p \rangle_{p^{(k)}}$$

Using musical isomorphisms we identify $X = \xi^\sharp \in T_p\mathcal{M}$,
where we call X a subgradient. Locally h_k minorizes h, i. e.

$$h_k(q) \leq h(q) \text{ locally around } p^{(k)}$$

$\Rightarrow$ Use $-h_k(p)$ as upper bound for $-h(p)$ in f.

Note. On $\mathbb{R}^n$ the function h_k is linear.
On a manifold h_k is not necessarily convex, even on a Hadamard manifold.

The Riemannian DC Algorithm

[RB, O. P. Ferreira, Santos, and Souza 2023]

Input: An initial point $p^0 \in \operatorname{dom}(g)$, g and $\partial_{\mathcal{M}} h$

Set $k = 0$.

while not converged **do**

  Take $X^{(k)} \in \partial_{\mathcal{M}} h(p^{(k)})$

  Compute the next iterate p^{k+1} as

$$p^{(k+1)} \in \operatorname*{arg\,min}_{p \in \mathcal{M}} g(p) - \left(X_k\,,\, \log_{p^{(k)}} p\right)_{p^{(k)}}. \qquad (*)$$

  Set $k \leftarrow k + 1$

end while

Note. In general the subproblem $(*)$ can not be solved in closed form. But an approximate solution yields a good candidate.

Convergence of the Riemannian DCA

[RB, O. P. Ferreira, Santos, and Souza 2023]

Let $\{p^{(k)}\}_{k\in\mathbb{N}}$ and $\{X^{(k)}\}_{k\in\mathbb{N}}$ be the iterates and subgradients of the RDCA.

Theorem.
If $\bar p$ is a cluster point of $\{p^{(k)}\}_{k\in\mathbb{N}}$, then $\bar p \in \operatorname{dom}(g)$ and there exists a cluster point $\bar X$ of $\{X^{(k)}\}_{k\in\mathbb{N}}$ s. t. $\bar X \in \partial g(\bar p) \cap \partial h(\bar p)$.

$\Rightarrow$ Every cluster point of $\{p^{(k)}\}_{k\in\mathbb{N}}$, if any, is a critical point of f.

Proposition. Let g be σ-strongly (geodesically) convex. Then

$$f(p_{k+1}) \leq f(p^{(k)}) - \frac{\sigma}{2} d^2(p^{(k)}, p_{k+1}).$$

and $\displaystyle\sum_{k=0}^{\infty} d^2(p^{(k)}, p_{k+1}) < \infty$, so in particular $\displaystyle\lim_{k\to\infty} d(p^{(k)}, p_{k+1}) = 0$.

Software

ManifoldsBase.jl

[Axen, Baran, RB, and Rzecki 2023]

Goal. Provide an interface to implement and use Riemannian manifolds.

Interface `AbstractManifold` to model manifolds

Functions like `exp(M, p, X)`, `log(M, p, X)` or `retract(M, p, X, method)`.

Decorators for implicit or explicit specification of an embedding, a metric, or a group,

Efficiency by providing in-place variants like `exp!(M, q, p, X)`

Manifolds.jl

Goal. Provide a library of Riemannian manifolds, that is efficiently implemented and well-documented

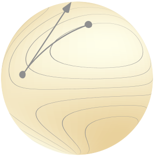
[Axen, Baran, RB, and Rzecki 2023]

Meta. generic implementations for $\mathcal{M}^{n\times m}$, $\mathcal{M}_1 \times \mathcal{M}_2$, vector- and tangent-bundles, esp. $T_p\mathcal{M}$, or Lie groups

Library. Implemented functions for

- Circle, Sphere, Torus, Hyperbolic, Projective Spaces
- (generalized, symplectic) Stiefel, (generalized) Grassmann, Rotations
- Symmetric Positive Definite matrices
- Multinomial, Symmetric, Symplectic matrices
- Tucker & Oblique manifold, Kendall's Shape space
- ...

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)`
$\Rightarrow$ an algorithm in the `Manopt.jl` interface

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

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

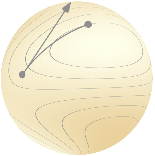
Manopt family.

manoptjl.org [RB 2022]

manopt.org [Boumal, Mishra, Absil, and Sepulchre 2014]

pymanopt.org [Townsend, Koep, and Weichwald 2016]

Manopt.jl



Algorithms.

Cost-based Nelder-Mead, Particle Swarm

Subgradient-based Subgradient Method

Gradient-based Gradient Descent, Conjugate Gradient, Stochastic, Momentum, Nesterov, Averaged, …
Quasi-Newton: (L-)BFGS, DFP, Broyden, SR1,…

Hessian-based Trust Regions, Adaptive Regularized Cubics (soon)

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

constrained Augmented Lagrangian, Exact Penalty, Frank-Wolfe

nonconvex Difference of Convex Algorithm, DCPPA

manoptjl.org

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Implementation of the DCA

The algorithm is implemented and released in Julia using `Manopt.jl`[1].
It can be used with any manifold from `Manifolds.jl`

A solver call looks like

```
q = difference_of_convex_algorithm(M, f, g, ∂h, p0)
```

where one has to implement `f(M, p)`, `g(M, p)`, and `∂h(M, p)`.

- a sub problem is automatically generated
- an efficient version of its cost and gradient is provided
- you can specify the sub-solver to using `sub_state=`
  to also set up the specific parameters of your favourite algorithm

[1] see `https://manoptjl.org/stable/solvers/difference_of_convex/`

Numerical Examples

The ℓ^2-TV Model

[Rudin, Osher, and Fatemi 1992; Lellmann, Strekalovskiy, Koetter, and Cremers 2013; Weinmann, Demaret, and Storath 2014]

For a manifold-valued image $q \in \mathcal{M}$, $\mathcal{M} = \mathcal{N}^{d_1,d_2}$, we compute

$$\operatorname*{arg\,min}_{p\in\mathcal{M}} \frac{1}{2\alpha} d^2_{\mathcal{M}}(p,q) + \|\Lambda(p)\|_{g,s,1}$$

with

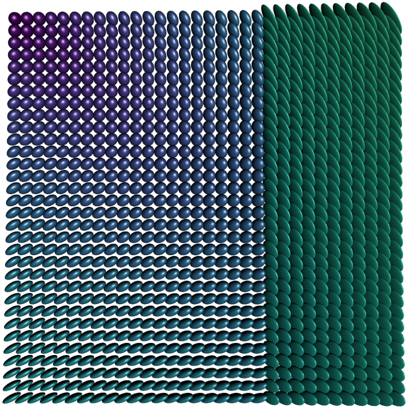
- "forward differences" $\Lambda\colon \mathcal{M} \to (T\mathcal{M})^{d_1-1,\ d_2-1,\ 2}$,

$$p \mapsto \Lambda(p) = \Bigl((\log_{p_i} p_{i+e_1},\ \log_{p_i} p_{i+e_2}) \Bigr)_{i\in\{1,\ldots,d_1-1\}\times\{1,\ldots,d_2-1\}}$$

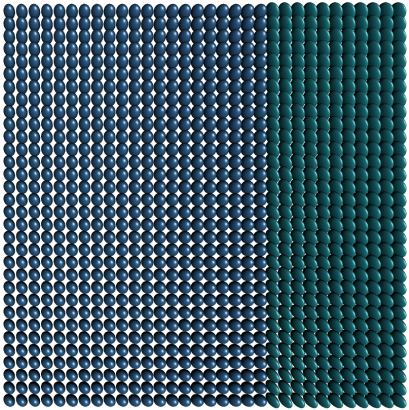
- $\|X\|_{g,s,1}$ similar to a collaborative TV, [Duran, Moeller, Sbert, and Cremers 2016]

$\Rightarrow$ anisotropic TV ($s = 1$) and isotropic TV ($s = 2$)

Numerical Example for a $\mathcal{P}(3)$-valued Image



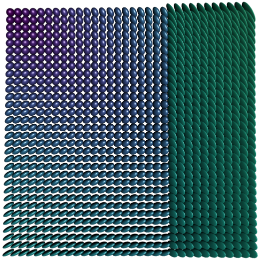
$\mathcal{P}(3)$-valued data.



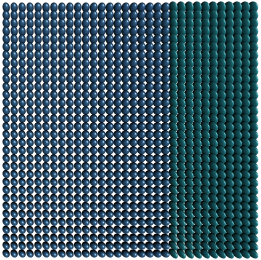
anisotropic TV, $\alpha = 6$.

- in each pixel we have a symmetric positive definite matrix
- Applications: denoising/inpainting e.g. of DT-MRI data

Numerical Example for a $\mathcal{P}(3)$-valued Image



$\mathcal{P}(3)$-valued data.



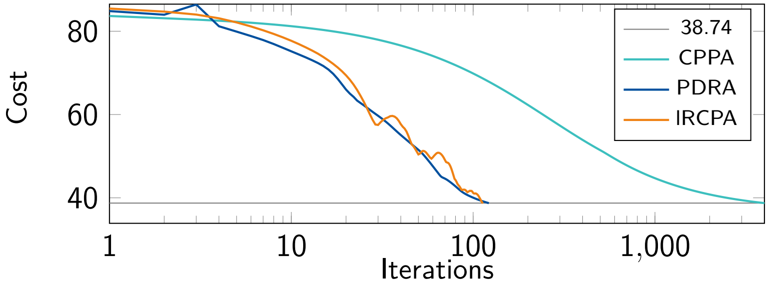
anisotropic TV, $\alpha = 6$.

Approach. CPPA as benchmark

[Bačák 2014; RB, Persch, and Steidl 2016; RB, Herzog, Silva Louzeiro, Tenbrinck, and Vidal-Núñez 2021]

	CPPA	PDRA	IRCPA
parameters	$\lambda_k = \frac{4}{k}$	$\lambda = 0.58$ $\beta = 0.93$	$\sigma = \tau = 0.4$ $\gamma = 0.2,\ m = I$
iterations	4000	122	**113**
runtime	1235 s.	380 s.	**96.1 s.**

Numerical Example for a $\mathcal{P}(3)$-valued Image



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Rosenbrock and First Order Methods

Problem. We consider the classical Rosenbrock example[2]

$$\operatorname*{arg\,min}_{x\in\mathbb{R}^2} a\bigl(x_1^2 - x_2\bigr)^2 + \bigl(x_1 - b\bigr)^2,$$

where $a, b > 0$, usually $b = 1$ and $a \gg b$, here: $a = 2 \cdot 10^5$.

Known Minimizer $x^* = \begin{pmatrix} b \\ b^2 \end{pmatrix}$ with cost $f(x^*) = 0$.

Goal. Compare first-order methods, e. g. using the (Euclidean) gradient

$$\nabla f(x) = \begin{pmatrix} 4a(x_1^2 - x_2) \\ -2a(x_1^2 - x_2) \end{pmatrix} + \begin{pmatrix} 2(x_1 - b) \\ 0 \end{pmatrix}$$

[2] available online in ManoptExamples.jl

A "Rosenbrock-Metric" on $\mathbb{R}^2$

NTNU

In our Riemannian framework, we can introduce a new metric on $\mathbb{R}^2$ as

$$G_p := \begin{pmatrix} 1+4p_1^2 & -2p_1 \\ -2p_1 & 1 \end{pmatrix}, \text{ with inverse } G_p^{-1} = \begin{pmatrix} 1 & 2p_1 \\ 2p_1 & 1+4p_1^2 \end{pmatrix}.$$

We obtain $(X, Y)_p = X^{\mathrm{T}} G_p Y$

The exponential and logarithmic map are given as

$$\exp_p(X) = \begin{pmatrix} p_1 + X_1 \\ p_2 + X_2 + X_1^2 \end{pmatrix}, \qquad \log_p(q) = \begin{pmatrix} q_1 - p_1 \\ q_2 - p_2 - (q_1 - p_1)^2 \end{pmatrix}.$$

`Manifolds.jl`:
Implement these functions on `MetricManifold(ℝ^2, RosenbrockMetric())`.

The Riemannian Gradient w.r.t. the new Metric

Let $f\colon \mathcal{M} \to \mathbb{R}$. Given the Euclidean gradient $\nabla f(p)$, its Riemannian gradient $\operatorname{grad} f\colon \mathcal{M} \to T\mathcal{M}$ is given by

$$\operatorname{grad} f(p) = G_p^{-1} \nabla f(p).$$

While we could implement this denoting $\nabla f(p) = \begin{pmatrix} f_1'(p) & f_2'(p) \end{pmatrix}^{\mathsf{T}}$ using

$$\Bigl\langle \operatorname{grad} f(q), \log_q p \Bigr\rangle_q = (p_1 - q_1) f_1'(q) + (p_2 - q_2 - (p_1 - q_1)^2) f_2'(q),$$

but it is automatically done in `Manopt.jl`.

The Experiment Setup

Algorithms. We now compare

1. The Euclidean gradient descent algorithm on $\mathbb{R}^2$,
2. The Riemannian gradient descent algorithm on $\mathcal{M}$,
3. The Difference of Convex Algorithm on $\mathbb{R}^2$,
4. The Difference of Convex Algorithm on $\mathcal{M}$.

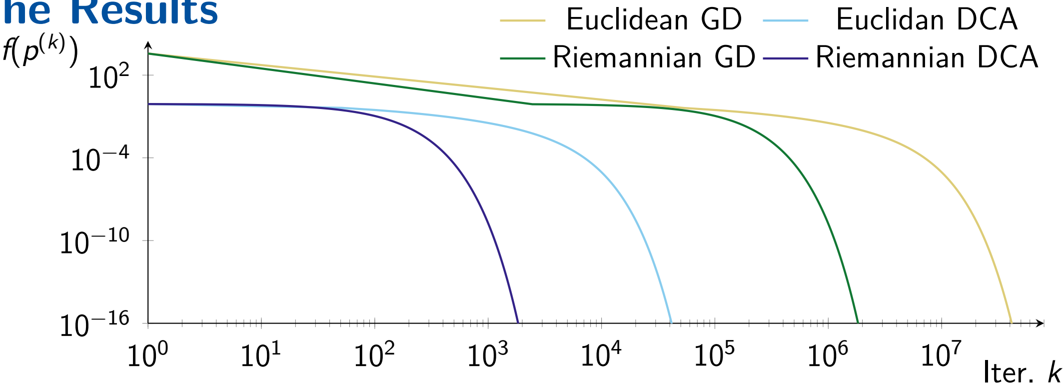
For DCA third we split f into $f(x) = g(x) - h(x)$ with

$$g(x) = a\bigl(x_1^2 - x_2\bigr)^2 + 2\bigl(x_1 - b\bigr)^2 \quad \text{and} \quad h(x) = \bigl(x_1 - b\bigr)^2.$$

Initial point. $p_0 = \frac{1}{10}\begin{pmatrix}1\\2\end{pmatrix}$ with cost $f(p_0) \approx 7220.81$.

Stopping Criterion. $d_{\mathcal{M}}(p^{(k)}, p^{(k-1)}) < 10^{-16}$ or $\lVert \operatorname{grad} f(p^{(k)}) \rVert_p < 10^{-16}$.

The Results



Algorithm	Runtime	# Iterations
Euclidean GD	305.567 sec.	53 073 227
Euclidean DCA	58.268 sec.	50 588
Riemannian GD	18.894 sec.	2 454 017
Riemannian DCA	7.704 sec.	2 459

Summary

We considered two different ways to generalize the Fenchel conjugate to Riemannian manifolds and how they are used in

- Nonsmooth Riemannian Optimization:
  m-Fenchel Dual and the Chambolle-Pock algorithm
- Nonconvex Riemannian Optimization:
  Fenchel Dual and the Difference of Convex algorithm
- Numerics in Julia:
  `Manopt.jl` together with `ManifoldsBase.jl` & `Manifolds.jl`

Selected References

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Boumal, N. (2023). *An introduction to optimization on smooth manifolds*. Cambridge University Press. URL: https://www.nicolasboumal.net/book.

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