The Riemannian Convex Bundle Method

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joint work with

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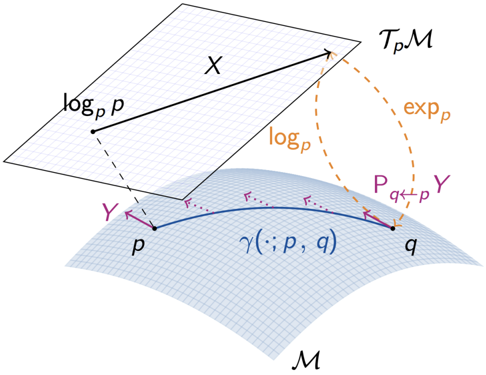
Riemannian Geometry

- Smooth Riemannian manifold $\mathcal{M}$
- Tangent space $\mathcal{T}_p\mathcal{M}$ at the point $p \in \mathcal{M}$
- Inner product $(\cdot,\cdot)_p : \mathcal{T}_p\mathcal{M} \times \mathcal{T}_p\mathcal{M} \to \mathbb{R}$
- Exponential map $\exp_p X_p = \gamma_{pq}(1) = q$
- Logarithmic map $\log_p q = \exp_p^{-1} q = X_p$
- Parallel transport $\mathrm{P}_{q\leftarrow p} : \mathcal{T}_p\mathcal{M} \to \mathcal{T}_q\mathcal{M}$
- Sectional curvature κ



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- $f\colon \mathcal{M} \to \overline{\mathbb{R}}$ is such that
  - $\operatorname{dom} f \neq \emptyset$ strongly geodesically convex
  - $\operatorname{diam}(\operatorname{dom} f) < \infty$ if $\kappa \neq 0$
  - $\operatorname{int}(\operatorname{dom} f) \neq \emptyset$ in $\mathcal{M}$
  - geodesically convex: $f \circ \gamma$ convex
  - lower semi-continuous: $\liminf_{q \to p} f(q) \geq f(p)$

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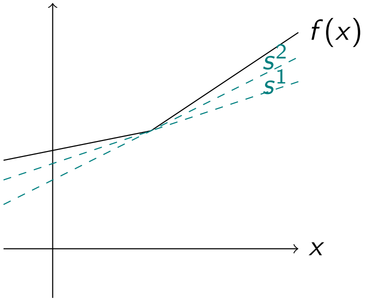
Goal. Solve this optimization problem with a convex bundle method.

The Convex Subdifferential(s)

For a convex function, the subdifferential is defined as

$$\partial f(x) = \left\{ s \in \mathbb{R}^n \,\middle|\, f(y) \geq f(x) + (s)^T (y - x) \text{ for all } y \in \mathbb{R}^n \right\}$$

and it is a non-empty, closed and convex subset.



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Let $\varepsilon > 0$. The $\varepsilon-$subdifferential is

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and

$$\partial f(x) \subseteq \partial_\varepsilon f(x)$$

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Goal. Approximate ∂f with $\partial_\varepsilon f$ on $\mathrm{int}(\mathrm{dom}\, f)$.

Approximating the $\varepsilon-$subdifferential

Given $x^{(0)}, \dots, x^{(k)} \in \mathbb{R}^n$, and $s^{(j)} \in \partial f(x^{(j)})$ for $j = 0, \dots, k$, and

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$$s^{(j)} \in \partial_{e_j^{(k)}} f(x^{(k)}).$$

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Characterize an inner approximation of $\partial_\varepsilon f(x^{(k)})$ as:

$$G_\varepsilon^{(k)} := \left\{ \sum_{j=0}^{k} \lambda_j s^{(j)} \;\middle|\; \sum_{j=0}^{k} \lambda_j \, e_j^{(k)} \leq \varepsilon,\; \sum_{j=0}^{k} \lambda_j = 1,\; \lambda_j \geq 0 \,\forall j = 0, \dots, k \right\}$$

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with $G_\varepsilon^{(k)} \subseteq \partial_\varepsilon f(x^{(k)})$.

Main challenge on manifolds: given $p^{(0)}, \dots, p^{(k)} \in \mathcal{M}$, and $X_{p^{(j)}} \in \partial f(p^{(j)})$, then

$$\mathrm{P}_{p^{(k)} \leftarrow p^{(j)}} X_{p^{(j)}} \in \partial_c f(p^{(k)}) \quad \text{for some} \quad c > 0?$$

Curvature Correction

Using the upper bound Ω on the curvature, define

$$c_j^{(k)} := f(p^{(k)}) - f(p^{(j)}) - \Big(X_{p^{(j)}}, \log_{p^{(j)}} p^{(k)}\Big) \quad \text{if } \Omega \leq 0,$$
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[Bergmann, Herzog, and HJ 2024].

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with $G_\varepsilon^{(k)} \subseteq \partial_\varepsilon f(p^{(k)})$, and $\mathrm{P}_{p^{(k)} \leftarrow p^{(j)}} X_{p^{(j)}} \in \partial_{c_j^{(k)}} f(p^{(k)})$.

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$$X_{q^{(j)}} \in \partial f(q^{(j)}) \implies \sum_{j=0}^{k} \lambda_j \mathrm{P}_{p^{(k)} \leftarrow q^{(j)}} X_{q^{(j)}} \in \partial_\varepsilon f(p^{(k)}) \quad \text{iff} \quad \varepsilon \geq \sum_{j=0}^{k} \lambda_j c_j^{(k)}$$

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The Euclidean Convex Bundle Method

Data: $x^{(0)} = y^{(0)} \in \mathbb{R}^n$, $g^{(0)} = s^{(0)} \in \partial f(x^{(0)})$, $m \in (0,1)$,
$\varepsilon^{(0)} = e_0^{(0)} = 0$, $k = 0$, $J^{(k)} = \{0\}$

while *not converged* **do**

Compute a solution $\lambda^{(k)} \in \mathbb{R}^{|J^{(k)}|}$ of the subproblem and set

$$g^{(k)} := \sum_{j \in J^{(k)}} \lambda_j^{(k)} s^{(j)}, \quad \varepsilon^{(k)} := \sum_{j \in J^{(k)}} \lambda_j^{(k)} e_j^{(k)},$$

$$d^{(k)} := -g^{(k)}, \quad \xi^{(k)} := -\|g^{(k)}\|^2 - \varepsilon^{(k)}$$

Set $y^{(k+1)} := x^{(k)} + d^{(k)}$.

If $f(y^{(k+1)}) \leq f(x^{(k)}) + m\xi^{(k)}$, then $x^{(k+1)} := y^{(k+1)}$, else $x^{(k+1)} := x^{(k)}$.

Compute $s^{(k+1)} \in \partial f(y^{(k+1)})$, update $J^{(k+1)}$, and for all $j \in J^{(k+1)}$

$$e_j^{(k+1)} := f(x^{(k+1)}) - f(y^{(j)}) - (s^{(j)})^T (x^{(k+1)} - y^{(j)})$$

end

Result: $x^{(k_*)}$, for some $k_* \in \mathbb{N}$.

The Riemannian Convex Bundle Method

Data: $p^{(0)} = q^{(0)} \in \operatorname{int}(\operatorname{dom} f)$, $g^{(0)} = X_1 \in \partial f(p^{(0)})$, $m \in (0,1)$,
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Set $t^{(k)} := 1$. While $q^{(k+1)} := \exp_{p^{(k)}}(t^{(k)} d^{(k)}) \notin \operatorname{int}(\operatorname{dom} f)$ or $\operatorname{dist}(q^{(k+1)}, p^{(k)}) < t^{(k)}\|d^{(k)}\|$ backtrack $t^{(k)} = \beta t^{(k)}$.

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Convergence

- In the Euclidean case [Geiger and Kanzow 2002, Theorem 6.80] holds.

Theorem

Let the solution set $S = \{x^* \in \mathbb{R}^n \mid f(x^*) = \inf_{x \in \mathbb{R}^n} f(x)\}$ *of the minimization problem be nonempty. Then every sequence* $\{x^{(k)}\}$ *generated by the bundle method algorithm converges to a minimizer of* f*.*

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- In the non-positive curvature case, assuming
  1. $t^{(k)} > m$ for all $k \geq k_*$, if a finite number of serious steps k_* occur
  2. no accumulation point of $p^{(k)}$ is allowed to lie on $\partial \operatorname{dom} f$

  we have an analogous result. [Bergmann, Herzog, and HJ 2024]

Implementation

The algorithm is implemented in Julia using `Manopt.jl` ([Bergmann 2022]) and `Manifolds.jl` ([Axen et al. 2023])[1]. A solver call looks like [2]

```
p* = convex_bundle_method(M, f, ∂f, p0;
        diameter = δ, domain = dom f, k_max = Ω, m = 10^-3)
```

where

- `M` is a Riemannian manifold
- `f` is the objective function
- `∂f` is a subgradient of the objective function
- `p0` is an initial point on the manifold

The default stopping criterion for the algorithm is set to

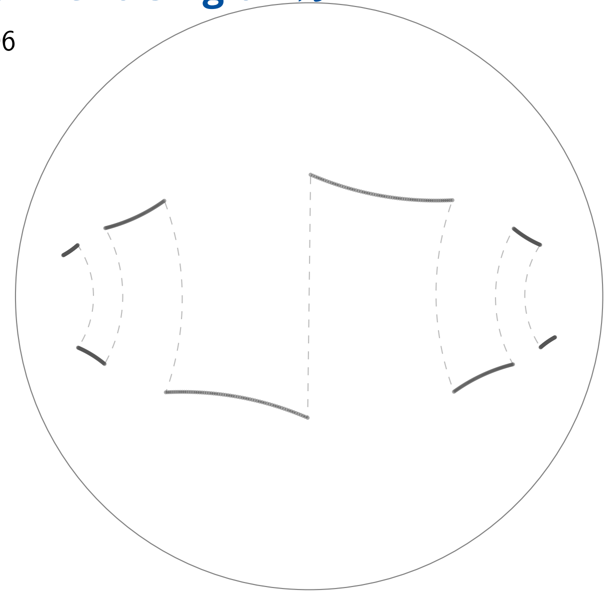
$$-\xi^{(k)} \leq 10^{-8}.$$

[1] For more on this: go to Ronny's talk on Wednesday at 12:30, building 208, room 64

[2] https://manoptjl.org/stable/solvers/convex_bundle_method/

Numerical Example: Signal Denoising on $\mathcal{H}^2$

- signal $q \in \mathcal{M} = (\mathcal{H}^2)^n$, $n = 496$



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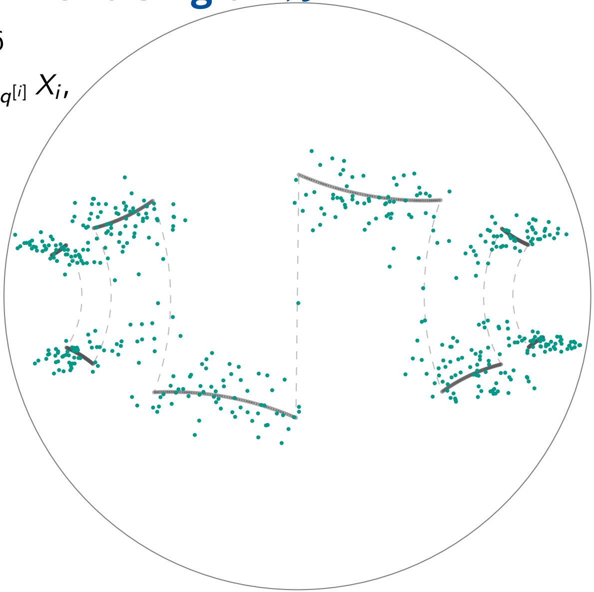

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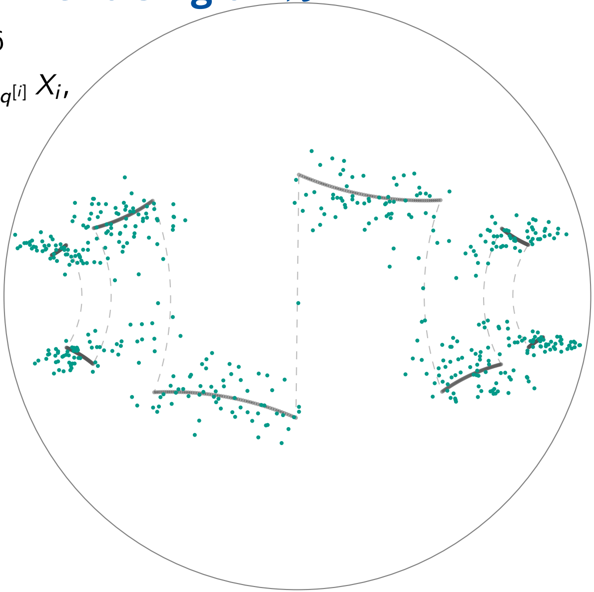
- ROF Model:

$$\operatorname*{arg\,min}_{p \in \mathcal{M}} \frac{1}{n} d_{\mathcal{M}}(p, q)^2 + \alpha \sum_{i=1}^{n-1} d_{\mathcal{H}^2}(p^{[i]}, p^{[i+1]})$$



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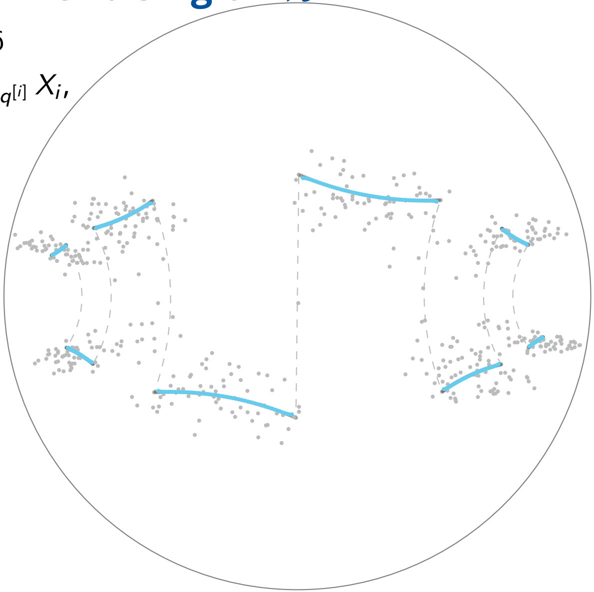
- Setting $\alpha = 0.05$ yields reconstruction p^*.



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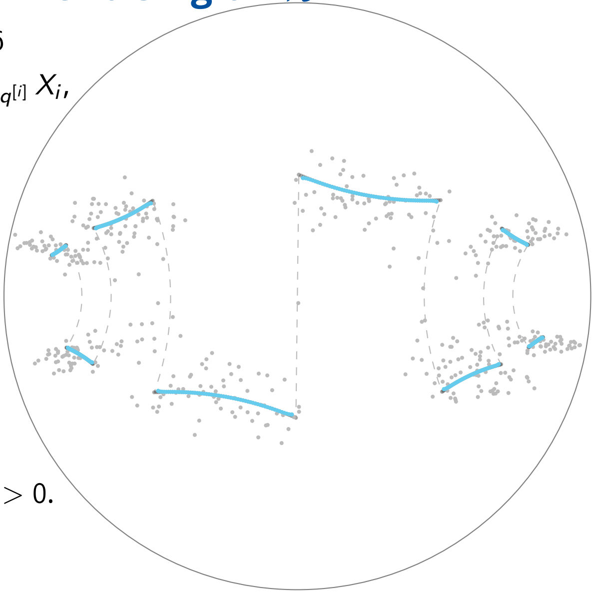
- Setting $\alpha = 0.05$ yields reconstruction p^*.
- in RCBM: set $\operatorname{diam}(\operatorname{dom} f) = b > 0$.
  (in practice: $b =$`floatmax()`$\approx 10^{308}$)



Signal Denoising - Algorithms[3]

- Riemannian Convex Bundle Method (RCBM) [Bergmann, Herzog, and HJ 2024]
- Proximal Bundle Algorithm (PBA) [Hoseini Monjezi, Nobakhtian, and Pouryayevali 2021]
- Subgradient Method (SGM) [Ferreira and Oliveira 1998]
- Cyclic Proximal Point Algorithm (CPPA) [Bačák 2014]

Algorithm	Iter.	Time (sec.)	Objective	Error
RCBM	3417	51.393	1.7929×10^{-3}	3.3194×10^{-4}
PBA	15 000	102.387	1.8153×10^{-3}	4.3874×10^{-4}
SGM	15 000	99.604	1.7920×10^{-3}	3.3080×10^{-4}
CPPA	15 000	94.200	1.7928×10^{-3}	3.3230×10^{-4}

[3] The code for the experiment is available at `juliamanifolds.github.io/ManoptExamples.jl/stable/examples/H2-Signal-TV/`

Numerical Example: Riemannian Median on $\mathcal{S}^d$

- $\mathcal{S}^d$ $d-$dimensional sphere
- $\bar{p}$ north pole
- $q^{(1)}, \ldots, q^{(n)} \in \mathcal{S}^d$ are $n = 1000$ Gaussian random data points in $B_{\frac{\pi}{8}}(\bar{p})$
- $\mathcal{D} = \{q^{(1)}, \ldots, q^{(n)} \mid q^{(j)} \in \mathcal{S}^d$ for all $j = 1, \ldots, n\}$

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Solve

$$p^* := \operatorname*{arg\,min}_{p \in \mathcal{S}^d} f(p)$$

Riemannian Median on $\mathcal{S}^d$ - Algorithms[4]

	RCBM			PBA		
Dimension	Iter.	Time (sec.)	Objective	Iter.	Time (sec.)	Objective
2	19	6.50×10^{-3}	0.192 89	20	5.30×10^{-3}	0.192 89
4	28	1.01×10^{-2}	0.198 81	23	5.99×10^{-3}	0.198 81
32	58	2.29×10^{-2}	0.195 76	28	1.13×10^{-2}	0.195 76
1024	48	3.91×10^{-1}	0.197 75	40	3.31×10^{-1}	0.197 75
32 768	43	7.54	0.192 90	21	4.16	0.192 90

	SGM		
Dimension	Iter.	Time (sec.)	Objective
2	5000	1.14	0.192 89
4	3270	8.09×10^{-1}	0.198 81
32	5000	2.18	0.195 76
1024	122	9.75×10^{-1}	0.197 75
32 768	172	5.25×10^{1}	0.192 90

[4] The code for the experiment is available at
`juliamanifolds.github.io/ManoptExamples.jl/stable/examples/RCBM-Median/`

Conclusion and Future Work

In summary:

- introduced the Riemannian Convex Bundle Method for non-smooth geodesically convex functions on Riemannian manifolds
- discussed convergence and related challenges
- showed two numerical examples

To do:

- further investigate the implications of positive curvature
- look into other non-smooth algorithms

Thank you!

Selected References

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Convergence

In [Geiger and Kanzow 2002, Theorem 6.80], they are able to show that

$$\sum_{j=k_*}^{+\infty} \left(\|g^{(j)}\|^2 + \varepsilon^{(j)}\right)^2 < +\infty$$

where $k_* \in \mathbb{N}$ is the index that corresponds to the last serious iterate, namely

$$p^{(k)} = p^{(k_*)} \quad \text{for all } k \geq k_*.$$

This is possible because from the definition of $e_j^{(k)}$ one gets a bound

$$\left(s^{(k)}, g^{(k-1)}\right) < m \left(\|g^{(k-1)}\|^2 + \varepsilon^{(k-1)}\right) - e_k^{(k)},$$

which is still valid in the case of non-positive curvature for $c_k^{(k)}$ with the added assumptions.