

001

Context and applications

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Optimization on manifolds, MATH 512 @ EPFL

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Step 0 in optimization

It starts with a **set** S and a **function** $f: S \rightarrow \mathbf{R}$. We want to compute:

$$\min_{x \in S} f(x)$$

These **bare objects** fully specify the problem.

Any additional **structure** on S and f may (and should) be exploited for **algorithmic purposes** but is not part of the problem.

Classical unconstrained optimization

The search space *is* a **linear space**, e.g., $S = \mathbf{R}^n$:

$$\min_{x \in \mathbf{R}^n} f(x)$$

We can *choose* to turn \mathbf{R}^n into a **Euclidean space**: $\langle u, v \rangle = u^\top v$.

If f is differentiable, we have a **gradient** $\text{grad}f$ and **Hessian** $\text{Hess}f$.

We can build **algorithms** with them: gradient descent, Newton's...

This course: optimization on manifolds

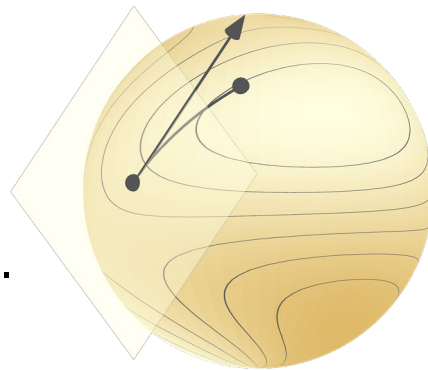
We target applications where $S = \mathcal{M}$ is a **smooth manifold**:

$$\min_{x \in \mathcal{M}} f(x)$$

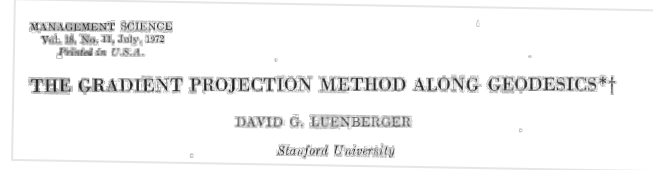
We can *choose* to turn \mathcal{M} into a **Riemannian manifold**.

If f is differentiable, we have a **Riemannian gradient** and **Hessian**.

We can build **algorithms** with them: gradient descent, Newton's...



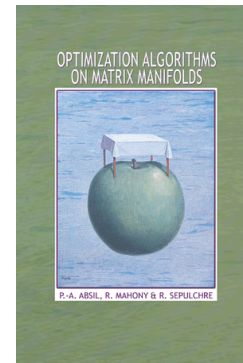
Proposed by Luenberger in 1972



Practical since 1990s with numerical linear algebra



Popularized in the 2010s by Absil et al.'s book



Becoming mainstream now.

How do manifolds come up in optimization?

Example 1: $A \in \mathbf{R}^{n \times n}$, $A = A^T$; want: the **largest eigenvalue** of A .

$$A = \sum_{i=1}^n \lambda_i v_i v_i^T, \quad \lambda_1 \geq \dots \geq \lambda_n; \quad v_1, \dots, v_n \in \mathbf{R}^n \text{ orthonormal.}$$

$$f(x) = x^T A x; \quad f(v_1) = \underbrace{v_1^T A v_1}_{\lambda_1, v_1} = \underbrace{d_1}_{1}, \quad \underbrace{v_1^T v_1}_1 = 1.$$

Claim: $\left[\max_{x \in \mathbf{R}^n} f(x) \text{ s.t. } \underbrace{x^T x = 1}_{\downarrow} \right] = \lambda_1.$

$S^{n-1} = \{x \in \mathbf{R}^n : x^T x = 1\}$ is a manifold.

Example 2: $M \in \mathbb{R}^{m \times n}$; want: the **largest singular value** of M .

SVD: $M = \sum_{i=1}^r \sigma_i u_i v_i^T$, $\sigma_1 \geq \dots \geq \sigma_r$
 u_1, \dots, u_r are orthonormal in \mathbb{R}^m
 v_1, \dots, v_r are orthonormal in \mathbb{R}^n .

$$f(x, y) = x^T M y; \quad f(u_i, v_i) = u_i^T M v_i = \sigma_i.$$

Claim: $\left[\begin{array}{c} \max_{\substack{x \in \mathbb{R}^m \\ y \in \mathbb{R}^n}} f(x, y) \text{ s.t. } x^T x = 1 \\ y^T y = 1 \end{array} \right] = \sigma_1.$

$S^{m-1} \times S^{n-1}$ is a manifold.

Example 3: $A \in \mathbf{R}^{n \times n}$, $A = A^T$; want: **top- k eigenspace** of A .

$$St(n, k) = \{X \in \mathbf{R}^{n \times k} : X^T X = I_k\}$$

Stiefel

$$f(X) = \text{Tr}[X^T A X]$$

Claim : $\left[\max_{X \in \mathbf{R}^{n \times k}} f(X) \text{ s.t. } X^T X = I_k \right] = \lambda_1 + \dots + \lambda_k$

(Courant-Fischer, Ky-Fan)

$$Q \in O(k) = \{ Q \in \mathbb{R}^{k \times k} : Q^T Q = Q Q^T = I_k \}$$

$$X \in St(n, k), Q \in O(k) \Rightarrow f(XQ) = \text{Tr}[(XQ)^T A XQ]$$

define: $X_1 \sim X_2 \Leftrightarrow X_1 = X_2 Q$ for some $Q \in O(k)$.

$$[X] = \{ XQ : Q \in O(k) \}$$

$$= \text{Tr}[Q^T X^T A X Q]$$

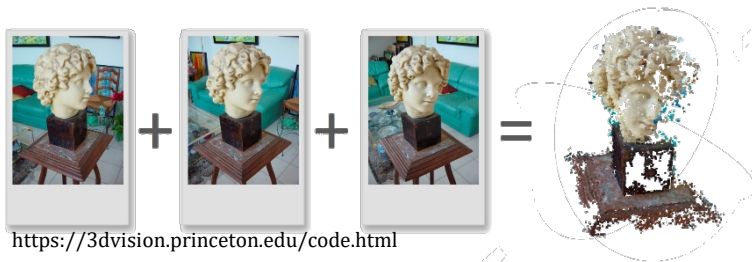
$$= \text{Tr}[X^T A X Q Q^T]$$

$$= f(X).$$

$$St(n, k) / \sim$$

More examples from applications

Structure from motion (SfM)



$$\mathbb{R}^3 \times SO(3)$$


$$SO(d) = \{ R \in \mathbb{R}^{d \times d} : R^T R = I_d, \det(R) = +1 \}$$

Simultaneous localization and mapping (SLAM)




[illegible]

Gaussian mixture models (GMM)



$$\mathbb{R}^d \times \{\Sigma \in \mathbb{R}^{d \times d} : \Sigma \succ 0\}$$

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