



Optimization over the intersection of manifolds

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- 1 Background: optimization with geometric constraints
- 2 Optimization over intersection of manifolds
- 3 Orthogonal tangent directions
- 4 Algorithm and convergence analysis
- 5 Numerical experiments

Background: optimization with geometric constraints

Optimization over a smooth manifold

Riemannian optimization problem

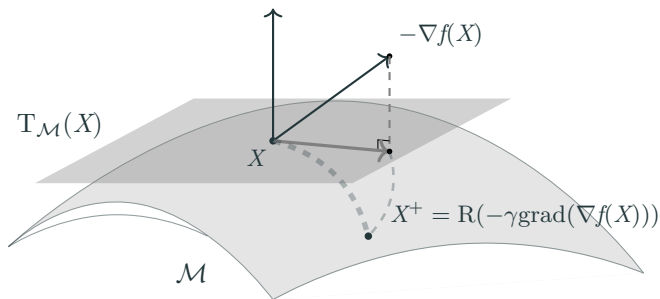
$$\min_{X \in \mathcal{M}} f(X)$$

with $\mathcal{M} \subseteq \mathbb{R}^m$ as a smooth manifold

Geometric ingredients

- Tangent space $T_{\mathcal{M}}(X)$
- Riemannian gradient $\text{grad}_{\mathcal{M}} f(X)$
- Retraction $R_x : T_{\mathcal{M}}(X) \rightarrow \mathcal{M}$

Riemannian gradient descent



Stiefel and Grassmann manifolds $\{X \in \mathbb{R}^{m \times p} \mid X^\top X = I_p\}$

- Principal component analysis problems [Jolliffe-Trendafilov-Uddin'03; Xu-Jiang-Liu-So'26]
- Computer vision and statistics on manifolds [Turaga-Veeraraghavan-Chellappa'08]
- Electronic structure calculations [Liu-Wang-Wen-Yuan'13; Jiang-Dai'16; Gao-Liu-Yuan'18]

Fixed-rank matrix manifold $\{X \in \mathbb{R}^{m \times n} \mid \text{rank}(X) = r\}$

- Low-rank matrix completion [Vandereycken'13]
- Magnetic resonance imaging (MRI) [Banco-Aeron-Hoge'16; Choi-Bao-Zhang'18; Fessler'20]
- Data analysis, e.g., weather forecast [Loucheur-Absil-Journée'23] and exoplanet detection [Daglayan-Vary-Absil-Cantalloube-Christiaens-Gillis-Jacques-Leplat-Absil'24]

Fixed-rank tensor manifolds $\{X \in \mathbb{R}^{n_1 \times n_2 \times \cdots \times n_d} \mid \text{rank}(X) = r\}$

- Tucker: tensor completion and parametric PDEs [Kressner-Steinlechner-Vandereycken'14]
- Tensor train: high-dimensional completion [Steinlechner'16; Peng-Zhu-Gao-Wang-Yuan'25]

Additional structures imposed on the manifold

$$\begin{array}{ll} \min_{X \in \mathcal{E}} & f(X) \\ \text{s. t.} & h(X) = 0 \\ & X \in \mathcal{M} \end{array}$$

Blanket assumptions

- Euclidean space $\mathcal{E}$ accommodates $\mathbb{R}^m$, $\mathbb{R}^{m \times n}$, or $\mathbb{R}^{n_1 \times n_2 \times \cdots \times n_d}$
- Objective $f: \mathcal{E} \rightarrow \mathbb{R}$ is continuously differentiable
- Differential Dh has full rank in a neighborhood of

$$\mathcal{H} := \{X \in \mathcal{E} \mid h(X) = 0\}$$

Additional structures imposed on the manifold

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- Euclidean space $\mathcal{E}$ accommodates $\mathbb{R}^m$, $\mathbb{R}^{m \times n}$, or $\mathbb{R}^{n_1 \times n_2 \times \cdots \times n_d}$
- Objective $f: \mathcal{E} \rightarrow \mathbb{R}$ is continuously differentiable
- Differential Dh has **full rank** in a neighborhood of

$$\mathcal{H} := \{X \in \mathcal{E} \mid h(X) = 0\}$$

$\mathcal{H}$ is a **smooth manifold** embedded in $\mathcal{E}$

Application I. Low rank + additional constraints

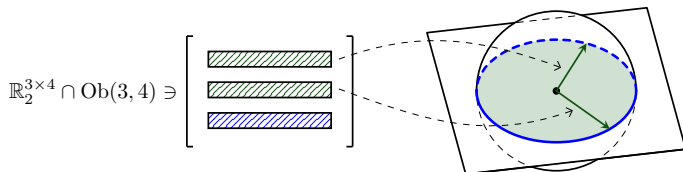
Fixed-rank constraint + an additional constraint

$$\begin{aligned} \min_{X \in \mathbb{R}^{m \times n}} \quad & f(X) \\ \text{s. t.} \quad & h(X) = 0 \\ & X \in \mathcal{M}_r = \{X \in \mathbb{R}^{m \times n} \mid \text{rank}(X) = r\} \end{aligned}$$

Low rank + oblique manifold

Low-rank data fitting on sphere [Chu-Del Buono-Lopez-Politi'05 SIMAX]

$$\mathcal{H} = \text{Ob}(m, n) := \{X \in \mathbb{R}^{m \times n} \mid \text{diag}(XX^\top) - \mathbf{1} = \mathbf{0}\}$$



Application I. Low rank + additional constraints (cont'd)

Low rank + Frobenius sphere

Approximation of graph similarity matrices [Cason-Absil-Van Dooren'13 LAA]

$$\mathcal{H} = S_F(m, n) := \{X \in \mathbb{R}^{m \times n} \mid \|X\|_F^2 - 1 = 0\}$$

Low rank + hyperbolic manifold

Approximation of hyperbolic embeddings [Jawanpuria-Meghwanshi-Mishra'19 CDC]

$$\mathcal{H} = \mathbb{H}_n^m := \{X \in \mathbb{R}^{m \times n} \mid \text{diag}(X \text{Diag}(-1, 1, \dots, 1)X^\top) - \mathbf{1} = \mathbf{0}\}$$

Low rank + Frobenius sphere (TT tensors)

Applications in quantum information theory [Peng-Zhu-Gao-Wang-Yuan'25]

$$\mathcal{H} = \{\mathbf{X} \in \mathbb{R}^{n_1 \times n_2 \times \dots \times n_d} \mid \|\mathbf{X}\|_F^2 - 1 = 0\}$$

Sparse constraint + an additional constraint

$$\begin{aligned} \min_{X \in \mathbb{R}^m} \quad & f(X) \\ \text{s. t.} \quad & h(X) = 0 \\ & X \in \mathcal{C}_s = \{X \in \mathbb{R}^m \mid \|X\|_0 = s\} \end{aligned}$$

Sparse + Frobenius sphere

Gene expression patterns and financial applications [Beck-Vaisbourd'16 JOTA]

$$\mathcal{H} = \{X \in \mathbb{R}^m \mid \|X\|_F^2 - 1 = 0\}$$

Sparse + Stiefel manifold

Sparse principal component analysis problems [Chen-Huang'26]

$$\mathcal{H} = \{X \in \mathbb{R}^{n \times p} \mid X^\top X - I_p = 0\}$$

Optimization over intersection of manifolds

Additional structures imposed on the general manifold $\mathcal{M}$

$$\begin{array}{ll} \min_{X \in \mathcal{E}} & f(X) \\ \text{s. t.} & X \in \mathcal{H} \cap \mathcal{M} \end{array}$$

where $\mathcal{H} = \{X \in \mathcal{E} \mid h(X) = 0\}$

Challenges introduced by the coupled constraints

- **Lack of manifold structure** on $\mathcal{H} \cap \mathcal{M}$
- **Geometry** of the coupled region $\mathcal{H} \cap \mathcal{M}$
 - Characterization of the tangent cone $\mathbf{T}_{\mathcal{H} \cap \mathcal{M}}(X)$
- **Difficulty** of preserving the feasibility $X \in \mathcal{H} \cap \mathcal{M}$
 - Absence of closed-form $\mathcal{P}_{\mathcal{H} \cap \mathcal{M}}(\cdot)$ - Iterates of alternating projections [von Neumann'50; Lewis-Mallick'08]

Optimization on $\mathcal{M}$ with equality constraints

$$\begin{array}{ll} \min_{X \in \mathcal{M}} & f(X) \\ \text{s. t.} & h(X) = 0 \end{array}$$

- Constraint qualifications and optimality conditions [Bergmannand-Herzog'19 SIOPT; Andreani-Couto-Ferreira-Haeser'24 SIOPT; Andreani-Couto-Ferreira-Haeser-Prudente'26 SIOPT]
- Riemannian augmented Lagrangian methods [Liu-Boumal'20; Zhou-Bao-Ding-Zhu'23 MP]
- Riemannian SQP methods [Schiela-Ortiz'21 SIOPT; Obara-Okuno-Takeda'22 SIOPT]
- Riemannian interior point methods [Lai-Yoshise'24 JOTA]
- Retractions by alternating projections [Chen-He-Huang'26]
- Exact penalty methods when $\mathcal{M}$ is convex [Xiao-Liu-Toh'24 MOR; Xiao-Tang-Wang-Toh'25]

Discussions

☹ A sequence of subproblems should be solved, e.g.,

$$\min_{X \in \mathcal{M}} f(X) + \langle \lambda, h(X) \rangle + \frac{\beta}{2} \|h(X)\|^2$$

Optimization over the intersection

$$\begin{array}{ll} \min_{X \in \mathcal{E}} & f(X) \\ \text{s. t.} & X \in \mathcal{H} \cap \mathcal{M} \end{array}$$

I. Feasibility

Find points $X \in \mathcal{H} \cap \mathcal{M}$

II. Optimality

Decrease f over $\mathcal{H} \cap \mathcal{M}$

Alternating projections

Method of alternating projections [von Neumann'50]

MAP Iteration

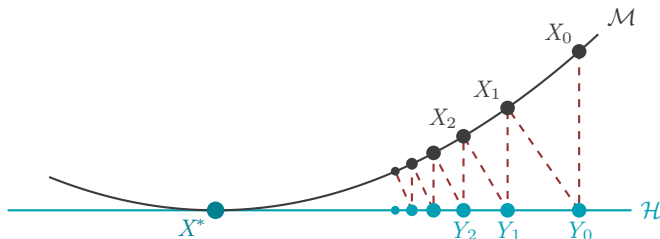
$$X_{k+1} \in \mathcal{P}_{\mathcal{M}}(\mathcal{P}_{\mathcal{H}}(X_k))$$



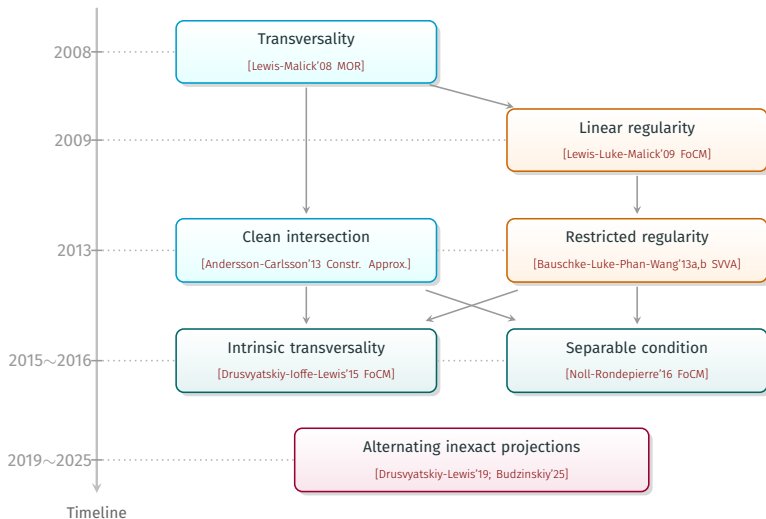
Feasibility Problem

Find a point $X^* \in \mathcal{H} \cap \mathcal{M}$

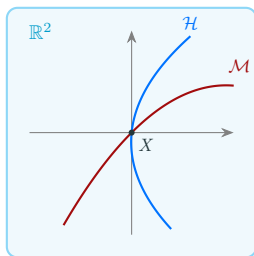
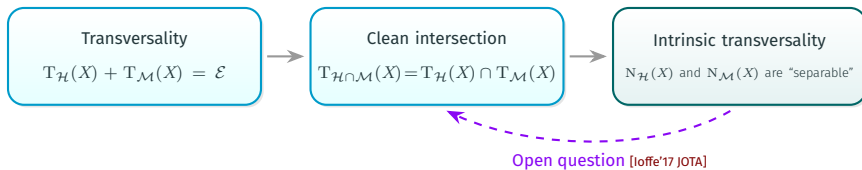
Illustration



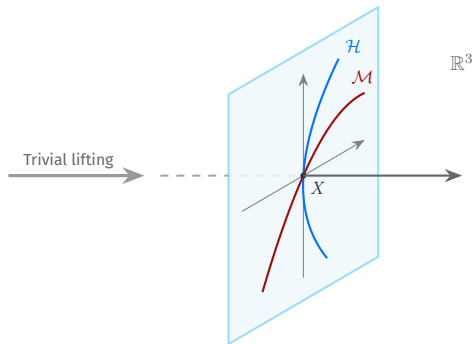
Developments and intersection conditions



Motivation of the notions



$T_{\mathcal{H}}(X) + T_{\mathcal{M}}(X) = \mathbb{R}^2$
Transversality holds



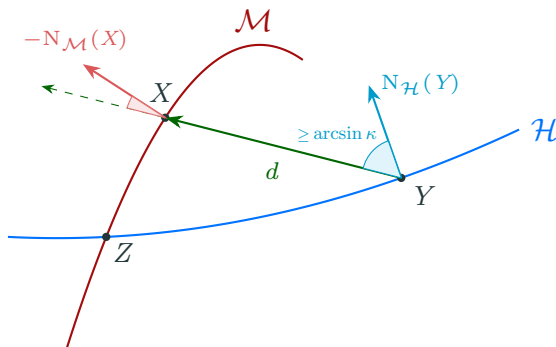
$T_{\mathcal{H}}(X) + T_{\mathcal{M}}(X) \subsetneq \mathbb{R}^3$
Transversality fails

Intrinsic transversality (IT)

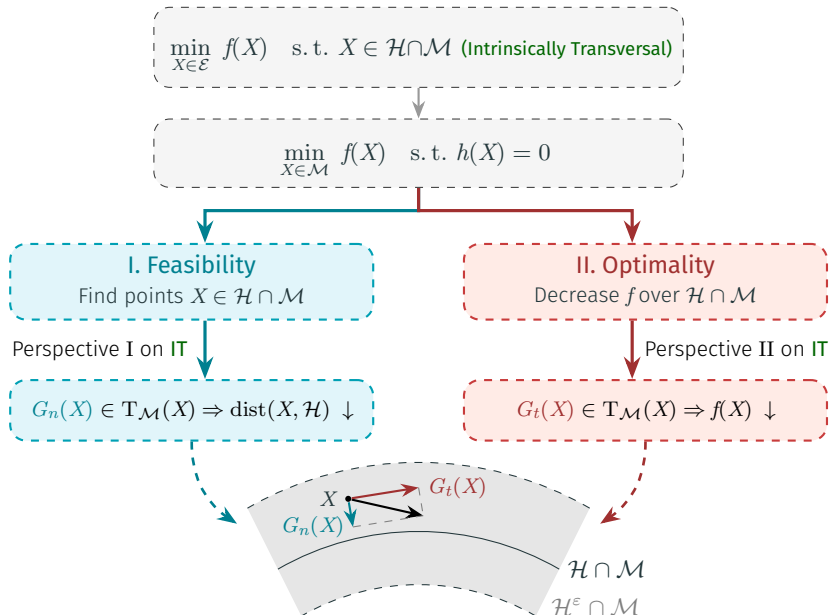
The sets $\mathcal{H}$ and $\mathcal{M}$ are *intrinsically transversal* at $z \in \mathcal{H} \cap \mathcal{M}$ if there exist $\kappa \in (0, 1]$ and a neighborhood $\mathcal{B}$ of Z such that for all $X \in (\mathcal{M} \cap \mathcal{B}) \setminus \mathcal{H}$ and $Y \in (\mathcal{H} \cap \mathcal{B}) \setminus \mathcal{M}$ with $d = \frac{\|X-Y\|}{\|X-Y\|}$, one has

$$\max \left\{ \text{dist} \left(d, -N_{\mathcal{M}}(X) \right), \text{dist} \left(d, N_{\mathcal{H}}(Y) \right) \right\} \geq \kappa$$

Illustration



A geometric framework

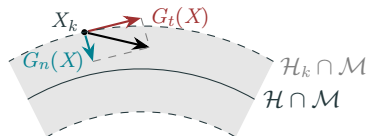


A geometric framework (cont'd)

Perturbed manifolds

$$\mathcal{H}(Y) := \{X \in \mathcal{E} \mid h(X) = h(Y)\}$$

$$\mathcal{H}_k := \mathcal{H}(X_k)$$



Update rule

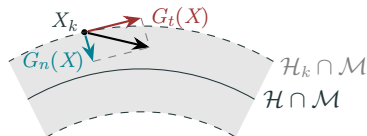
$$X_{k+1} = \mathbf{R}_{X_k}^{\mathcal{M}} (\alpha_k G_n(X_k) + \beta_k G_t(X_k))$$

A geometric framework (cont'd)

Perturbed manifolds

$$\mathcal{H}(Y) := \{X \in \mathcal{E} \mid h(X) = h(Y)\}$$

$$\mathcal{H}_k := \mathcal{H}(X_k)$$



Update rule

$$X_{k+1} = R_{X_k}^{\mathcal{M}}(\alpha_k G_n(X_k) + \beta_k G_t(X_k))$$

Important observation

Given two manifolds $\mathcal{X}_1, \mathcal{X}_2 \subseteq \mathcal{E}$ with a point $X \in \mathcal{X}_1 \cap \mathcal{X}_2$. Then for any $d \in N_{\mathcal{X}_2}(X)$ and $\eta \in \mathcal{E}$, it holds that

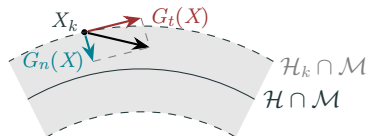
$$\langle \mathcal{P}_{T_{\mathcal{X}_1}(X)}(d), \mathcal{P}_{T_{\mathcal{X}_1 \cap \mathcal{X}_2}(X)}(\eta) \rangle = 0$$

A geometric framework (cont'd)

Perturbed manifolds

$$\mathcal{H}(Y) := \{X \in \mathcal{E} \mid h(X) = h(Y)\}$$

$$\mathcal{H}_k := \mathcal{H}(X_k)$$



Update rule

$$X_{k+1} = R_{X_k}^{\mathcal{M}}(\alpha_k G_n(X_k) + \beta_k G_t(X_k))$$

Important observation

Given two manifolds $\mathcal{X}_1, \mathcal{X}_2 \subseteq \mathcal{E}$ with a point $X \in \mathcal{X}_1 \cap \mathcal{X}_2$. Then for any $d \in N_{\mathcal{X}_2}(X)$ and $\eta \in \mathcal{E}$, it holds that

$$\langle \mathcal{P}_{T_{\mathcal{X}_1}(X)}(d), \mathcal{P}_{T_{\mathcal{X}_1 \cap \mathcal{X}_2}(X)}(\eta) \rangle = 0$$

$$G_n(X_k) = \mathcal{P}_{T_{\mathcal{M}}(X_k)}(d_k)$$

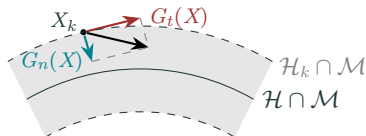
$$G_t(X_k) = \mathcal{P}_{T_{\mathcal{H}_k \cap \mathcal{M}}(X_k)}(\eta_k)$$

A geometric framework (cont'd)

Perturbed manifolds

$$\mathcal{H}(Y) := \{X \in \mathcal{E} \mid h(X) = h(Y)\}$$

$$\mathcal{H}_k := \mathcal{H}(X_k)$$



Update rule

$$X_{k+1} = R_{X_k}^{\mathcal{M}} \left(\alpha_k \mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k) + \beta_k \mathcal{P}_{\mathcal{T}_{\mathcal{H}_k \cap \mathcal{M}}(X_k)}(\eta_k) \right)$$

Important observation

Given two manifolds $\mathcal{X}_1, \mathcal{X}_2 \subseteq \mathcal{E}$ with a point $X \in \mathcal{X}_1 \cap \mathcal{X}_2$. Then for any $d \in \mathcal{N}_{\mathcal{X}_2}(X)$ and $\eta \in \mathcal{E}$, it holds that

$$\left\langle \mathcal{P}_{\mathcal{T}_{\mathcal{X}_1}(X)}(d), \mathcal{P}_{\mathcal{T}_{\mathcal{X}_1 \cap \mathcal{X}_2}(X)}(\eta) \right\rangle = 0$$

$$G_n(X_k) = \mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k)$$

$$G_t(X_k) = \mathcal{P}_{\mathcal{T}_{\mathcal{H}_k \cap \mathcal{M}}(X_k)}(\eta_k)$$

Orthogonal tangent directions

Bouligand tangent cone tangent space for a manifold

$$\mathcal{T}_{\mathcal{X}}(X) = \{\eta \in \mathcal{E} \mid \exists t_i \rightarrow 0, \text{ s. t. } \text{dist}(X + t_i \eta, \mathcal{X}) = o(t_i)\}$$

Given $X \in \mathcal{X}_1 \cap \mathcal{X}_2$, it holds that

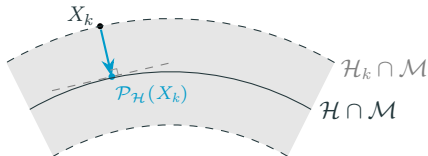
$$\mathcal{T}_{\mathcal{X}_1 \cap \mathcal{X}_2}(X) \subseteq \mathcal{T}_{\mathcal{X}_1}(X) \cap \mathcal{T}_{\mathcal{X}_2}(X) \quad \text{and} \quad \mathcal{N}_{\mathcal{X}_1 \cap \mathcal{X}_2}(X) \supseteq \mathcal{N}_{\mathcal{X}_1}(X) + \mathcal{N}_{\mathcal{X}_2}(X)$$

$\mathcal{M}_r$ as a smooth manifold based on the SVD $X = U\Sigma V^\top$

$$\begin{aligned} \mathcal{T}_{\mathcal{M}_r}(X) &= \left\{ [U \ U_\perp] \begin{bmatrix} \mathbb{R}^{r \times r} & \mathbb{R}^{r \times (n-r)} \\ \mathbb{R}^{(m-r) \times r} & \mathbb{0}^{(m-r) \times (n-r)} \end{bmatrix} [V \ V_\perp]^\top \right\} \\ \mathcal{N}_{\mathcal{M}_r}(X) &= \left\{ [U \ U_\perp] \begin{bmatrix} \mathbb{0}^{r \times r} & \mathbb{0}^{r \times (n-r)} \\ \mathbb{0}^{(m-r) \times r} & \mathbb{R}^{(m-r) \times (n-r)} \end{bmatrix} [V \ V_\perp]^\top \right\} \end{aligned}$$

$$G_n(X_k) = \mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k)$$

$$d_k \in \mathcal{N}_{\mathcal{H}_k}(X_k)$$



Construction of $d_k \in \mathcal{N}_{\mathcal{H}_k}(X_k) = \text{span}\{\nabla h(X_k)\}$

- Projection direction $\tilde{d}_k = X_k - \mathcal{P}_{\mathcal{H}}(X_k)$
- Gauss–Newton direction $d_k = -\nabla h(X_k)(\nabla h(X_k)^\top \nabla h(X_k))^{-1} h(X_k)$

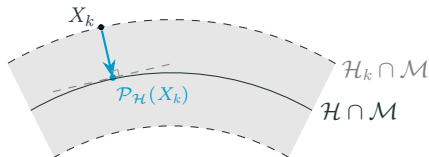
$$d_k = \min_{d \in \mathcal{N}_{\mathcal{H}_k}(X_k)} \|h(X_k) + \nabla h(X_k)^\top d\|^2$$

- First-order surrogate $\|\tilde{d}_k - d_k\| = \mathcal{O}(\|\tilde{d}_k\|^2)$

Tangent direction toward feasibility

$$G_n(X_k) = \mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k)$$

$$d_k \in \mathcal{N}_{\mathcal{H}_k}(X_k)$$



Construction of $d_k \in \mathcal{N}_{\mathcal{H}_k}(X_k) = \text{span}\{\nabla h(X_k)\}$

- Projection direction $\tilde{d}_k = X_k - \mathcal{P}_{\mathcal{H}}(X_k)$
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$$d_k = \min_{d \in \mathcal{N}_{\mathcal{H}_k}(X_k)} \|h(X_k) + \nabla h(X_k)^\top d\|^2$$

- First-order surrogate $\|\tilde{d}_k - d_k\| = \mathcal{O}(\|\tilde{d}_k\|^2)$

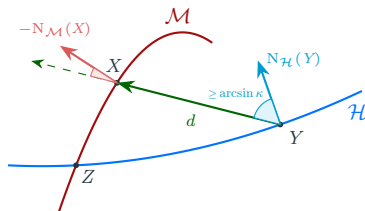
Can $\mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k)$ still guarantee $\text{dist}(X_k, \mathcal{H}) \downarrow$?

Perspective I on intrinsic transversality

Intrinsic transversality is defined via

all (X, Y) pairs around Z

$$\max\{\text{dist}(d, -N_{\mathcal{M}}(X)), \text{dist}(d, N_{\mathcal{H}}(Y))\} \geq \kappa$$

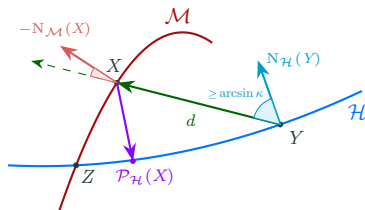


Perspective I on intrinsic transversality

Intrinsic transversality is defined via

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$$\max\{\text{dist}(d, -N_{\mathcal{M}}(X)), \text{dist}(d, N_{\mathcal{H}}(Y))\} \geq \kappa$$



Projection-based transversality $\mathcal{H}, \mathcal{M}$ are C^2 submanifolds

There exists $\kappa' \in (0, 1]$ such that for the **specific** pairs, it holds that

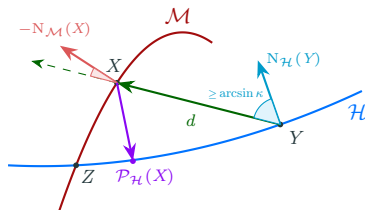
$$(X, \mathcal{P}_{\mathcal{H}}(X)) \Rightarrow \text{dist}(d, -N_{\mathcal{M}}(X)) \geq \kappa' \quad (Y, \mathcal{P}_{\mathcal{M}}(Y)) \Rightarrow \text{dist}(d, N_{\mathcal{H}}(Y)) \geq \kappa'$$

Perspective I on intrinsic transversality

Intrinsic transversality is defined via

all (X, Y) pairs around Z

$$\max\{\text{dist}(d, -N_{\mathcal{M}}(X)), \text{dist}(d, N_{\mathcal{H}}(Y))\} \geq \kappa$$



Projection-based transversality $\mathcal{H}, \mathcal{M}$ are C^2 submanifolds

There exists $\kappa' \in (0, 1]$ such that for the **specific** pairs, it holds that

$$(X, P_{\mathcal{H}}(X)) \Rightarrow \text{dist}(d, -N_{\mathcal{M}}(X)) \geq \kappa' \quad (Y, P_{\mathcal{M}}(Y)) \Rightarrow \text{dist}(d, N_{\mathcal{H}}(Y)) \geq \kappa'$$

Theorem

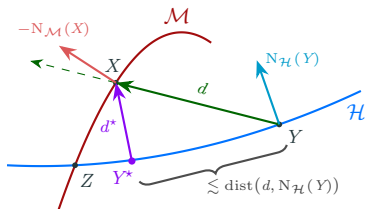
Intrinsic transversality $\iff$ **Projection-based transversality**

Intuition and proof sketch

Theorem $\mathcal{H}, \mathcal{M}$ are C^2 submanifolds

Intrinsic transversality $\iff$ **Projection-based transversality**

Nontrivial direction “ $\Leftarrow$ ”



- Assume **IT** fails: (X, Y) with d **nearly normal** to both $\mathcal{H}, \mathcal{M}$; $Y^* := \mathcal{P}_{\mathcal{H}}(X)$

- Prox-regularity of manifolds gives $\|Y - Y^*\| \lesssim \text{dist}(d, N_{\mathcal{H}}(Y))$, and thus

$$\begin{aligned} \text{dist}(d^*, N_{\mathcal{M}}(X)) &\leq \text{dist}(d, N_{\mathcal{M}}(X)) + C_1 \|d - d^*\| \\ &\leq \text{dist}(d, N_{\mathcal{M}}(X)) + C_2 \text{dist}(d, N_{\mathcal{H}}(Y)) \end{aligned}$$

- IT** fails $\iff$ **both terms are small** $\implies (X, Y^*)$ leads to a **contradiction**

Tangent direction I: projected Gauss–Newton direction

$$\begin{array}{ll} \min_{X \in \mathcal{E}} & f(X) \\ \text{s. t.} & X \in \mathcal{H} \cap \mathcal{M} \end{array}$$

$$\begin{aligned} G_n(X_k) &= \mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k) \\ d_k &= -\nabla h(X_k)(\nabla h(X_k)^\top \nabla h(X_k))^{-1} h(X_k) \end{aligned}$$

Projection-based transversality

$$\|\mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k)\| \geq \kappa' \|d_k\|$$

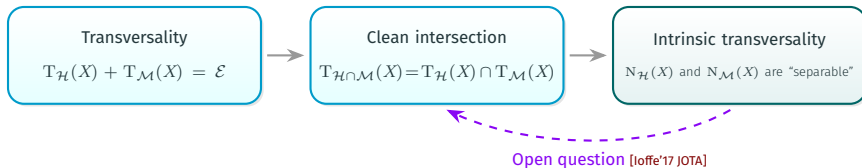
Non-degeneracy of ∇h

$$\|d_k\| \geq \sigma_{\max}^{-1}(\nabla h(X_k)) \|h(X_k)\|$$

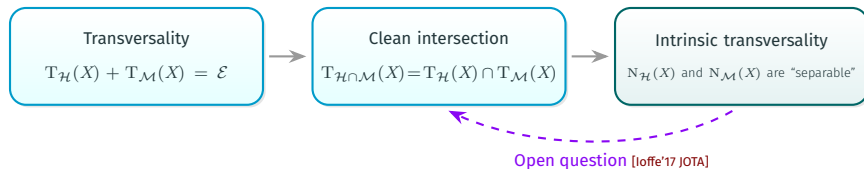
Optimality analysis

$$\begin{aligned} G_n(X_k) = 0 &\iff \mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X_k)}(d_k) = 0 \\ &\implies h(X_k) = 0 \end{aligned}$$

Perspective II on intrinsic transversality



Perspective II on intrinsic transversality



Theorem answers the open question

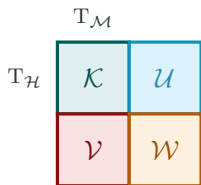
Let $\mathcal{H}, \mathcal{M} \subseteq \mathcal{E}$ be C^1 manifolds, and they are intrinsically transversal at X . Then they intersect *cleanly* near X : there exists a neighborhood $\mathcal{B}$ of X such that $\mathcal{H} \cap \mathcal{M} \cap \mathcal{B}$ is a C^1 manifold and, for all $Y \in \mathcal{B}$, it holds that

$$T_{\mathcal{H} \cap \mathcal{M}}(Y) = T_{\mathcal{H}}(Y) \cap T_{\mathcal{M}}(Y)$$

Theorem $\mathcal{H}, \mathcal{M}$ are C^1 submanifolds, intrinsically transversal at Z

$\mathcal{H} \cap \mathcal{M}$ is a C^1 submanifold near Z with $T_{\mathcal{H} \cap \mathcal{M}} = T_{\mathcal{H}} \cap T_{\mathcal{M}}$

- Intersection regularities are invariant under diffeomorphisms
- **Flatten** $\mathcal{H}$ into a linear space; orthogonally decompose $\mathcal{E}$ along $(T_{\mathcal{H}}, T_{\mathcal{M}})$



$$\mathcal{E} = \mathcal{K} \oplus \mathcal{U} \oplus \mathcal{V} \oplus \mathcal{W}$$

$$\mathcal{K} = T_{\mathcal{H}} \cap T_{\mathcal{M}} \text{ and } \mathcal{W} = (T_{\mathcal{H}} + T_{\mathcal{M}})^{\perp}$$

$$\text{Graph representation } \begin{cases} \mathcal{M} = \{(k, a(k, v), v, b(k, v)) \mid (k, v) \in \mathcal{K} \oplus \mathcal{V}\} \\ \mathcal{H} = \{(k, u, 0, 0) \mid (k, u) \in \mathcal{K} \oplus \mathcal{U}\} \end{cases}$$

- ★ Intrinsic transversality implies that $b(k, 0) \equiv 0$ for all $k \in \mathcal{K}$ small enough
- $\mathcal{H} \cap \mathcal{M} = \{(k, a(k, 0), 0, 0) \mid k \in \mathcal{K}\}$ is a graph on $\mathcal{K}$, thus C^1 **embedded**

Tangent direction II: projected anti-gradient direction

$$\begin{array}{ll} \min_{X \in \mathcal{E}} & f(X) \\ \text{s. t.} & X \in \mathcal{H} \cap \mathcal{M} \end{array}$$

$$G_t(X_k) = \mathcal{P}_{\mathcal{T}_{\mathcal{H}_k \cap \mathcal{M}}(X_k)}(-\nabla f(X_k))$$

Optimality analysis

$$\begin{aligned} G_t(X_k) = 0 &\iff \mathcal{P}_{\mathcal{T}_{\mathcal{H}_k \cap \mathcal{M}}(X_k)}(-\nabla f(X_k)) = 0 \\ &\iff -\nabla f(X_k) \in \mathcal{N}_{\mathcal{H}_k \cap \mathcal{M}}(X_k) \end{aligned}$$

Descent property

$$\langle \mathcal{P}_{\mathcal{T}_{\mathcal{M}}(X)}(\nabla f(X)), \mathcal{P}_{\mathcal{T}_{\mathcal{H} \cap \mathcal{M}}(X)}(-\nabla f(X)) \rangle = -\|\mathcal{P}_{\mathcal{T}_{\mathcal{H} \cap \mathcal{M}}(X)}(-\nabla f(X))\|^2$$

Proposition $S(X) = T_{\mathcal{H}(X)}(X) \cap T_{\mathcal{M}}(X)$

Assume that $\mathcal{H}(X)$ and $\mathcal{M}$ are intrinsically transversal at X , and let

$\Phi_{\mathcal{M}}(X) := \mathcal{P}_{T_{\mathcal{M}}(X)} \circ Dh_X^*$. Then for any $\xi \in \mathcal{E}$,

$$\mathcal{P}_{S(X)}(\xi) = \mathcal{P}_{T_{\mathcal{M}}(X)}(\xi) - \Phi_{\mathcal{M}}(X)(Dh_X \circ \Phi_{\mathcal{M}}(X))^{\dagger} Dh_X(\mathcal{P}_{T_{\mathcal{M}}(X)}(\xi))$$

When they are transversal, the pseudoinverse reduces to the ordinary inverse

☺ Computing $G_t(X) = \mathcal{P}_{T_{\mathcal{H} \cap \mathcal{M}}(X)}(-\nabla f(X))$ is tractable

Projection onto the tangent space (cont'd)

Manifold	Level set of h	$\mathcal{P}_{\mathcal{T}_{\mathcal{H} \cap \mathcal{M}}(X)}$	Format
$\mathcal{M}_r$	$\{X \in \mathbb{R}^{m \times n} \mid \mathcal{A}(X) = b\}$	[Yang-Gao-Yuan'25]	low-rank
$\mathcal{M}_r$	$\mathcal{H}$ is orthogonally invariant	[Yang-Gao-Yuan'26 MP]	
$\mathcal{M}_r$	$\mathcal{H}$ is hyperbolic	Appendix A	
$\mathcal{S}_r(n)$	$\{X \in \mathcal{S}(n) \mid \ X\ _{\mathbb{F}}^2 = 1\}$	[Li-Xiu-Zhou'20 JOTA]	
$\mathcal{M}_r^{\text{ht}}$	$\{\mathbf{X} \in \mathbb{R}^{n_1 \times n_2 \times \dots \times n_d} \mid \ \mathbf{X}\ _{\mathbb{F}}^2 = 1\}$	[Yang-Gao-Yuan'25]	
$\mathcal{M}_r^{\text{tt}}$	Reshaped Stiefel manifold	Appendix B	
$\mathcal{C}_s$	$\{X \in \mathbb{R}^n \mid \ X\ _{\mathbb{F}}^2 = 1\}$	[Beck-Hallak'16 MOR]	sparse
$\mathcal{C}_s$	$\{X \in \mathbb{R}^{n \times p} \mid X^\top X = I_p\}$	[Chen-Huang'26]	
$\mathcal{M}$	$\mathcal{H} \cap \mathcal{M}$ is intrinsically transversal	Our proposition	general

Algorithm and convergence analysis

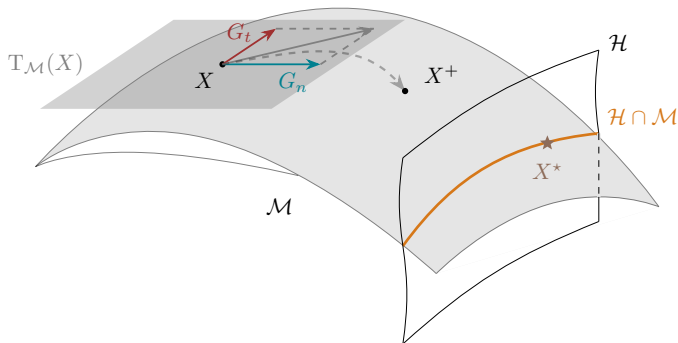
A Geometric method via Orthogonal Tangent Directions (GOTD)

$$d_k = -\nabla h(X_k)(\nabla h(X_k)^\top \nabla h(X_k))^{-1} h(X_k)$$

$$\eta_k = -\nabla f(X_k)$$

$$X_{k+1} = R_{X_k}^{\mathcal{M}} \left(\alpha_k \mathcal{P}_{T_{\mathcal{M}}(X_k)}(d_k) + \beta_k \mathcal{P}_{T_{\mathcal{H} \cap \mathcal{M}}(X_k)}(\eta_k) \right)$$

Illustration



Assumptions

- There exists a constant $\rho > 0$ such that ∇h has full rank on

$$\mathcal{K}(\rho) := \{X \in \mathbb{R}^m \mid \|h(X)\| \leq \rho\}$$

- The intersection $\mathcal{H}(Y) \cap \mathcal{M}$ is intrinsically transversal for $Y \in \mathcal{K}(\rho)$
- Riemannian L -smoothness of f on $\mathcal{M}$

Optimality

- The condition $\|G_t(X)\| \leq \varepsilon$ reveals $\|\mathcal{P}_{\mathcal{T}_{\mathcal{H}(X) \cap \mathcal{M}}}(-\nabla f(X))\| \leq \varepsilon$
- When $\varepsilon = 0$ and $h(X) = 0$, the first-order optimality holds

$$\mathcal{P}_{\mathcal{T}_{\mathcal{H} \cap \mathcal{M}}(X)}(-\nabla f(X)) = 0$$

Theorem

In GOTD, with appropriate constant step sizes α, β , the iterates $\{X_k\}$ satisfy

$$\frac{1}{K} \sum_{k=1}^K \left(\|G_t(X_k)\|^2 + \text{dist}(X_k, \mathcal{H}) \right) = \mathcal{O}\left(\frac{1}{K}\right)$$

Numerical experiments

Low-rank approximation of spherical data

Approximate $A \in \mathcal{H} = \text{Ob}(m, n)$ with a low-rank matrix [Chu et al., 2005 SIAMX]

$$\begin{aligned} \min_{X \in \mathbb{R}^{m \times n}} \quad & \frac{1}{2} \|\mathcal{P}_\Omega(X - A)\|^2 \\ \text{s. t.} \quad & \text{diag}(XX^\top) - \mathbf{1} = 0 \\ & \text{rank}(X) = r \end{aligned}$$

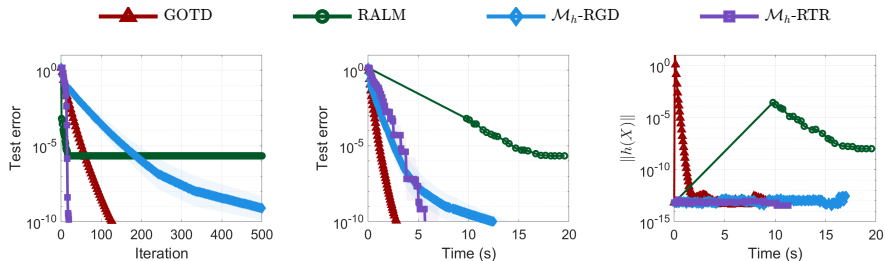
Methods based on Manopt v8.0

- GOTD (ours)
- Riemannian augmented Lagrangian method (RALM) [Liu-Boumal'20]
- Space-decoupling parameterization $\mathcal{M}_h$ [Yang-Gao-Yuan'26 MP]

Settings

- Synthetic $A \in \mathcal{M}_{\leq r} \cap \text{Ob}(m, n)$, $(m, n) = (5000, 6000)$
- rank parameter $r = r^* = 10$, oversampling factor $\text{OS} = 6$

Test on synthetic data



- ☺ **RALM** and **$\mathcal{M}_h$ -RTR** exhibit better iteration complexity, but they should solve a subproblem for each iterate
- ☺ **GOTD** recovers the matrix faster than **RALM** and methods on $\mathcal{M}_h$
- ☺ Geometric methods achieve better precision

Low-rank approximation of hyperbolic embeddings

Approximate $A \in \mathbb{H}_n^m$ under hyperbolic distance [Nickel-Kiela'17]

$$\begin{aligned} \min_{X \in \mathbb{R}^{(n+1) \times m}} \quad & \sum_{i=1}^m \operatorname{arccosh}(-\langle X_i, A_i \rangle_{\mathcal{L}})^2 \\ \text{s. t.} \quad & X \in \mathbb{H}_n^m \\ & \operatorname{rank}(X) = r + 1 \end{aligned}$$

$$\mathcal{H} = \mathbb{H}_n^m := \{X \in \mathbb{R}^{(n+1) \times m} \mid \operatorname{diag}(X^\top \operatorname{Diag}(-1, 1, \dots, 1)X) - \mathbf{1} = \mathbf{0}\}$$

Methods

- GOTD (ours)
- Riemannian augmented Lagrangian method (RALM) [Liu-Boumal'20]
- Riemannian parameterization (RGD, RTR) [Jawanpuria-Meghwanshi-Mishra'19 CDC]

Settings

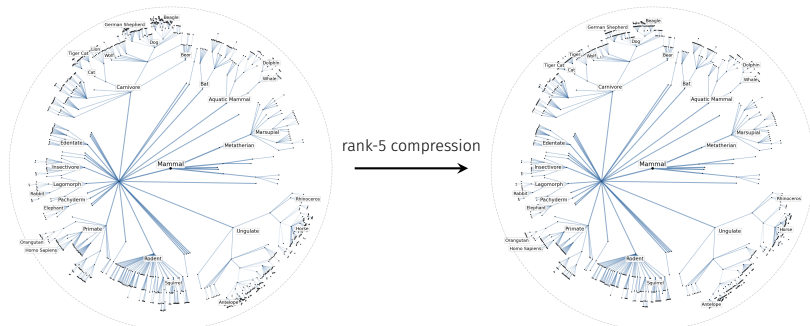
- The mammal subtree of the WordNet database
- $(n, m) = (300, 1170)$, rank parameter $r = 5, 10, 20$

Results of low-rank hyperbolic embeddings

Evaluation on mean average precision (original embeddings: 0.9385)

Rank	GOTD (Ours)	RALM	RGD	RTR
$r = 5$	0.8869	0.6637	0.8881	0.8883
$r = 10$	0.9039	0.8117	0.8961	0.9024
$r = 20$	0.9003	0.8463	0.8989	0.8981

Illustration on 2-dimensional Poincaré ball



Spatially localized solutions of the Schrödinger's equation

$$\begin{array}{ccc} \min_{X \in \mathbb{R}^{n \times p}} & \text{tr}(X^\top H X) & \\ \text{s. t.} & X \in \text{St}(n, p) & \\ & X \in \mathcal{M} = \{Y \in \mathbb{R}^{n \times p} \mid \|Y\|_0 = s\} & \end{array} \xrightarrow{\text{penalty}} \begin{array}{ccc} \min_{X \in \mathbb{R}^{n \times p}} & \text{tr}(X^\top H X) + \mu \|X\|_1 & \\ \text{s. t.} & X \in \text{St}(n, p) & \end{array}$$

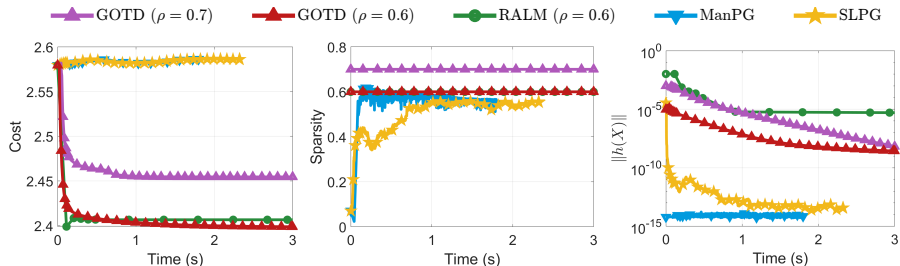
Methods

- GOTD (ours)
- Riemannian augmented Lagrangian method (RALM) [Liu-Boumal'20]
- Manifold proximal gradient method (ManPG) [Chen-Ma-So-Zhang'20]
- Sequential linearized proximal gradient (SLPG) [Liu-Xiao-Yuan'24]

Settings

- H is symmetric, discretizing the Hamiltonian $-\frac{1}{2}\partial_x^2$
- $(n, p) = (256, 15)$, sparsity $\rho := (np - \|X\|_0)/np \in \{0.6, 0.7\}$

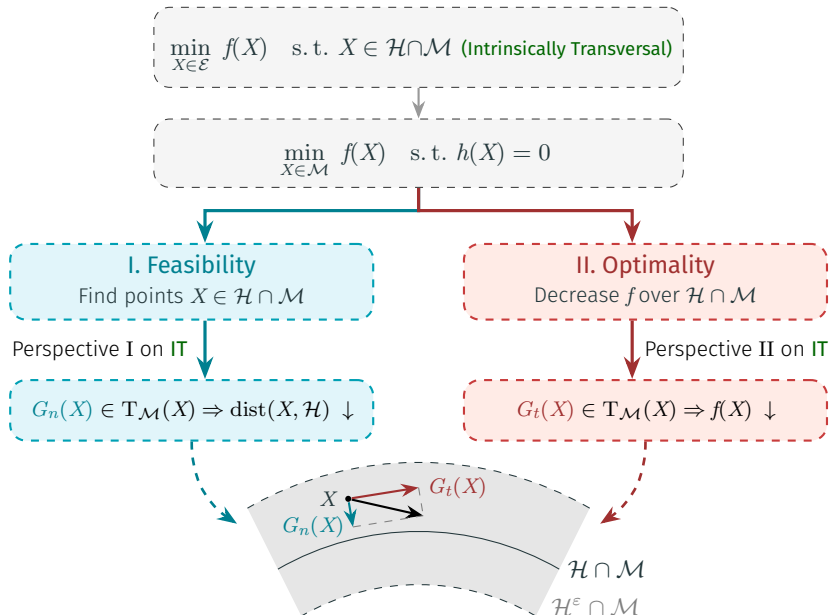
Comparison on cost, sparsity, and feasibility



😊 GOTD finds lower cost with lower density than ManPG and SLPG

😊 GOTD achieves better feasibility than RALM

Conclusion



Conclusion and future work

- ☺ Efficient algorithm exploiting the geometry [Yang-Gao-Yuan'25]

$$\mathbf{T}_{\mathcal{H} \cap \mathcal{M}}(X) = \mathbf{T}_{\mathcal{H}}(X) \cap \mathbf{T}_{\mathcal{M}}(X)$$

- ❓ Second-order development beneficial from the property [Yang-Gao-Yuan'25]

$$\mathbf{T}_{\mathcal{H} \cap \mathcal{M}}^2(X; \eta) = \mathbf{T}_{\mathcal{H}}^2(X; \eta) \cap \mathbf{T}_{\mathcal{M}}^2(X; \eta)$$

- ❓ Reasonable extension to multiple manifolds $\mathcal{M}, \mathcal{H}_1, \dots, \mathcal{H}_N$
- ❓ Technical adaptation to non-smooth sets, e.g., $\mathcal{M} = \mathcal{M}_{\leq r}, \mathcal{C}_{\leq s}$
- ❓ Stochastic oracles and variance-reduction algorithms

References

Yan Yang, Bin Gao, Ya-xiang Yuan. *A space-decoupling framework for optimization on bounded-rank matrices with orthogonally invariant constraints.*

Mathematical Programming (2026)

Yan Yang, Bin Gao, Ya-xiang Yuan. *Variational analysis of determinantal varieties.*
arXiv:2511.22613 (2025)

Thanks for your attention!

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