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CLT and Smeariness for Means on Riemannian Manifolds

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Introduction

– In search of a well-defined mean point for random variables on Riemannian manifolds, inspiration from the Euclidean mean value has been crucial.

1. **x** has a unique Fréchet mean $\mu \in \mathcal{M}$ and $\mu_n \xrightarrow{\mathbb{P}} \mu$. 2. Almost Surely Locally Lipschitz and Differentiable at Mean of dist $(p,q)^2$

3. For some $r \ge 2$, rotation matrix $R \in SO(m)$ and $T_1, ..., T_m$ it holds that





- Most commonly studied is the Fréchet mean whose definition originates from the least squared distance property of the Euclidean mean.
- Existence, uniqueness and estimators of the Fréchet mean are still heavily studied.
- Under certain conditions, the Central Limit Theorem can be extended to Fréchet means and the extended definition of smeariness can further reveal behavior of the Fréchet estimator.
- Less studied are Maximum Likelihood means on Riemannian Manifolds for which CLT results have not been extended.



Figure 1: The illustration exemplifies two different distributions on the sphere S^2 and the difficulty in finding a unique mean point.

$$F(x) = F(0) + \sum_{j=1}^{r} T_j |(Rx)_j|^r + o(||x||^r)$$

where $F(x) = \mathbb{E}[\text{dist}(\mathbf{x}, \exp_p(x))^2].$

Theorem 1 (Eltzner and Huckemann [2]) Under assumption 1. - 3. it holds that $\sqrt{n}(V_1^n, ..., V_m^n)^T \xrightarrow{\mathcal{D}} \mathcal{N}(0, \Sigma)$ (5)where 1. $V_n^i = (R \log_{\mu}(\mu_n))_i | (R \log_{\mu}(\mu_n))_i |^{r-2}$ 2. $\Sigma = \frac{1}{r^2}T^{-1}Cov[grad|_{x=0}dist(x, X)^2]T^{-1}$ 3. $T = diag(T_1, ..., T_m)$

Smeariness

When generalizing the classical CLT theorem, the definition of smeariness arises to fit other convergence rates.

Definition 1 *A sequence* $\mu_n \xrightarrow{\mathbb{P}} \mu$ *is said to be k-smeary* with limiting distribution X if

 $n^{\frac{1}{2(k+1)}}\log_u(\mu_n) \xrightarrow{\mathcal{D}} X$ (6)**Note:** Theorem 1 can be restated as $(V_1^n, ..., V_m^n)^T$ be**Figure 3:** The variance of the Fréchet estimator for different values of α . Black line indicates 0-smeary and dotted line indicates 2-smeary.

Maximum Likelihood Mean

The heat kernel $p(x, \mu, t)$ is the transition density of the Brownian motion B_t with initial value μ .

Definition 2 *A point* $\mu \in \mathcal{M}$ *is a Maximum Likelihood* mean of X if $\mu \in \operatorname{arg\,min}_{\mu \in \mathcal{M}} \mathbb{E}[-\ln p(X, y, t)]$ for $t \in \mathbb{R}_+$

As for the Fréchet mean, we are interested in a CLT or smearieness result for the estimator

$$\mu_n \in \arg\min_{y \in \mathcal{M}} -\frac{1}{n} \sum_{i=1}^n \ln p(X_i, y, T)$$
(8)
Goals

Riemannian manifolds

A Riemannian manifold is a pair of a smooth manifold \mathcal{M} and a Riemmanian metric g ie. a collection of inner products $g_p(v, u) = \langle v, u \rangle_p$ for each $p \in \mathcal{M}$. The Riemannian metric induces a distance on \mathcal{M} $\operatorname{dist}(p,q) = \min_{\gamma} \int_0^1 ||\dot{\gamma}(t)||_{\gamma(t)} dt$ (1)where γ is a continuous differentiable curve from pto *q*. The exponential $\exp_p : T_p\mathcal{M} \to \mathcal{M} \setminus \mathcal{C}(p)$ are maps on each tangent space $T_p\mathcal{M}$ defined by

 $\exp_p(v) = \gamma_v(1)$ (2)where γ_v is the unique maximal geodesic with $\gamma_v(0) = p$ and $\dot{\gamma}_v(0) = v$. These are diffeomorphisms with inverse denoted by \log_p .

Fréchet means

A point $\mu \in \mathcal{M}$ is a **Fréchet mean** of the random point $\mathbf{x}: \Omega \to \mathcal{M}$ if

ing 0–smeary.

Example: An odd distribution



Figure 2: The distribution of *X*. Let *X* be a random point on S^2 with the following distribution (see Figure 4):

1. uniformly distributed on the lower hemisphere $\mathbb{L} = \{(q_1, q_2, q_3) \in S^2 | q_2 \leq 0\}$ with total mass $0 < \alpha < 1$

2. point mass in the north pole $\mu = (0, 1, 0)$ with

1. Existence and uniqueness results for this mean

2. CLT result for MLE under reasonable assumptions

3. Smeariness result for MLE for certain distributions

The odd distribution revisited



Figure 4: Estimated Maximum likelihood means for X with t =0.1, 0.5, 1 [1].



 $\mu \in \arg \min \mathbb{E}[\operatorname{dist}(\mathbf{x}, \boldsymbol{y})^2]$

Note: There might not exist such a point or there might be more than one!

Let $F_n(x) = \frac{1}{N} \sum_{i=1}^N \operatorname{dist}(x, X_i)^2$ be the Empirical Fréchet function. We want to consider the behavior of the mean estimator μ_n which is a measurable collection where

 $\mu_n \in \arg\min_{x\in\mathcal{M}}F_n(x)$

Central Limit Theorem

For the CLT for Fréchet means of random points **x** on Riemmanian *m*-manifold \mathcal{M} we assume:

probability $1 - \alpha$.

(3)

(4)

Theorem 2 (Eltzner and Huckemann [2]) Let μ_n be the Fréchet estimator of X. For $\alpha = \left(1 + \frac{vol(S^3)}{2vol(S^2)}\right)^{-1} \approx$ 0.56 the only Fréchet mean of X is μ and there exists a *full-rank matrix* Σ *such that* $(n^{1/6}\log_u(\mu_n))^3 \to \mathcal{N}(0,\Sigma).$ (7)*ie. the Fréchet estimator* μ_n *is* 2*—smeary.*

1. For $1 > \alpha > 0.56$ the Fréchet mean is not unique. 2. For $0 \le \alpha < 0.56$ the Fréchet mean is unique, but as seen in Figure 3 the Fréchet estimator slowly approaches 0-smeariness when α decreases.

Data points n Data points n

Data points n

Figure 5: Variance for Maximum Likelihood estimator for t =0.1, 0.5, 1[1]

References

[1] Benjamin Eltzner. Illustration generated from code.

[2] Benjamin Eltzner and Stephan F. Huckemann. A Smeary Central Limit Theorem for Manifolds with Application to High Dimensional Spheres. *arXiv:1801.06581 [math, stat],* January 2018. arXiv: 1801.06581.