

A Lower Bound for Estimating Fréchet Means In Memory of Laurent Cavalier († 2014)

CIRM Workshop: Geometric Sciences in Action:
from Geometric Statistics to Shape Analysis
at Luminy (May 27 - 31, 2024)

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joint work with Benjamin Eltzner and **Shayan Hundrieser**

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Felix Bernstein Institute for Mathematical Statistics in the Biosciences

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DFG GK 2088



Fréchet (1948) Means

Ingredients:

- metric space (\mathfrak{X}, d) , $\rho : \mathfrak{X} \times \mathfrak{X} \rightarrow \mathbb{R}$ continuous,
- Borel m'ble random variables $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} X \sim \mathbb{P}$ on \mathfrak{X}

\rightsquigarrow Fréchet ρ -mean sets

$$\text{population } \mathbb{M}(\mathbb{P}) := \operatorname{argmin}_{x \in \mathfrak{X}} \mathbb{E}[\rho(x, X)],$$

$$\text{sample } \mathbb{M}_n := \operatorname{argmin}_{x \in \mathfrak{X}} \frac{1}{n} \sum_{j=1}^n \rho(x, X_j).$$

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Existence for $\rho = d^2$:

- $\mathbb{M}_n \neq \emptyset$ a.s. if (\mathfrak{X}, d) complete,
- $\mathbb{M}(\mathbb{P}) \neq \emptyset$ if additionally, $\exists x \in \mathfrak{X}$ with $\mathbb{E}[d(x, X)] < \infty$.

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Uniqueness:

- $|\mathbb{M}(\mathbb{P})| = 1$ if additionally $\operatorname{supp}(X)$ in ball, smaller than a goodesic half ball (Karcher, 1977; Kendall, 1990; Le, 2001; Groisser, 2005; Afsari, 2011).
- $|\mathbb{M}_n| = 1$ a.s. if additionally \mathfrak{X} is a Riemannian manifold and X is absolutely continuous w.r.t. Riemannian volume (Arnaudon and Miclo, 2014).

Strong Law of Large Numbers

Kuratowski (1948) convergence of sets $C_n \subseteq \mathfrak{X}$, $n \in \mathbb{N}$:

$$Ls_{n \rightarrow \infty} C_n := \{x \in Q : \liminf_{n \rightarrow \infty} d(x, C_n) = 0\} = \bigcap_{n=1}^{\infty} \overline{\bigcup_{k=n}^{\infty} C_k}$$

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Theorem (Ziezold (1977); Bhattacharya and Patrangenaru (2003))

If $\exists \in \mathfrak{X}$ with $\mathbb{E}[d(x, X)] < \infty$, \mathfrak{X} separable, then

(ZC) $Ls_{n \rightarrow \infty} M_n \subseteq M(\mathbb{P})$ a.s.,

(BPC) if \mathfrak{X} is Heine-Borel and $M(\mathbb{P}) \neq \emptyset$ then $M(\mathbb{P}) = Li_{n \rightarrow \infty} M_n$ a.s.

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Extensions to generalized Fréchet means by H. (2011); e.g.

$$\operatorname{argmin}_{\gamma \in \Gamma} \frac{1}{n} \sum_{j=1}^n d(\gamma, X_j)^2 \rightarrow \operatorname{argmin}_{\gamma \in \Gamma} \mathbb{E}[d(\gamma, X)^2]$$

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Recent extensions by Schötz (2022); Wiechers et al. (2023); Evans and Jaffe (2024): (ZC) inclusion can be strict.

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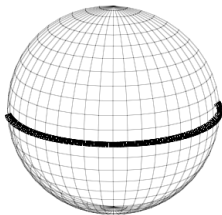
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 - see [Mahshid's poster](#),
 - that comes in different flavors (Lammers et al., 2023).
 - Can it be turned into a blessing?
 - See [Lars' poster](#),

Nonuniqueness

Consider $x, y \in \mathfrak{X} = \mathbb{S}^2$ with

- $d_E(x, y) = \|x - y\|$ = extrinsic metric
- $d_I(x, y) = \arccos y^T x$ = intrinsic (spherical) metric
- $d_R(x, y) = \|x - yy^T x\|$ = residual quasi metric

and $X \sim$ uniform on equator:

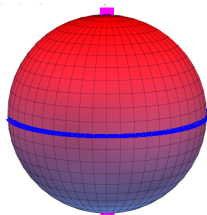
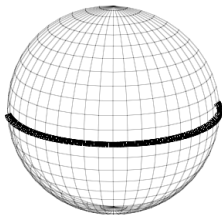


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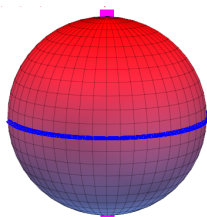
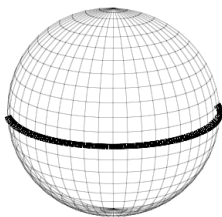


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How, and how good is the estimation of random variables “near” X ?

Honesty

Definition

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Lemma 1 (Instability of Nonuniqueness)

For all honest \mathbb{M} on \mathfrak{X} , all $t \in (0, 1]$ and all $x \in \mathbb{M}(\mathbb{P})$ we have

$$\mathbb{M}(\mathbb{P}_{x,t}) = \{x\}$$

with the perturbed measure $\mathbb{P}_{x,t} := (1 - t)\mathbb{P} + t\delta_x$.

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Fréchet d^2 -means based on a metric d are honest, however, not if based on the residual quasi metric.

Lower Bound

Theorem 1

Let the Fréchet ρ -mean \mathbb{M} be honest,

- $|\mathbb{M}(\mathbb{P})| > 1$,
- $n \in \mathbb{N}$ fixed, whereas $x \in \mathbb{M}(\mathbb{P})$, $0 < t \leq 1$ arbitrary
- $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathbb{P}_{x,t}$,
- $\hat{\mu}_n$ any estimator of \mathbb{M} , e.g. $\hat{\mu}_n = \mathbb{M}_n$,

then for all $\eta > 0$,

$$\sup_{\substack{x \in \mathbb{M}(\mathbb{P}) \\ 0 < t \leq 1}} \mathbb{P}_{x,t}^{\otimes n} \left\{ d(\hat{\mu}_n, \mathbb{M}(\mathbb{P}_{x,t})) \geq \frac{\text{diam } \mathbb{M}(\mathbb{P}) - \eta}{2} \right\} \geq \frac{1}{2}.$$

Apply argument chain of Tsybakov (2009, p. 79 ff.):

$$\textcircled{1} \quad y, z \in \mathbb{M}(\mathbb{P}), d(y, z) \geq \text{diam}(\mathbb{M}(\mathbb{P})) - \eta,$$

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(2.9), p.80
 $\stackrel{\Delta \text{ ineq}}{\geq} \inf_{\psi_n} \max_{x \in \{y,z\}} \mathbb{P}_{x,t}^{\otimes n} \{\psi_n \neq x\} =: p_{e,1}$

over all tests $\psi_n : \mathfrak{X}^n \rightarrow \{y, z\};$

a candidate for ψ_n is the test to reject if distance to $\hat{\mu}_n$ is $\geq s,$
 and to do a coin flip (reject less often) if both are $\geq s$ (both cannot be $< s$),

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- ⑦ $t \rightarrow 0 \Rightarrow \alpha \rightarrow 0 \Rightarrow \text{Theorem 1 (max above} \leq \text{sup of theorem).}$

Step 5: The Missing Inequality

Tsybakov (2009, p. 83, 86), two prob. distributions P, Q :

- squared Hellinger distance

$$H(P, Q)^2 := \int \left(\sqrt{\frac{dP}{d\nu}} - \sqrt{\frac{dQ}{d\nu}} \right)^2 d\nu, \nu = P + Q,$$

- total variation distance $TV(P, Q) := \sup_{A \text{ m'ble}} |P(A) - Q(A)|$,
- $H(P^{\otimes n}, Q^{\otimes n})^2 = 2 \left(1 - \left(1 - \frac{H(P, Q)^2}{2} \right)^n \right)$,
- Le Cam's inequalities $H^2/2 \leq TV \leq H$.

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- $TV(\mathbb{P}_{y,t}^{\otimes n}, \mathbb{P}_{z,t}^{\otimes n})^2 \leq H(\mathbb{P}_{y,t}^{\otimes n}, \mathbb{P}_{z,t}^{\otimes n})^2 \leq 2(1 - (1 - t)^n).$

Remark 1

Given $\mathbb{M}(\mathbb{P}) \ni y \neq z \in \mathbb{M}(\mathbb{P})$, uniformly over

$$\{\mathbb{P}_{x,t} : x \in \{y, z\}, t \in (0, \epsilon)\}, \forall 0 < \epsilon \leq 1$$

no test $\psi_n: \mathfrak{X}^n \rightarrow \{y, z\}$ will perform better than a coin flip.

Corollary 1

Markov inequality $\frac{1}{2} \leq \mathbb{P}\{Y \geq s\} \leq \frac{\mathbb{E}[Y]}{s}$ and $\eta \rightarrow 0$ gives

$$\inf_{\hat{\mu}_n} \sup_{\substack{x \in \mathbb{M}(\mathbb{P}) \\ 0 < t \leq 1}} \mathbb{E}_{\mathbb{P}_{x,t}^{\otimes n}} [d(\hat{\mu}_n, \mathbb{M}(\mathbb{P}_{x,t}))] \geq \frac{\text{diam } \mathbb{M}(\mathbb{P})}{4}.$$

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Example:

- $\mathbb{P} = \frac{\delta_N + \delta_S}{2}$ on \mathbb{S}^2 with poles N, S , resp.,
- d : spherical distance,
- $\mathbb{M}(\mathbb{P}) = \text{equator}$, $\text{diam} = \pi$,
- pick $x \in \text{equator}$, zero meridian,
- as $t \rightarrow 0$ (by symmetry)
 - \mathbb{M}_n of $\mathbb{P}_{x,t}^{\otimes n}$ tends to be on far side with 50%,
 - in these cases $d(\mathbb{M}_n, x) \geq \pi/2$,
 - in the mean, $d(\mathbb{M}_n, x) \geq \pi/4$.

The Wasserstein World

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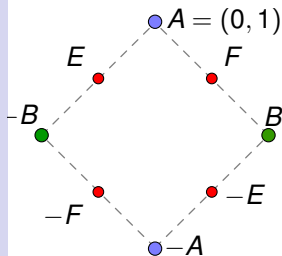
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- it's metric, hence its Fréchet means are honest.



Nonuniqueness in the Wasserstein World

In \mathbb{R}^2 , let

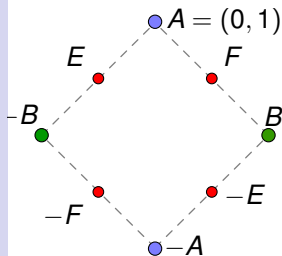
$$\mu := \frac{1}{2} (\delta_A + \delta_{-A}),$$

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yielding,

$$\mathbb{M}(\mathbb{P}) = \left\{ \frac{\alpha}{2} (\delta_E + \delta_{-E}) + \frac{1-\alpha}{2} (\delta_F + \delta_{-F}) : 0 \leq \alpha \leq 1 \right\}.$$



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By Corollary 1, for \mathbb{M}_n of $\mu_1, \dots, \mu_n \stackrel{i.i.d.}{\sim} \mathbb{P}_{\mu,t} = (1-t)\mathbb{P} + t\delta_\mu$, $0 < t \leq 1$ (by symmetry):

$$\sup_{t>0} \mathbb{E}_{\mathbb{P}_{\mu,t}^{\otimes n}} [\mathcal{W}(\mathbb{M}_n, \mu)] \geq \frac{\text{diam } \mathbb{M}(\mathbb{P})}{4} = \frac{1}{4},$$

as $\|F - E\| = 1 = \|F + E\|$.

Parametric Rates (1/n)

Theorem (Le Gouic et al. (2022), Cor. 1.2)

Let/assume:

- $0 < \alpha \leq \beta$, $\Phi_{\alpha,\beta} := \left\{ \phi \in \mathcal{C}^1(\mathbb{R}^m \rightarrow \mathbb{R}) : \right.$
 $\left. \phi(\mathbf{y}) \geq \phi(\mathbf{x}) + \nabla\phi(\mathbf{x})^T(\mathbf{y} - \mathbf{x}) + \frac{\alpha}{2}\|\mathbf{x} - \mathbf{y}\|^2 \right.$

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Then, if $\beta < \alpha + 1$,

$$\mathbb{E}_{\mathbb{P}^{\otimes n}}[\mathcal{W}(\mathbb{M}_n, \tau)^2] \leq \frac{1}{n} \frac{4 \mathbb{E}_{\mathbb{P} \sim \mathbb{P}}[\mathcal{W}(\mathbb{P}, \tau)^2]}{(\beta - \alpha - 1)^2}.$$

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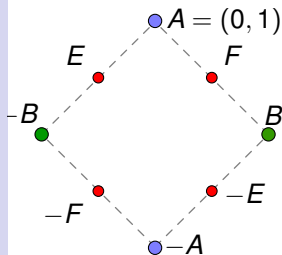
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Question

Is $\beta < \alpha + 1$ sharp for parametric rates?



Partial Answer

Let

$$\mu := \frac{1}{2} (\delta_A + \delta_{-A}),$$

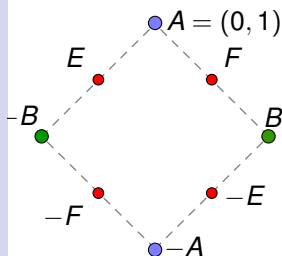
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Theorem 2

Let $0 < \alpha < \beta$. Then

- (i) $\mu = (\nabla\phi)_{\#}\tau$ with $\phi \in \Phi_{\alpha,\beta}$
 $\Rightarrow \beta > \alpha + 2$
- (ii) $\forall \delta > 0 \exists \beta \leq \alpha + 2 + \delta$ such that
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Hence $\beta \leq \alpha + 2$ is a realistic upper bound.

Conjecture

Under Le Gouic et al. (2022) hypotheses, with C indep. of \mathbb{P} ,
 $\mathbb{E}_{\mathbb{P}^{\otimes n}}[\mathcal{W}(\mathbb{M}_n, \tau)^2] \leq \frac{1}{n} \frac{C \mathbb{E}_{\mathbb{P} \sim \mathbb{P}}[\mathcal{W}(P, \tau)^2]}{(\beta - \alpha - 2)^2}$ for all $0 < \alpha < \beta < \alpha + 2$.

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E.g. Gower (1975), H. (2010, 2012), Dryden and Mardia (2016),

$2 \leq m < k$:

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- chart at $\xi \in \mathbb{S}^{m \times (k-1)-1}$ for $\text{tr}(x^T \xi) > 0$: $\phi_\xi : x \mapsto \frac{x - \text{tr}(x^T \xi) \xi}{\text{tr}(x^T \xi)}$.

A CLT for Procrustes Means

Theorem 3

Let $Z_1, \dots, Z_n, Z^{i.i.d.} \mathbb{P} \in \mathcal{P}(\Sigma_m^k)$ be random shapes, that a.s. assume $\Sigma_{[\xi]}^{**}, \mathbb{M}(\mathbb{P}) = \{[\xi]\}, \hat{\mu}_n \in \mathbb{M}_n$ m'ble selection. Then

$$\sqrt{n} \text{vec}(\phi_\xi \circ \psi_\xi(\hat{\mu}_n)) \xrightarrow{\mathcal{D}} \mathcal{N}(0, H^- D H^-)$$

with

$$D = \text{cov}[\text{vec}(\psi_\xi(Z)) \text{vec}(\psi_\xi(Z))^T] = \sum_{j=1}^N \lambda_j \mathbf{v}_j \mathbf{v}_j^T,$$

$$H^- = \frac{1}{2} \sum_{j=2}^{N+1} (\lambda_1 - \lambda_j)^{-1} \mathbf{v}_j \mathbf{v}_j^T$$

where $N = m(k-1)$, $\lambda_1 > \lambda_2 \geq \dots \geq \lambda_N$, $\text{vec}(\xi) = \mathbf{v}_1$, $(\mathbf{v}_1, \dots, \mathbf{v}_N) \in \text{SO}(N)$.

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Remark

The $\mathbf{v}_2, \dots, \mathbf{v}_N$ span the tangent space of \mathbb{S}^{N-1} at $\text{vec}(\xi)$.

If $\lambda_1 - \lambda_2 \rightarrow 0$ we loose uniqueness, H^- explodes, i.e. the constants deteriorate.

Lower Bound

Elt/Huc/Hun

Fréchet Means

Lower Bound

Examples

Outlook

References

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