

## Context

Manifold estimation has been deeply investigated in the  $C^k$ -regularity model in [1]. However, data do not always lie on such a regular shape, our goal is to study geometric estimators under weaker hypothesis from the geometric measure theory standpoint [2]. For this purpose we use the varifolds framework, a weak version of manifold born in the 60's that is well adapted to surface approximation and that we now intend to analyse from a statistical perspective. Our approach take root in the seminal work [4].

## Question

Given:

- a  $d$ -dimensional object  $S$  example: 2-sphere in  $\mathbb{R}^3$
- a set of points  $\{x_i\}_{i=1\dots N}$  sampling  $S$  example: a scan acquisition of  $S$

**Problem:** How to attribute weights  $\{m_i\}_{i=1\dots N}$  so as to correct sampling irregularities: we want that  $\sum_{i=1}^N m_i \delta_{x_i}$  is close to the superficial measure  $\mathcal{H}_S^d$ .

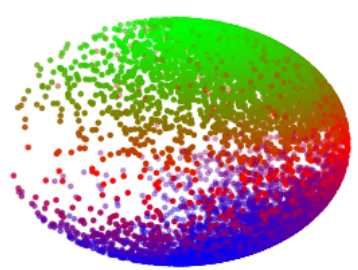


Fig. 1: Non uniformly sampled sphere

## Statistical framework

We model the non uniformity of the sampling by a density  $\theta$ : we assume that we have access to i.i.d samples  $X_1, \dots, X_N$  following the same law  $\mu = \theta \mathcal{H}_S^d$ .

**Definition 1** (Empirical measure). Let  $N \in \mathbb{N}^*$ ,  $X_1, \dots, X_N$  be  $N$  random independent variables with the same law  $\mu$ , the associated empirical measure  $\mu_N$  is defined as:

$$\mu_N = \frac{1}{N} \sum_{i=1}^N \delta_{X_i}$$

**Question:** how to recover  $\theta$  and then  $\mathcal{H}_S^d$  from the knowledge of  $\mu_N$ ?

## A proper distance

**Definition 2** (Bounded Lipschitz distance). For  $\mu, \nu$  two Radon measures in  $E$  ( $E$  can be  $\mathbb{R}^n$  or  $\mathbb{R}^n \times \text{Sym}_+(n)$ ), the bounded Lipschitz distance is defined by:

$$\beta(\mu, \nu) = \sup \left\{ \left| \int_E f d(\mu - \nu) \right| : f \in C_c(E, \mathbb{R}), \|f\|_\infty \leq 1, \text{Lip}(f) \leq 1 \right\}$$

Lipschitz functions link the variation in the image spaces to the variation in  $E$ . It gives rougher convergence:

$$\beta(\delta_{\frac{1}{k+1}}, \delta_0) \leq \text{Lip}(f) \frac{1}{k+1} \xrightarrow{k \rightarrow +\infty} 0$$

comparatively to the total variation distance

$$d_{TV}(\delta_{\frac{1}{k+1}}, \delta_0) = \sup \left\{ \left| \int_{\mathbb{R}} f d(\delta_{\frac{1}{k+1}} - \delta_0) \right| : f \in C_c(\mathbb{R}, \mathbb{R}), \|f\|_\infty \leq 1 \right\} = 2.$$

## Ahlfors regular measure

**Definition 3** (Ahlfors regular measure). Let  $\mu$  be a Radon measure in  $\mathbb{R}^n$ , for  $d > 0$ , we say that  $\mu$  is a  $d$ -Ahlfors regular measure if  $\exists C_0 > 0$  such that  $\forall x \in \text{supp}(\mu) = S, \forall r \in ]0, \text{diam}(S)[$ :

$$\frac{1}{C_0} r^d \leq \mu(B(x, r)) \leq C_0 r^d.$$

Examples: sphere, square, Koch snowflake, four-corner Cantor,...

## Rectifiability

**Definition 4** ( $d$ -rectifiable set). A set  $S$  is  $d$ -rectifiable if there exists a countable family  $(f_i)_{i \in \mathbb{N}}$  of Lipschitz maps from  $\mathbb{R}^d$  to  $\mathbb{R}^n$  such that

$$\mathcal{H}^d \left( S \setminus \bigcup_{i \in \mathbb{N}} f_i(\mathbb{R}^d) \right) = 0$$

**Definition 5** (Rectifiable measures). Let  $\mu$  be a Radon measure in  $\mathbb{R}^n$ . We say that  $\mu$  is  $d$ -rectifiable if there exist a  $d$ -rectifiable set  $S$  and a Borel function  $\theta : S \rightarrow \mathbb{R}_+$  such that  $\mu = \theta \mathcal{H}_S^d$ .

Now we want to analyse the local behaviour of our Radon measure  $\mu$  around  $x \in \mathbb{R}^n$ , we use the rescaled measures for  $r > 0$ :

$$\mu_{x,r}(B) := \mu(x + rB) \quad \text{for } B \in \text{Bor}(\mathbb{R}^n)$$

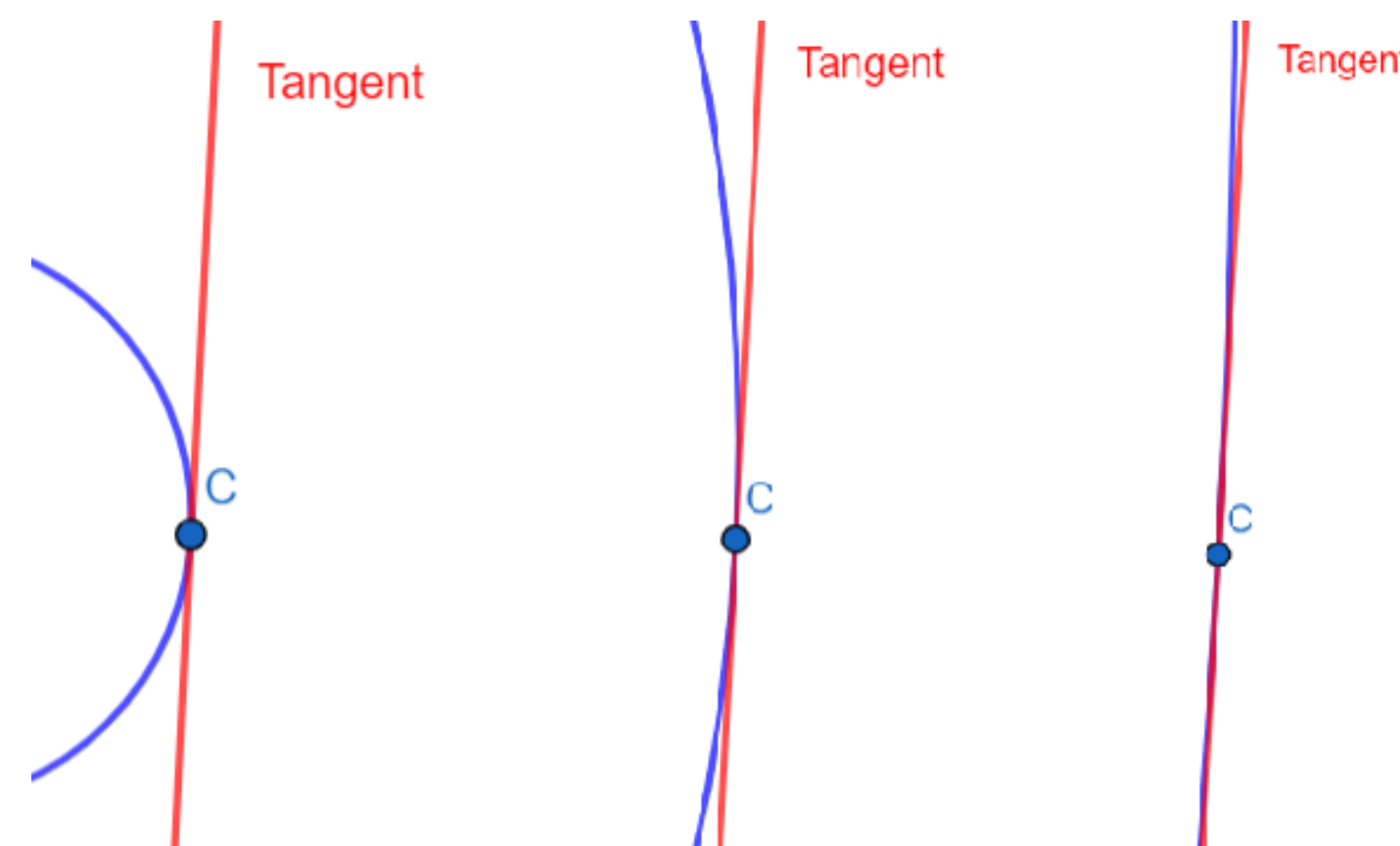


Fig. 2: Zoom the map to understand the local behaviour

## Approximate tangent plane

**Definition 6** (Approximate tangent plane). Let  $\mu$  be a Radon measure and let  $x \in \mathbb{R}^n$ . We say that  $\mu$  has approximate tangent space  $P \in G_{d,n}$  with multiplicity  $\theta \in \mathbb{R}_+$  at  $x$ , if  $r^{-d} \mu_{x,r}$  weak-\* converges to  $\theta \mathcal{H}_P^d$  in  $\mathbb{R}^n$  as  $r \rightarrow 0_+$ . That is:

$$\lim_{r \rightarrow 0_+} r^{-d} \int_{\mathbb{R}^n} \phi \left( \frac{y-x}{r} \right) d\mu(y) = \theta \int_P \phi(y) d\mathcal{H}^d(y) \quad \forall \phi \in C_c(\mathbb{R}^n).$$

**Proposition 1.** If  $\mu = \theta \mathcal{H}_S^d$  is  $d$ -rectifiable then  $\mu$  admits an approximate tangent plan for  $\mathcal{H}^d$  almost every  $x \in S$

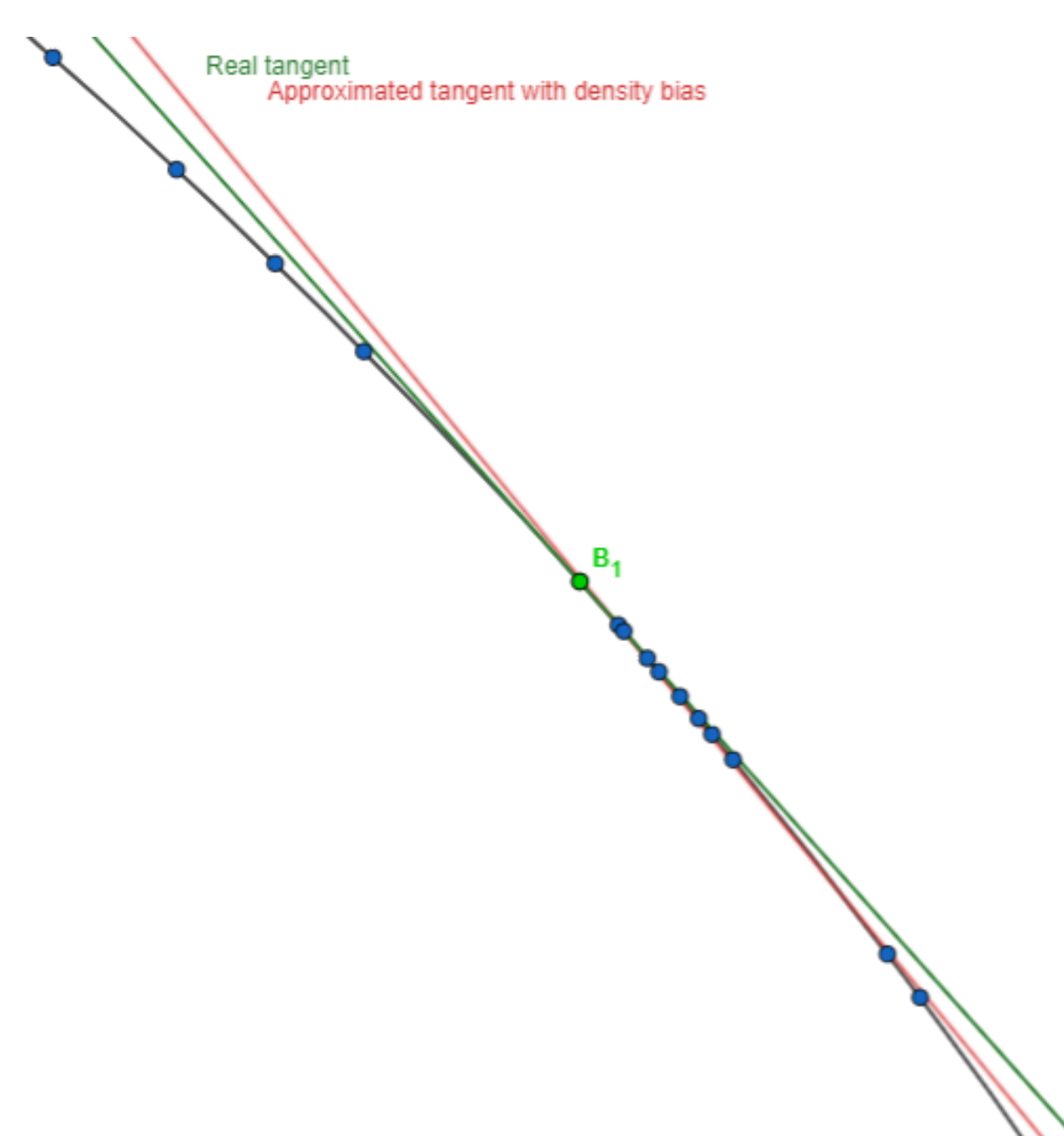


Fig. 3: Effect of the density on the tangent choice

## Density Estimators

The framework is the following:

- $S \subset \mathbb{R}^n$   $d$ -dimensional set:  $\mathcal{H}^d(S) < +\infty$
- $\mu = \theta \mathcal{H}_S^d$   $d$ -Ahlfors probability measure
- $N \in \mathbb{N}$  and  $\mu_N$  the empirical measure
- choose  $\eta : \mathbb{R} \rightarrow \mathbb{R}_+$  satisfying  $\text{supp}(\eta) \subset [-1, 1]$  and  $\|\eta\|_\infty + \text{Lip}(\eta) \leq 1$

For  $\delta > 0$  we introduce

$$\forall x \in \mathbb{R}^n, \quad \theta_{\delta,N}(x) := \frac{1}{c_\eta \delta^d} \int_{\mathbb{R}^n} \eta \left( \frac{|x-y|}{\delta} \right) d\mu_N(y)$$

and

$$\theta_\delta(x) := \frac{1}{c_\eta \delta^d} \int_{\mathbb{R}^n} \eta \left( \frac{|x-y|}{\delta} \right) d\mu(y)$$

**Theorem 1.** Let  $(\delta_N)_{N \in \mathbb{N}^*}$  be a positive sequence tending to 0 and such that  $\delta_N N^{\frac{1}{d}} \xrightarrow{N \rightarrow +\infty} +\infty$ , then for  $\mathcal{H}^d$ -a.e.  $x \in S$ ,

$$\mathbb{E} \left[ \left| \theta_{\delta_N,N}(x) - \theta(x) \right| \right] \leq C \frac{N^{-\frac{1}{d}}}{\delta_N} + |\theta_{\delta_N,N}(x) - \theta(x)| \xrightarrow{N \rightarrow +\infty} 0.$$

## Tangent plane estimators

Let  $\Phi$  be a Lipschitz truncation of the inverse function, for  $0 < \tau \leq 1$  and  $t > 0$ ,

$$\Phi(t) = \frac{\chi_\tau(t)}{t} \quad \text{and} \quad \chi_\tau(t) = \begin{cases} 0 & \text{if } 0 < t < \frac{\tau}{2} \\ \frac{2}{\tau}t - 1 & \text{if } \frac{\tau}{2} \leq t \leq \tau \\ 1 & \text{if } t > \tau \end{cases}.$$

We introduce

$$\nu_{\delta,N} := \frac{1}{N} \sum_{i=1}^N \Phi(\theta_{\delta,N}(X_i)) \delta_{X_i} = (\Phi \circ \theta_{\delta,N}) \mu_N \quad \text{and} \quad \nu_\delta = (\Phi \circ \theta_\delta) \mu$$

$\beta_B$ : localized version of  $\beta$  with test functions supported in  $B$

**Definition 7** (Covariance matrix associated with a measure). Let  $0 < d \leq n$ ,  $r > 0$  and let  $\lambda$  be a Radon measure in  $\mathbb{R}^n$ . We define for  $x \in \mathbb{R}^n$ , the  $n \times n$  matrix

$$\Sigma_r(x, \lambda) = \frac{1}{\sigma_\phi r^d} \int_{\mathbb{R}^n} \phi \left( \frac{|y-x|}{r} \right) \frac{y-x}{r} \otimes \frac{y-x}{r} d\lambda(y),$$

where  $z \otimes z$  is the rank one matrix of  $(i, j)$ -coefficient  $z_i z_j$ , for  $z \in \mathbb{R}^n$  and  $\sigma_\phi = \omega_d \int_{r=0}^1 \phi(r) r^{d+1} dr$ .

**Proposition 2.** Let  $\mu = \theta \mathcal{H}_S^d$  be a  $d$ -rectifiable measure, then for  $\mathcal{H}^d$ -a. e.  $x \in S$ ,

$$\Sigma_r(x, \mu) \xrightarrow{r \rightarrow 0_+} \theta(x) \Pi_{T_x S}$$

where  $\Pi_{T_x S}$  is the matrix of orthogonal projection on the approximate tangent space  $T_x S$ .

## Varifold estimators

**Definition 8.** Let  $W_{r,\delta,N} := \nu_{\delta,N} \otimes \delta_{\Sigma_r(x,\nu_{\delta,N})}$  and  $W_{r,\delta} := \nu_\delta \otimes \delta_{\Sigma_r(x,\nu_\delta)}$ , our Radon measures on  $\mathbb{R}^n \times \text{Sym}_+(n)$  that will converge to the varifold structure behind  $S$ .

**Theorem 2.** Assume that  $S$  is  $d$ -rectifiable,  $0 < \theta_{\min} \leq \theta \leq \theta_{\max}$  and  $\mu$  is  $d$ -Ahlfors regular with  $C_0$  the regularity constant of  $\mu$ . Then there exists a constant  $M' = M'(d, C_0, \eta, \phi) > 0$  such that for all open ball  $B \subset \mathbb{R}^n$  of radius  $R_B < 1$ , for all  $r, \delta > 0$  and  $N \in \mathbb{N}^*$  satisfying  $N^{-\frac{1}{d}} < R_B$  and  $N^{-\frac{1}{d}} < \min(\delta, r)$ ,

$$\mathbb{E} \left[ \beta_B(W_{r,\delta,N}, W_{r,\delta}) \right] \leq \begin{cases} \frac{M' \mu(B)}{\tau^2 \min(\delta, r)} N^{-\frac{1}{2}} \ln N & \text{if } d = 2 \\ \frac{M' \mu(B)}{\tau^2 \min(\delta, r)} N^{-\frac{1}{d}} & \text{if } d > 2 \end{cases}.$$

## References

- [1] Eddie Aamari and Clément Levrard. *Non-Asymptotic Rates for Manifold, Tangent Space, and Curvature Estimation*. 2017. DOI: 10.48550/ARXIV.1705.00989. URL: <https://arxiv.org/abs/1705.00989>.
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