

# ON THE ASSOCIATED ZONOID AND ASYMPTOTIC COVARIANCE MATRICES OF STATIONARY POISSON HYPERPLANE PROCESSES

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## Outline of the talk

1. Stationary Poisson hyperplane processes in  $\mathbb{R}^d$  and their  $k$ -flat intersection processes for  $k = 0, 1, \dots, d - 1$
2. CLTs for the number of of intersection  $k$ -flats and their total  $k$ -volume in  $B_r^d$
3. Basic facts on CLTs for (random) U-statistics
4. Zonoids and distributions on  $S_+^{d-1}$   
Basic notions from convex geomtry
5. Formulae for asymptotic variances and covariances in terms of the associated zonoid
6. Some Applications and properties of the asymptotic covariance matrices

# 1. Stationary Poisson hyperplane processes in $\mathbb{R}^d$ and their k-flat intersection processes for $k = 0, 1, \dots, d - 1$

$[\Omega, \sigma(\Omega), \mathsf{P}]$ : common prob.spc.,  $\mathsf{E}$ ,  $\mathsf{Var}$  = expectation, variance

$\mathcal{A}_k^d$  : space of all affine  $k$ -dim. subspaces in  $\mathbb{R}^d$ ,  $k = 0, 1, \dots, d - 1$

Parametrization of an undirected hyperplane  $H \in \mathcal{A}_{d-1}^d$ :

$$H(p, v) = \{x \in \mathbb{R}^d : \langle v, x \rangle = p\} \quad p \in \mathbb{R}^1, v \in S_+^{d-1}$$

with *orientation vector*  $v \in S_+^{d-1}$  and signed perpendicular distance  $p \in \mathbb{R}^1$  from the origin.

$d = 2$

Poisson process  $\Psi$

Fig.1: Straight line in  
Hessian normal form

Fig. 2: Poisson points  $P_i$  on  
the line with marks  $V_i$

## Stationary Poisson Hyperplane Processes $\Phi$

with *intensity*  $\lambda$  and *orientation distribution*  $\Theta(\cdot)$  (on  $S_+^{d-1}$ )

$\triangleq$  a random point process on  $[\mathcal{A}_{d-1}^d, \mathcal{B}(\mathcal{A}_{d-1}^d)]$ , i.e.  $\Phi : \Omega \rightarrow N(\mathcal{A}_{d-1}^d)$  is a  $(\sigma(\Omega), \mathcal{N}(\mathcal{A}_{d-1}^d))$ -measurable mapping defined by

$$\Phi(\cdot) = \sum_{i \geq 1} \delta_{H(P_i, V_i)}(\cdot), \quad \text{where } \Psi(\cdot) = \sum_{i \geq 1} \delta_{[P_i, V_i]}(\cdot)$$

is a stationary and independently marked Poisson point process on the real line  $\mathbb{R}^1$  with intensity  $\lambda$  and mark distribution  $\Theta(\cdot)$  on the mark space  $S_+^{d-1}$ .

**Stationary  $k$ -flat intersection process  $\Phi_k$  induced by  $\Phi$**

$\triangleq$  a random point process on  $[\mathcal{A}_k^d, \mathcal{B}(\mathcal{A}_k^d)]$ , i.e.

$\Phi_k : \Omega \rightarrow N(\mathcal{A}_k^d)$  is a  $(\sigma(\Omega), \mathcal{N}(\mathcal{A}_k^d))$ -measurable mapping, defined by intersections of  $d - k$  distinct hyperplanes (=atoms of  $\Phi$ ) leading to the representation as multiple sum over  $d - k$  pairwise distinct indices:

$$\Phi_k(\cdot) = \frac{1}{(d-k)!} \sum_{i_1, \dots, i_{d-k} \geq 1}^* \delta_{\cap_{j=1}^{d-k} H(P_{ij}, V_{ij})}(\cdot)$$

for  $k = 0, 1, \dots, d-1$ , where  $\Phi_{d-1}$  is identified with  $\Phi$ .

Stationarity of  $\Phi$  (and thus of all  $\Phi_k$ , i.e.  $\text{supp}(\Phi_k) + x \stackrel{d}{=} \text{supp}(\Phi_k) \forall x \in \mathbb{R}^d$ ) follows by the stationarity and the Poisson property of  $\Psi(\cdot)$ .

*Isotropy* of  $\Phi$  (and thus of all  $\Phi_k$ , i.e.  $O(\text{supp}(\Phi_k)) \stackrel{d}{=} \text{supp}(\Phi_k) \forall$  orthogonal  $O$  with  $\det(O) = 1$ ) holds iff  $\Theta(\cdot)$  is the uniform distribution on  $S_+^{d-1}$ .

**The intensities  $\lambda_k$ ,  $k = 0, 1, \dots, d-1$ :**

$$\lambda_k = \frac{\mathbb{E}\Phi_k(\{L \in \mathcal{A}_k^d : L \cap B_r^d \neq \emptyset\})}{\nu_{d-k}(B_r^{d-k})} \quad \text{for any } r > 0,$$

where  $B_r^d = \{x \in \mathbb{R}^d : \|x\| \leq r\}$  or, alternatively,

$$\begin{aligned} \lambda_k &= \frac{1}{\nu_d(B)} \mathbb{E} \left( \sum_{L \in \text{supp}(\Phi_k)} \nu_k(L \cap B) \right) \quad \text{for any } B \in \mathcal{B}(\mathbb{R}^d) \\ &= \text{mean total } k\text{-volume of all } k\text{-flats in the unit cube } [0, 1]^d. \end{aligned}$$

## 2. CLTs for the number of intersection $k$ -flats and their total $k$ -volume in $B_r^d$

$$\begin{aligned} \Psi_k^{(d)}(B_r^d) &= \Phi_k(\{L \in \mathcal{A}_k^d : L \cap B_r^d \neq \emptyset\}) \\ &\stackrel{d}{=} \frac{1}{(d-k)!} \sum_{1 \leq i_1, \dots, i_{d-k} \leq N_r}^* \chi(\cap_{j=1}^{d-k} H(P_{i_j}, V_{i_j}) \cap B_r^d), \end{aligned}$$

where  $\chi(K) = 1$  for  $K \neq \emptyset$  and  $\chi(\emptyset) = 0$ , and

$$\begin{aligned} \zeta_k^{(d)}(B_r^d) &= \sum_{L \in \text{supp}(\Phi_k)} \nu_k(L \cap B_r^d) \\ &\stackrel{d}{=} \frac{1}{(d-k)!} \sum_{1 \leq i_1, \dots, i_{d-k} \leq N_r}^* \nu_k(\cap_{j=1}^{d-k} H(P_{i_j}, V_{i_j}) \cap B_r^d), \end{aligned}$$

where  $N_r = \Psi([-r, r] \times S_+^{d-1}) \sim \text{Poi}(2\lambda r)$  is independent of the i.i.d. random vectors  $(P_i, V_i), i = 0, 1, \dots$  with independent component such that  $P_0 \sim U[-r, r]$  and  $V_0 \sim \Theta$ .

### Mean values

$$\begin{aligned} \mathbb{E}\Psi_k^{(d)}(B_r^d) &= \lambda_k \nu_{d-k}(B_r^{d-k}) = \lambda_k \kappa_{d-k} r^{d-k} \\ &= \mathbb{E}\binom{N_r}{d-k} \mathbb{E}\chi(\cap_{i=1}^{d-k} H(P_i, V_i) \cap B_r^d \neq \emptyset) \\ &= \frac{(2\lambda r)^{d-k}}{(d-k)!} \mathbb{P}(\cap_{i=1}^{d-k} H(P_i, V_i) \cap B_r^d \neq \emptyset), \end{aligned}$$

$$\begin{aligned} \mathbb{E}\zeta_k^{(d)}(B_r^d) &= \lambda_k \nu_d(B_r^d) = \lambda_k \kappa_d r^d \\ &= \frac{(2\lambda r)^{d-k}}{(d-k)!} \mathbb{E}\nu_k(\cap_{i=1}^{d-k} H(P_i, V_i) \cap B_r^d) \end{aligned}$$

Note that always  $\lambda_{d-1} = \lambda$  and  $\lambda_k > 0$  for  $k = 0, 1, \dots, d-2$   
if  $\Theta(H(0, v) \cap S_+^{d-1}) < 1$  for all  $p \in \mathbb{R}^1$  (Non-degeneracy of  $\Phi$ !)

**Centered and normalized total number /  $k$ -volume in  $B_r^d$**

$$Z_{k,r}^{(d)}(\chi) := \frac{(d-k-1)!}{(2\lambda r)^{d-k-1/2}} \left( \Psi_k(B_r^d) - \mathbb{E} \Psi_k(B_r^d) \right)$$

and

$$Z_{k,r}^{(d)}(\nu) := \frac{(d-k-1)! r^{-k}}{(2\lambda r)^{d-k-1/2}} \left( \zeta_k(B_r^d) - \mathbb{E} \zeta_k(B_r^d) \right)$$

**Theorem 1.**(Heinrich, H. & V. Schmidt, to appear in 2006)  
Let  $\Phi$  be a non-degenerate PHP in  $\mathbb{R}^d$ . Then, for  $k = 0, \dots, d-1$ ,

$$Z_{k,r}^{(d)}(\chi) \xrightarrow[r \rightarrow \infty]{\text{d}} \mathcal{N}\left(0, \sigma_{kd}^2(\chi)\right) \quad \text{and} \quad Z_{k,r}^{(d)}(\nu) \xrightarrow[r \rightarrow \infty]{\text{d}} \mathcal{N}\left(0, \sigma_{kd}^2(\nu)\right),$$

where

$$\begin{aligned} \sigma_{kd}^2(\chi) &:= \mathbb{E} \chi(\cap_{i=1}^{d-k} H(P_i, V_i) \cap B_r^d) \chi(\cap_{i=d-k}^{2d-2k-1} H(P_i, V_i) \cap B_r^d) \\ &= \mathbb{E} \chi(\cap_{i=1}^{d-k} H(Q_i, V_i) \cap B_1^d) \chi(\cap_{i=d-k}^{2d-2k-1} H(Q_i, V_i) \cap B_1^d) \\ &= \mathbb{E} (g_{kd}^{(\chi)}(Q_0, V_0))^2, \\ \sigma_{kd}^2(\nu) &:= r^{-2k} \mathbb{E} \nu_k(\cap_{i=1}^{d-k} H(P_i, V_i) \cap B_r^d) \nu_k(\cap_{i=d-k}^{2d-2k-1} H(P_i, V_i) \cap B_r^d) \\ &= \mathbb{E} \nu_k(\cap_{i=1}^{d-k} H(Q_i, V_i) \cap B_1^d) \nu_k(\cap_{i=d-k}^{2d-2k-1} H(Q_i, V_i) \cap B_1^d) \\ &= \mathbb{E} (g_{kd}^{(\nu)}(Q_0, V_0))^2. \end{aligned}$$

Here,  $Q_i$ ,  $i = 1, 2, \dots$ , are independent copies of  $Q_0 \sim U[-1, 1]$  and the functions  $g_{kd}^{(\chi)}(p, v)$ ,  $g_{kd}^{(\nu)}(p, v)$  defined on  $[-1, 1] \times S_+^{d-1}$  are the *conditional expectations*

$$\begin{aligned} g_{kd}^{(\chi)}(p, v) &= \mathsf{E}\chi(\cap_{i=1}^{d-k-1} H(Q_i, V_i) \cap H(p, v) \cap B_1^d) \\ &= \mathsf{P}(\cap_{i=1}^{d-k-1} H(Q_i, V_i) \cap H(p, v) \cap B_1^d \neq \emptyset) \end{aligned}$$

and

$$g_{kd}^{(\nu)}(p, v) = \mathsf{E}\nu_k(\cap_{i=1}^{d-k} H(Q_i, V_i) \cap H(p, v) \cap B_1^d).$$

The proof of Thm. 1 is based on techniques from the theory of U-statistics (Hoeffding's decomposition) and the following

**Lemma 1.** For each  $k = 0, \dots, d - 1$ ,

$$\lim_{r \rightarrow \infty} \frac{\mathsf{Var} \Psi_k^{(d)}(B_r^d)}{r^{2d-2k-1}} = \frac{(2\lambda)^{2d-2k-1}}{((d-k-1)!)^2} \sigma_{kd}^2(\chi),$$

$$\lim_{r \rightarrow \infty} \frac{\mathsf{Var} \zeta_k^{(d)}(B_r^d)}{r^{2d-1}} = \frac{(2\lambda)^{2d-2k-1}}{((d-k-1)!)^2} \sigma_{kd}^2(\nu).$$

PROOF.

$$\begin{aligned} \mathsf{Var} \Psi_k^{(d)}(B_r^d) &= \sum_{j=1}^{d-k} \frac{(2\lambda r)^{2d-2k-j}}{j!((d-k-j)!)^2} \mathsf{E}\chi(\cap_{s=1}^{d-k} H(P_s, V_s) \cap B_r^d) \\ &\quad \times \chi(\cap_{t=d-k-j+1}^{2(d-k)-j} H(P_t, V_t) \cap B_r^d) \end{aligned}$$

and

$$\begin{aligned} \mathsf{Var} \zeta_k^{(d)}(B_r^d) &= \sum_{j=1}^{d-k} \frac{(2\lambda r)^{2d-2k-j}}{j!((d-k-j)!)^2} \mathsf{E}\nu_k(\cap_{s=1}^{d-k} H(P_s, V_s) \cap B_r^d) \\ &\quad \times \nu_k(\cap_{t=d-k-j+1}^{2(d-k)-j} H(P_t, V_t) \cap B_r^d). \end{aligned}$$

Furthermore, the mean values  $\mathsf{E}\Psi_k^{(d)}(B_r^d)$  and  $\mathsf{E}\zeta_k^{(d)}(B_r^d)$  are expressible by  $g_{kd}^{(\chi)}(p, v)$  and  $g_{kd}^{(\nu)}(p, v)$ , respectively:

$$\mathsf{E}\Psi_k^{(d)}(B_r^d) = \frac{(2\lambda)^{d-k}}{(d-k)!} r^{d-k} \mathsf{E}g_{kd}^{(\chi)}(Q_0, V_0)$$

$$\mathsf{E}\zeta_k^{(d)}(B_r^d) = \frac{(2\lambda)^{d-k}}{(d-k)!} r^d \mathsf{E}g_{kd}^{(\nu)}(Q_0, V_0)$$

**Aim:** Finding expression for  $g_{kd}^{(\chi)}(p, v)$  and  $g_{kd}^{(\nu)}(p, v)$  in dependence of  $\Theta$  (Use Crofton's formula if  $\Theta$  is uniform!)

$$\begin{aligned} g_{kd}^{(\chi)}(p, v) &= \mathsf{P}(\cap_{i=1}^{d-k-1} H(Q_i, V_i) \cap H(p, v) \cap B_1^d \neq \emptyset) \\ &= \frac{1}{2^{d-k-1}} \int_{S_+^{d-1}} \cdots \int_{S_+^{d-1}} \int_{-1}^1 \cdots \int_{-1}^1 \chi(\cap_{i=1}^{d-k} H(q_i, v_i) \\ &\quad \times \cap H(p, v) \cap B_1^d) dq_1 \dots dq_{d-k-1} \Theta(dv_1) \dots \Theta(dv_{d-k-1}) \\ g_{kd}^{(\nu)}(p, v) &= \mathsf{E}\nu_k(\cap_{i=1}^{d-k} H(Q_i, V_i) \cap H(p, v) \cap B_1^d) \\ &= \frac{1}{2^{d-k-1}} \int_{S_+^{d-1}} \cdots \int_{S_+^{d-1}} \int_{-1}^1 \cdots \int_{-1}^1 \nu_k(\cap_{i=1}^{d-k} H(q_i, v_i) \\ &\quad \times \cap H(p, v) \cap B_1^d) dq_1 \dots dq_{d-k-1} \Theta(dv_1) \dots \Theta(dv_{d-k-1}). \end{aligned}$$

### 3. Basic facts on (random) U-statistics

$X_1, X_2, \dots$  be a sequence of i.i.d. random elements in some meas. space  $[E, \sigma(E)]$  and, for fixed  $m \geq 2$ , let  $f : E^m \rightarrow \mathbb{R}^1$  be a meas. symmetric function such that  $\mathsf{E}|f(X_1, \dots, X_m)| < \infty$ .

**Def.:** A  $U$ -statistic  $U_n^{(m)}(f)$  of order  $m$  with *kernel function*  $f$  is defined by

$$U_n^{(m)}(f) = \frac{1}{\binom{n}{m}} \sum_{1 \leq i_1 < \dots < i_m \leq n} f(X_{i_1}, \dots, X_{i_m}) \quad \text{for } n \geq m.$$

Note that  $U_n^{(m)}(f)$  is an unbiased estimator for  $\mu = \mathsf{E}f(X_1, \dots, X_m)$ .

By *Hoeffding's decomposition*,

$$U_n^{(m)}(f) - \mu = \frac{m}{n} \sum_{i=1}^n (g(X_i) - \mu) + R_n^{(m)}(f),$$

where  $g(x) = \mathsf{E}(f(X_1, X_2, \dots, X_m) | X_1 = x) = \mathsf{E}f(x, X_2, \dots, X_m)$ .

and (as crucial outcome of Hoeffding's decomposition)

$$\mathsf{E}(R_n^{(m)}(f))^2 \leq \frac{c_m}{n^2} \mathsf{E}f^2(X_1, \dots, X_m) \quad \text{for } n \geq m$$

and for some constant  $c_m < \infty$  only depending on  $m$ .

#### Hoeffding's CLT for $U$ -statistics

If  $\mathsf{E}f^2(X_1, \dots, X_m) < \infty$ , then

$$\sqrt{n} (U_n^{(m)}(f) - \mu) \xrightarrow[n \rightarrow \infty]{d} \mathcal{N}(0, m^2(\mathsf{E}g^2(X_1) - \mu^2)),$$

where  $\xrightarrow{d}$  denotes convergence in distribution.

## 4. Zonoids and distributions on $S_+^{d-1}$ Basic notions from convex geometry

1. Support function of a convex body  $K \subset \mathbb{R}^d$ :

$$h(K, u) = \max_{x \in K} \langle u, x \rangle \quad \text{for } u \in \mathbb{R}^d$$

Geometric meaning:

$h(K, u)$  = signed perpendicular distance of the support plane to  $K$  with exterior normal vector  $u$  from the origin (for  $u \in S^{d-1}$ )

Important properties:

$$h(\alpha K \oplus \beta L, \cdot) = \alpha h(K, \cdot) + \beta h(L, \cdot) \text{ for } \alpha, \beta \geq 0$$

$$d_H(K, L) = \max_{u \in S^{d-1}} |h(K, u) - h(L, u)|, \quad h(K, \cdot) \in C(S^{d-1})$$

$$h(K, \gamma u) = \gamma h(K, u) \text{ and } h(K, u+v) \leq h(K, u) + h(K, v) \\ \text{for } \gamma \geq 0; u, v \in \mathbb{R}^d$$

i.e. support functions of convex bodies are *sublinear* on  $\mathbb{R}^d$ .

CONVERSELY, IF  $h : \mathbb{R}^d \mapsto \mathbb{R}^1$  IS A SUBLINEAR FUNCTION,  
THEN THERE EXISTS A UNIQUE CONVEX BODY IN  $\mathbb{R}^d$  WITH  
SUPPORT FUNCTION  $h(\cdot)$ .

Examples:

1. Ellipse  $E : \frac{x_1^2}{a^2} + \frac{x_2^2}{b^2} \leq 1 \Rightarrow h(E, u_1, u_2) = \sqrt{a^2 u_1^2 + b^2 u_2^2}$
2. Diamond  $D : |x_1| + |x_2| \leq 1 \Rightarrow h(D, u_1, u_2) = \max\{|u_1|, |u_2|\}$
3. Square  $S : \max\{|x_1|, |x_2|\} \leq 1 \Rightarrow h(S, u_1, u_2) = |u_1| + |u_2|$

Fig. 3: Illustration of the support function of a planar ovoid

## 2. Centrally symmetric zonotopes in $\mathbb{R}^d$ :

A *zonotope* in  $\mathbb{R}^d$  is a polytope of the form  $Z = S_1 \oplus \cdots \oplus S_n$   
( = Minkowski sum of the segments  $S_1, \dots, S_n$ );

$Z$  is *centrally symmetric*, if it generated by segments of the form  
 $S_i = \text{conv}\{-\alpha_i u_i, \alpha_i u_i\}$  with  $u_i \in \mathbb{S}_+^{d-1}$ ,  $\alpha_i > 0$  for  $i = 1, \dots, n$ .

$$h(Z, u) = \sum_{i=1}^n \alpha_i |\langle u, u_i \rangle| \quad \text{for } u \in \mathbb{R}^d$$

Fig. 4: Illustration of a planar zonotope generated by  $n = 3$  segments

$$\begin{aligned} S_1 &= \text{conv}\{-(\alpha_1, 0), (\alpha_1, 0)\}, \quad S_2 = \text{conv}\{-(0, \alpha_2), (0, \alpha_2)\}, \\ S_3 &= \text{conv}\{-(\alpha_3, \alpha_3), (\alpha_3, \alpha_3)\} \Rightarrow Z = [-\alpha_1, \alpha_1] \times [-\alpha_2, \alpha_2] \oplus S_3. \end{aligned}$$

Note that any centrally symmetric polygon is a zonotope in  $\mathbb{R}^2$ .  
In  $\mathbb{R}^d$ ,  $d \geq 3$ , further conditions are needed.

## 3. Zonoids in $\mathbb{R}^d$ :

= limits of sequences of centrally symmetric zonotopes in  $\mathbb{R}^d$   
(in the sense of the Hausdorff metric)

or equivalently

A centrally symmetric convex body  $Z_\varrho$  in  $\mathbb{R}^d$  is said to be a *zonoid* with generating measure  $\varrho(\cdot)$  if its support function can represented in the form

$$h(Z_\varrho, u) = \int_{\mathbb{S}_+^{d-1}} |\langle u, v \rangle| \varrho(dv) \quad \text{for } u \in \mathbb{R}^d$$

with some (finite) measure  $\varrho(\cdot)$  on  $\mathbb{S}^{d-1}$ .

Note that there is a one-to-one correspondence between zonoids and their generating measures, i.e.

$$Z_{\varrho_1} = Z_{\varrho_2} \iff h(Z_{\varrho_1}, \cdot) = h(Z_{\varrho_2}, \cdot) \iff \varrho_1(\cdot) = \varrho_2(\cdot)$$

Hence, to any given orientation distribution  $\Theta(\cdot)$  of a stationary PHP there exists a zonoid  $Z_\Theta$  such that

$$h(Z_\Theta, u) = \int_{S_+^{d-1}} |\langle u, v \rangle| \Theta(dv) \quad \text{for } u \in \mathbb{R}^d .$$

$$\Theta(\cdot) = \frac{\nu_{d-1}(\cdot)}{d \kappa_d / 2} \quad \text{uniform distribution} \iff Z_\Theta = \frac{\kappa_{d-1}}{d \kappa_d} B_1^d$$

#### 4. Intrinsic volumes $V_k^{(d)}(K)$ of a convex body $K \subset \mathbb{R}^d$

Definition by means of Steiner's formula:

$$\nu_d(K \oplus B_r^d) = \sum_{k=0}^d r^{d-k} \kappa_{d-k} V_k^{(d)}(K) \quad \text{for } r \geq 0$$

$$V_0^{(d)}(K) = 1 , \quad V_d^{(d)}(K) = \nu_d(K) , \quad V_{d-1}^{(d)}(K) = \frac{1}{2} \nu_{d-1}(\partial K)$$

For the zonoid  $Z_\Theta$  associated with  $\Theta$  it holds (cf. W. Weil (1979))

$$V_k^{(d)}(Z_\Theta) = \frac{1}{k} \int_{S_+^{d-1}} V_{k-1}^{(d-1)}(Z_\Theta^v) \Theta(dv) \quad \text{for } k = 1, \dots, d ,$$

where  $K^v$  denotes the image of the convex body  $K$  under orthogonal projection onto the hyperplane  $H(0, v)$ .

## 5. Formulae for asymptotic variances and covariances in terms of the associated zonoid

**Theorem 2.** Let  $\Phi$  be a non-degenerate PHP in  $\mathbb{R}^d$ .

Then, for  $k = 0, \dots, d-1$  and  $(p, v) \in [-1, 1] \times S_+^{d-1}$ ,

$$g_{kd}^{(\chi)}(p, v) = \frac{(d-k-1)! \kappa_{d-k-1}}{2^{d-k-1}} (1-p^2)^{(d-k-1)/2} V_{d-k-1}^{(d-1)}(Z_\Theta^v)$$

$$g_{kd}^{(\nu)}(p, v) = \frac{(d-k-1)! \kappa_{d-1}}{2^{d-k-1}} (1-p^2)^{(d-1)/2} V_{d-k-1}^{(d-1)}(Z_\Theta^v).$$

$\implies$  (together with  $\int_{-1}^1 (1-p^2)^j/2 dp = \kappa_{j+1}/\kappa_j$ )

$$\begin{aligned} \mathbb{E} g_{kd}^{(\chi)}(Q_0, V_0) &= \frac{(d-k-1)! \kappa_{d-k}}{2^{d-k}} \int_{S_+^{d-1}} V_{d-k-1}^{(d-1)}(Z_\Theta^v) \Theta(dv) \\ &= \frac{(d-k)! \kappa_{d-k}}{2^{d-k}} V_{d-k}^{(d)}(Z_\Theta) \\ &\implies \lambda_k = \lambda^{d-k} V_{d-k}^{(d)}(Z_\Theta) \end{aligned}$$

$$\mathbb{E} g_{kd}^{(\nu)}(Q_0, V_0) = \frac{(d-k)! \kappa_d}{2^{d-k}} V_{d-k}^{(d)}(Z_\Theta)$$

$$\sigma_{kd}^2(\chi) = \frac{\left(((d-k-1)!)^2 \kappa_{d-k-1}\right)^2}{(2d-2k-1)!} \int_{S_+^{d-1}} \left(V_{d-k-1}^{(d-1)}(Z_\Theta^v)\right)^2 \Theta(dv)$$

$$\sigma_{kd}^2(\nu) = \frac{\left(2^k (d-k-1)! (d-1)! \kappa_{d-1}\right)^2}{(2d-1)!} \int_{S_+^{d-1}} \left(V_{d-k-1}^{(d-1)}(Z_\Theta^v)\right)^2 \Theta(dv).$$

**Isotropic case:**

$$Z_\Theta = \frac{\kappa_{d-1}}{d \kappa_d} B_1^d \implies V_{d-k}^{(d)}(Z_\Theta) = \left(\frac{\kappa_{d-1}}{d \kappa_d}\right)^{d-k} \binom{d}{k} \frac{\kappa_d}{\kappa_k}$$

$$\implies$$

$$Z_\Theta^v = \frac{\kappa_{d-1}}{d \kappa_d} B_1^{d-1}, \quad V_{d-k-1}^{(d-1)}(Z_\Theta^v) = \left(\frac{\kappa_{d-1}}{d \kappa_d}\right)^{d-k-1} \binom{d-1}{k} \frac{\kappa_{d-1}}{\kappa_k},$$

where

$$\kappa_d := \nu_d(B_1^d) = \pi^{\frac{d}{2}} / \Gamma\left(\frac{d}{2} + 1\right).$$

Solution of the *isoperimetric* problem yields

$$\max_{\Theta} \lambda_0 = \lambda_0 \Big|_{\Theta=\text{unif.dist.}} = \lambda^d \kappa_d \left(\frac{\kappa_{d-1}}{d \kappa_d}\right)^d \quad \text{for fixed } \lambda_{d-1} = \lambda$$

**Lemma 2.** Let  $\Theta$  be the uniform distribution on  $S_+^{d-1}$  and  $k \in \{0, 1, \dots, d-1\}$ . Then, for  $k = 0, 1, \dots, d-1$ ,

$$\lambda_k = \binom{d}{k} \frac{\kappa_d}{\kappa_k} \left(\frac{\kappa_{d-1}}{d \kappa_d}\right)^{d-k} \lambda^{d-k},$$

$$\sigma_{kd}^{(\chi)} = \frac{(\kappa_{d-k-1} (d-k-1)!)^2}{(2d-2k-1)!} \left(\frac{d! \kappa_d}{k! \kappa_k}\right)^2 \left(\frac{\kappa_{d-1}}{d \kappa_d}\right)^{2(d-k)}$$

and

$$\sigma_{kd}^{(\nu)} = \frac{(2^k \kappa_{d-1} (d-1)!)^2}{(2d-1)!} \left(\frac{d! \kappa_d}{k! \kappa_k}\right)^2 \left(\frac{\kappa_{d-1}}{d \kappa_d}\right)^{2(d-k)}.$$

**Multivariate CLTs :** Joint asymptotic behaviour (as  $r \rightarrow \infty$ ) of the closely correlated random variables  $Z_{0,r}^{(d)}(\chi), \dots, Z_{d-1,r}^{(d)}(\chi)$  as well as of  $Z_{0,r}^{(d)}(\nu), \dots, Z_{d-1,r}^{(d)}(\nu)$

**Theorem 3.** (Heinrich, H. & V. Schmidt, to appear in 2006)  
Let  $\Phi$  be a non-degenerate PHP in  $\mathbb{R}^d$ . Then,

$$(Z_{k,r}^{(d)}(\chi))_{k=0}^{d-1} \xrightarrow[r \rightarrow \infty]{\text{d}} \mathcal{N}(0, \Sigma^{(d)}(\chi)) \text{ and } (Z_{k,r}^{(d)}(\nu))_{k=0}^{d-1} \xrightarrow[r \rightarrow \infty]{\text{d}} \mathcal{N}(0, \Sigma^{(d)}(\nu))$$

with (asymptotic) covariance matrices

$$\Sigma^{(d)}(\chi) = (\sigma_{kl}^{(d)}(\chi))_{k,l=0}^{d-1} \quad \text{and} \quad \Sigma^{(d)}(\nu) = (\sigma_{kl}^{(d)}(\nu))_{k,l=0}^{d-1},$$

where the mixed second moments are given by (cf. Heinrich & Schertz (2006))

$$\begin{aligned} \sigma_{kl}^{(d)}(\chi) &= \mathbb{E}(g_{kd}^{(\chi)}(Q_0, V_0) g_{ld}^{(\chi)}(Q_0, V_0)) \\ &= a_{kl}^{(d)} \int_{S_+^{d-1}} V_{d-k-1}^{(d-1)}(Z_\Theta^v) V_{d-l-1}^{(d-1)}(Z_\Theta^v) \Theta(dv) \end{aligned}$$

$$\text{with } a_{kl}^{(d)} = \kappa_{d-k-1} \kappa_{d-l-1} \left( \Gamma(d - \frac{k+l}{2}) \right)^2 \frac{(d-k-1)! (d-l-1)!}{(2d-k-l-1)!}$$

and

$$\begin{aligned} \sigma_{kl}^{(d)}(\nu) &= \mathbb{E}(g_{kd}^{(\nu)}(Q_0, V_0) g_{ld}^{(\nu)}(Q_0, V_0)) \\ &= b_{kl}^{(d)} \int_{S_+^{d-1}} V_{d-k-1}^{(d-1)}(Z_\Theta^v) V_{d-l-1}^{(d-1)}(Z_\Theta^v) \Theta(dv) \end{aligned}$$

$$\text{with } b_{kl}^{(d)} = (d-k-1)! (d-l-1)! 2^{k+l} \kappa_{d-1}^2 \frac{((d-1)!)^2}{(2d-1)!}.$$

## Computation of the mixed second-order moments when $\Phi$ isotropic

**Lemma 3.** Let  $\Theta$  be the uniform distribution on  $S_+^{d-1}$  and let  $k, l \in \{0, \dots, d-1\}$ . Then,

$$\begin{aligned}\sigma_{kl}^{(d)}(\chi) &= \frac{(d! \kappa_d)^2 \kappa_{d-k-1} \kappa_{d-l-1}}{k! l! \kappa_k \kappa_l 2^{2d-k-l-1}} \frac{\kappa_{2d-k-l-1}}{\kappa_{2d-k-l-2}} \left( \frac{\kappa_{d-1}}{d \kappa_d} \right)^{2d-k-l} \\ &= \sqrt{\sigma_{kk}^{(d)}(\chi) \sigma_{ll}^{(d)}(\chi)} \frac{B\left(\frac{2d-k-l}{2}, \frac{2d-k-l}{2}\right)}{\sqrt{B(d-k, d-k) B(d-l, d-l)}},\end{aligned}$$

where  $B(s, t) := \int_0^1 x^{s-1} (1-x)^{t-1} dx$  denotes Euler's Beta function, and

$$\sigma_{kl}^{(d)}(\nu) = \frac{(\kappa_d d! (d-1)!)^2 2^{k+l}}{k! l! \kappa_k \kappa_l (2d-1)!} \left( \frac{\kappa_{d-1}}{d \kappa_d} \right)^{2d-k-l} = \sqrt{\sigma_{kk}^{(d)}(\nu) \sigma_{ll}^{(d)}(\nu)}.$$

**Corollary.** The rank of the covariance matrix  $\Sigma^{(d)}(\nu)$  equals 1 for any dimension  $d \geq 1$ , whereas  $\Sigma^{(d)}(\chi)$  possesses always full rank  $d$ .

Furthermore,

$$\frac{Z_{l,r}^{(d)}(\nu)}{\sqrt{\sigma_{ll}^{(d)}(\nu)}} - \frac{Z_{k,r}^{(d)}(\nu)}{\sqrt{\sigma_{kk}^{(d)}(\nu)}} \xrightarrow[r \rightarrow \infty]{P} 0 \quad \text{for } 0 \leq k < l \leq d-1.$$

## 6. Some Applications and properties of the asymptotic covariance matrices

Let  $\Phi$  be a stationary PHP with intensity  $\lambda > 0$  and non-degenerate orientation distribution  $\Theta$ .

Then

$$\widehat{\lambda}_{k,r}^{(d)} := \frac{\Psi_k^{(d)}(B_r^d)}{\nu_{d-k}(B_r^{d-k})} \quad \text{and} \quad \widetilde{\lambda}_{k,r}^{(d)} := \frac{\zeta_k^{(d)}(B_r^d)}{\nu_d(B_r^d)}$$

are unbiased, strongly consistent estimators for the intensity  $\lambda_k$  of the stationary  $k$ -flat intersection process generated by  $\Phi$ .  
(!  $\Phi$  is ergodic, even mixing, cf. Schneider & Weil (2000))

Lemma 1 and Theorem 2 yield

$$\lim_{r \rightarrow \infty} r \operatorname{Var} \left( \widehat{\lambda}_{k,r}^{(d)} \right) = \lambda^{2d-2k-1} c_{d-k} \int_{S_+^{d-1}} (V_{d-k-1}^{(d-1)}(Z_\Theta^v))^2 \Theta(dv)$$

$$\lim_{r \rightarrow \infty} r \operatorname{Var} \left( \widetilde{\lambda}_{k,r}^{(d)} \right) = \lambda^{2d-2k-1} c_d \int_{S_+^{d-1}} (V_{d-k-1}^{(d-1)}(Z_\Theta^v))^2 \Theta(dv)$$

for  $k = 0, \dots, d-1$ , where  $c_j = \frac{2^{2j-1}}{(2j-1)!} \left( \frac{(j-1)! \kappa_{j-1}}{\kappa_j} \right)^2$  for  $j \geq 1$ . This implies that

$$\lim_{r \rightarrow \infty} \frac{\operatorname{Var} \left( \widehat{\lambda}_{k,r}^{(d)} \right)}{\operatorname{Var} \left( \widetilde{\lambda}_{k,r}^{(d)} \right)} = \frac{c_{d-k}}{c_d} < 1,$$

since  $c_j < c_{j+1}$  for  $j \geq 1$ . Thus, it holds that

$$\lim_{r \rightarrow \infty} r \operatorname{Var} \left( \widehat{\lambda}_{k,r}^{(d)} \right) < \lim_{r \rightarrow \infty} r \operatorname{Var} \left( \widetilde{\lambda}_{k,r}^{(d)} \right) \quad \text{for } k = 1, \dots, d-1.$$

## The rank of the covariance matrices $\Sigma^{(d)}(\chi)$ and $\Sigma^{(d)}(\nu)$

**Theorem 4.**( Heinrich & Schertz (2006)) We have

1.  $\text{rank}(\Sigma^{(d)}(\chi)) = d \iff \nu_d(Z_\Theta) = V_d^{(d)}(Z_\Theta) > 0$   
( iff  $\Theta(\cdot)$  is non-degenerate)
2.  $\text{rank}(\Sigma^{(d)}(\nu)) = d \iff \Theta(\cdot)$  is non-degenerate and there is no vector  $(t_0, \dots, t_{d-1}) \neq 0$  such that

$$\Theta\left(\{u \in S_+^{d-1} : \sum_{k=0}^{d-1} t_k V_k^{(d-1)}(Z_\Theta^u) = 0\}\right) = 1$$

3.  $\text{rank}(\Sigma^{(d)}(\nu)) = 1 \iff \text{For } k = 2, \dots, d,$

$$\Theta\left(\{u \in S_+^{d-1} : V_{k-1}^{(d-1)}(Z_\Theta^u) = \text{const } (= k V_k^{(d)}(Z_\Theta))\}\right) = 1 .$$

**Special case  $d = 2$ :**

$$\Sigma^{(2)}(\chi) = \begin{pmatrix} \frac{2}{3} \int (V_1^{(1)}(Z_\Theta^u))^2 \Theta(du) & \frac{\pi}{2} V_2^{(2)}(Z_\theta) \\ \frac{\pi}{2} V_2^{(2)}(Z_\theta) & 1 \end{pmatrix}$$

$$\Sigma^{(2)}(\nu) = \begin{pmatrix} \frac{2}{3} \int (V_1^{(1)}(Z_\Theta^u))^2 \Theta(du) & \frac{8}{3} V_2^{(2)}(Z_\theta) \\ \frac{8}{3} V_2^{(2)}(Z_\theta) & \frac{8}{3} \end{pmatrix}$$

$$\text{rank}(\Sigma^{(2)}(\nu)) = 1 \Leftrightarrow \det(\Sigma^{(2)}(\nu)) = 0 \Leftrightarrow \Theta(\{u : V_1^{(1)}(Z_\Theta^u) = c\}) = 1$$

**Example:**  $\Theta$  concentrated on  $u_i = (\cos \alpha_i, \sin \alpha_i)$  for  $i = 1, 2$

with  $0 \leq \alpha_1 < \alpha_2 < \pi$  and  $\Theta(\{u_1\}) = \Theta(\{u_2\}) = 1/2$   
 $\implies V_1^{(1)}(Z_\Theta^{u_1}) = V_1^{(1)}(Z_\Theta^{u_2}) = \sin(\alpha_2 - \alpha_1)$

Note that, by definition of the support function and  $Z_\Theta = -Z_\Theta$ ,

$$V_1^{(d-1)}(Z_\Theta^u) = 2 h(Z_\Theta, u^\perp) = 2 \int_{S_+^{d-1}} |\langle u^\perp, v \rangle| \Theta(dv) \quad \text{for } u \in \mathbb{R}^d$$

so that

$$V_2^{(d)}(Z_\Theta) = \frac{1}{2} \int_{S_+^{d-1}} V_1^{(d-1)}(Z_\Theta^u) \Theta(du) = \int_{S_+^{d-1}} \int_{S_+^{d-1}} |\langle u^\perp, v \rangle| \Theta(dv) \Theta(du).$$

**Example (continued):**  $\Theta$  concentrated on  $u_i = (\cos \alpha_i, \sin \alpha_i)$  for  $i = 1, 2$ ,  $0 \leq \alpha_1 < \alpha_2 < \pi$ , with  $\Theta(\{u_1\}) = 1 - \Theta(\{u_2\}) = p$

$\implies$

$$\begin{aligned} V_1^{(1)}(Z_\Theta^{u_1}) &= 2(1-p) \sin(\alpha_2 - \alpha_1), \\ V_1^{(1)}(Z_\Theta^{u_2}) &= 2p \sin(\alpha_2 - \alpha_1), \\ V_2^{(2)}(Z_\Theta) &= 4p(1-p) \sin(\alpha_2 - \alpha_1) \end{aligned}$$

**Variational problem for the planar case:** ( Heinrich & Schertz (2006))

$$\int (V_1^{(1)}(Z_\Theta^u))^2 \Theta(du) = 4 \int_0^\pi \left( \int_0^\pi |\sin(\beta - \alpha)| \Theta(d\alpha) \right)^2 \Theta(d\beta) \mapsto \min!$$

under the condition

$$V_2^{(2)}(Z_\Theta) = \int_0^\pi \int_0^\pi |\sin(\beta - \alpha)| \Theta(d\alpha) \Theta(d\beta) = \text{const} \left( \leq \frac{1}{\pi} \right)$$

In the above case this means to minimize the integral

$$\int (V_1^{(1)}(Z_\Theta^u))^2 \Theta(du) = 4p(1-p) \sin^2(\alpha_2 - \alpha_1) = \frac{(V_2^{(2)}(Z_\Theta))^2}{p(1-p)}.$$

Obviously, this minimum is attained for  $p = 1/2$ .

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