

# Estimation of Specific Intrinsic Volumes and Asymptotical Tests

Ursa Pantle

University of Ulm

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## 1 Introduction

- Germ–grain models
- Associated random fields

## 2 Estimation of the mean

- Unbiasedness and Consistency
- Asymptotic normality

## 3 Estimation of the asymptotic variance

- Weighted covariance estimator
- Consistency
- Empirical covariance estimator

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# 1 Introduction

## Germ–grain models

- $X = \{X_i\}$  point process of **germs**
- $M = \{M_i\}$  process of **grains**,  $M_i \stackrel{d}{=} M_0$  i.i.d. RACS
- If  $\mathbb{E}|M_0 \oplus \check{K}| < \infty$ ,  $K \subset \mathbb{R}^d$  compact, then  $\Xi = \bigcup_{i=1}^{\infty} (M_i + X_i)$  is well defined.

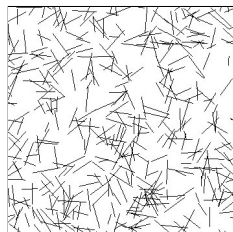
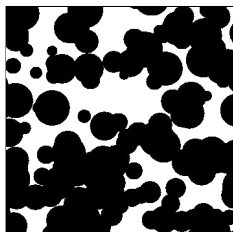


Figure: Germ–grain models of discs and line segments

# 1 Introduction

## Random fields associated with GGM

Stationary germ–grain model  $\Xi$  such that  $\Xi \cap K \in \mathcal{R}$ ,  $K \in \mathcal{K}$ .

- $\varphi : \mathcal{R} \rightarrow \mathbb{R}$  additive, i.e.,  $\varphi(\emptyset) = 0$ ,

$$\varphi(K_1 \cup K_2) = \varphi(K_1) + \varphi(K_2) - \varphi(K_1 \cap K_2)$$

- conditionally bounded:

$$\sup\{|\varphi(K')| : K' \subseteq K, K' \in \mathcal{K}\} < \infty$$

- Random field  $Y = \{Y(x), x \in \mathbb{R}^d\}$ , test set  $K \in \mathcal{K}$ :

$$Y(x) = \varphi((\Xi - x) \cap K), \quad x \in \mathbb{R}^d.$$

Objective: Estimation of  $\mu = \mathbb{E}Y(x)$ .

# 1 Introduction

## Examples

Stationary GGM  $\Xi$ , random field  $Y(x) = \varphi((\Xi - x) \cap K)$ ,  $x \in \mathbb{R}^d$ ,  
test set  $K \in \mathcal{K}$ .

- $Y_1(x) = \mathbb{I}((\Xi - x) \cap \{o\}) = \mathbb{I}(x \in \Xi)$   
with  $\mathbb{E}Y_1(x) = \mathbb{E}(|\Xi \cap [0, 1]^d|) = p$       volume fraction
- $Y_2(x) = \mathbb{I}((\Xi - x) \cap K) = \mathbb{I}(x \in \Xi \oplus \check{K})$   
with  $\mathbb{E}Y_2(x) = P(\Xi \cap K \neq \emptyset) = T_\Xi(K)$       capacity functional
- $Y_3(x) = V_0((\Xi - x) \cap B_r(o)) = V_0(\Xi \cap B_r(x))$ ,  $r > 0$   
with  $\mathbb{E}Y_3(x) = \mathbb{E}V_0(\Xi \cap B_r(o))$       local Euler charakteristic  
 $= \sum_{j=0}^d r^{d-j} \kappa_{d-j} \bar{V}_j(\Xi)$       spec. intrinsic volumes

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 $= \sum_{j=0}^d r^{d-j} \kappa_{d-j} \bar{V}_j(\Xi)$  spec. intrinsic volumes



# 1 Introduction

## Examples

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## 2 Estimation of the mean

Preliminaries:

- **Stationary random field**  $Y(x) = \varphi((\Xi - x) \cap K)$ ,  $x \in \mathbb{R}^d$ ,  $K \in \mathcal{K}$  with  $\mu = \mathbb{E}Y(x)$ .
- **Observation window**  $W_n = nW_0$  with  $W_0 \in \mathcal{K}$ ,  $o \in \text{int}(W_0)$ .
- **Weighting functional**  $G : \mathcal{B}_0^d \times \mathbb{R}^d \rightarrow [0, \infty)$  with

$$G(W_n, x) = 0, \quad x \in \mathbb{R}^d \setminus W_n \ominus \check{K}, \quad \int_{W_n} G(W_n, x) dx = 1.$$

**Unbiased estimator** of  $\mu$ :  $\mathbb{E}(\hat{\mu}_n) = \mu$  for

$$\hat{\mu}_n = \int_{W_n} Y(x) G(W_n, x) dx$$

## 2.1 Consistent estimation of the mean

Conditions:

- $\text{Cov}_Y(x) = \text{Cov}(Y(o), Y(x))$  satisfies  $\int_{\mathbb{R}^d} |\text{Cov}_Y(x)| dx < \infty$ .
- Weighting functional  $G$  satisfying:

$$\sup_{x \in \mathbb{R}^d} G(W_n, x) \leq \frac{c_0}{|W_n|} \quad \text{and} \quad \lim_{n \rightarrow \infty} |W_n| \Gamma_n(x) = \theta.$$

for  $\Gamma_n(x) = \int G(W_n, y) G(W_n, x + y) dy$  and  $c_0, \theta < \infty$ .

Mean-square consistency of  $\hat{\mu}_n$ :  $\lim_{n \rightarrow \infty} \mathbb{E}(\hat{\mu}_n - \mu)^2 = 0$ , since

$$\lim_{n \rightarrow \infty} |W_n| \text{Var}(\hat{\mu}_n) = \theta \int_{\mathbb{R}^d} \text{Cov}_Y(x) dx.$$

## 2.2 Asymptotic normality

Conditions:

Germ–grain model  $\Xi = \bigcup_{i \geq 1} (M_i + X_i)$  is

- a Boolean model with  $\mathbb{E}(|M_0 \oplus \check{K}|^2) < \infty$
- or  $\mathbb{E} 2^{(2+\delta)N(\Xi \cap K)} < \infty$ , point process  $X = \{X_i\}$  is 'strongly mixing' and  $\mathbb{E}(\|M_0 \oplus \check{K}\|^{2d(1+1/\delta)+\varepsilon}) < \infty$ ,  $\delta, \varepsilon > 0$ ;  $\|A\| = \sup\{|x| : x \in A\}$ .

Then it holds that

$$\sqrt{|W_n|} (\hat{\mu}_n - \mu) \xrightarrow{d} \mathcal{N}(0, \sigma^2),$$

for  $\sigma^2 = \theta \int_{\mathbb{R}^d} \text{Cov}_Y(x) dx$ .

## 2.2 Asymptotic normality

Conditions:

Germ–grain model  $\Xi = \bigcup_{i \geq 1} (M_i + X_i)$  is

- a Boolean model with  $\mathbb{E}(|M_0 \oplus \check{K}|^2) < \infty$

$$\implies \int_{\mathbb{R}^d} |\text{Cov}_Y(x)| dx < \infty$$

Then it holds that

$$\sqrt{|W_n|} (\hat{\mu}_n - \mu) \xrightarrow{d} \mathcal{N}(0, \sigma^2),$$

for  $\sigma^2 = \theta \int_{\mathbb{R}^d} \text{Cov}_Y(x) dx$ .

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### 3 Estimation of the asymptotic variance

Define

$$\widehat{\sigma}_n^2 = \int_{U_n} \widehat{\text{Cov}}_n(x) \gamma(W_n, x) dx$$

for

- asymp. unbiased estimator  $\widehat{\text{Cov}}_n(x)$  of  $\text{Cov}_Y(x)$ ,
- weight  $\gamma(W_n, x) = |W_n| \Gamma_n(x)$ ,  $x \in \mathbb{R}^d$ ,
- averaging window  $U_n \subseteq (W_n \ominus \check{K}) \oplus (-W_n \ominus \check{K})$ ,  $o \in U_n$  and

$$\lim_{n \rightarrow \infty} \frac{|U_n|^2}{|W_n|} = 0 \quad \text{and} \quad \lim_{n \rightarrow \infty} \sup_{x \in U_n} |\theta - \gamma(W_n, x)| = 0.$$



## 3.1 Weighted variance estimator

Put  $W_n^K = W_n \ominus \check{K}$ .

Uniform weights:  $G(W_n, x) = \mathbb{I}(x \in W_n^K) / |W_n^K|$ .

Define

$$\widehat{\text{Cov}}_n(x) = \int_{W_n^K \cap (W_n^K - x)} \frac{\mathbf{Y}(y) \mathbf{Y}(y+x) - \widehat{\mu}_n^2}{|W_n^K \cap (W_n^K - x)|} dy$$

and let

$$\widehat{\sigma}_n^2 \approx \int_{U_n} \widehat{\text{Cov}}_n(x) \frac{|W_n^K \cap (W_n^K - x)|}{|W_n^K|} dx.$$

## 3.2 Unbiasedness and Consistency

Boolean model  $\Xi = \bigcup_{i \geq 1} (M_i + X_i)$

If  $\mathbb{E}(|M_0 \oplus \check{K}|^2) < \infty$  then

$$\lim_{n \rightarrow \infty} \mathbb{E} \hat{\sigma}^2 = \sigma^2, \quad \text{asymptotically unbiased}$$

and

$$\lim_{n \rightarrow \infty} \mathbb{E} (\hat{\sigma}^2 - \sigma^2)^2 = 0, \quad \text{mean-square consistent}$$

for  $\sigma^2 = \theta \int_{\mathbb{R}^d} \text{Cov}_Y(x) dx$ .

## 3.2 Unbiasedness and Consistency

Germ–grain model  $\Xi = \bigcup_{i \geq 1} (M_i + X_i)$

- If  $\int_{\mathbb{R}^d} |\text{Cov}_Y(x)| dx < \infty$  then

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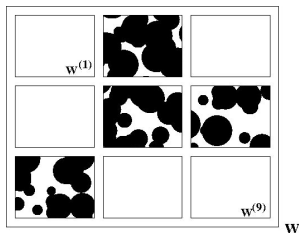
- If  $\sup_{x_1, x_2} \int_{\mathbb{R}^d} |\text{Cov}(Y(o)Y(x_1), Y(y)Y(x_2 + y))| dy < \infty$  and  $\sup_{x_1, x_2} \int_{\mathbb{R}^d} |\mathbb{E}((Y(o) - \mu)(Y(y) - \mu)Y(x_1)Y(x_2))| dy < \infty$  (or  $Y$  is uniformly bounded) then

$$\lim_{n \rightarrow \infty} \mathbb{E} (\hat{\sigma}^2 - \sigma^2)^2 = 0, \quad \text{mean–square consistent.}$$

### 3.3 Empirical covariance estimator

Subdivision of the sampling window:

Let  $W_n^{(1)}, \dots, W_n^{(m)}$  for  $m = m(n)$   
such that  $\bigcup_{k=1}^m W_n^{(k)} \subseteq W_n$  and  
 $\text{int}(W_n^{(k)}) \cap \text{int}(W_n^{(\ell)}) = \emptyset, k \neq \ell$



and define

$$\tilde{\sigma}_n^2 = \frac{1}{m-1} \sum_{k=1}^m \left( \hat{\mu}_n^{(k)} - \bar{\mu}_n \right)^2$$

for  $\hat{\mu}_n^{(k)}$  estimate of  $\mu$  on  $W_n^{(k)}$  and  $\bar{\mu}_n = \frac{1}{m} \sum_{k=1}^m \hat{\mu}_n^{(k)}$ .

### 3.3 Empirical covariance estimator

Germ–grain model  $\Xi = \bigcup_{i \geq 1} (M_i + X_i)$

- If  $\int_{\mathbb{R}^d} |\text{Cov}_Y(x)| dx < \infty$  then

$$\lim_{n \rightarrow \infty} \mathbb{E} \tilde{\sigma}^2 = \sigma^2, \quad \text{asymptotically unbiased,}$$

- If  $\int_{\mathbb{R}^{3d}} |s^{(4)}(o, x_1, x_2, x_3)| d(x_1, x_2, x_3) < \infty$  and  $m(n) \rightarrow \infty$  then

$$\lim_{n \rightarrow \infty} \mathbb{E} (\tilde{\sigma}^2 - \sigma^2)^2 = 0, \quad \text{mean–square consistent.}$$

Example:

$\Xi$  Boolean model and  $Y(x) = \mathbb{1}((\Xi - x) \cap K)$ , then assume that

$$\mathbb{E} (|M_0 \oplus \check{K}|^4) < \infty.$$

- Germ–grain model  $\Xi = \bigcup_{i \geq 1} (M_i + X_i)$ ,
- Random field  $Y(x) = \varphi((\Xi - x) \cap K)$ ,  $x \in \mathbb{R}^d$  with  $\mu = \mathbb{E} Y(x)$  and  $\text{Cov}_Y(x)$  unknown,  $\varphi$  bounded valuation,  $K \in \mathcal{K}$  test set,
- weighted average  $\hat{\mu}_n = \int_{W_n} Y(x) G(W_n, x) dx$  as unbiased and mean-square consistent estimator of  $\mu$ ,
- asymptotic normality of  $\sqrt{|W_n|} (\hat{\mu}_n - \mu)$  with asympt. variance  $\sigma^2 = \int_{\mathbb{R}^d} \text{Cov}_Y(x) dx$ ,
- weighted average  $\hat{\sigma}_n = \int_{U_n} \widehat{\text{Cov}}_n(x) \gamma(W_n, x) dx$  as asymptotically unbiased and mean-square consistent estimator of  $\sigma^2$ .

## 5 References

- 1 Böhme S., Heinrich L. and Schmidt V. (2004), [Asymptotic properties of estimators for the volume fraction of jointly stationary random sets](#). *Statistica Neerlandica* **58**, 388–406.
- 2 Heinrich L., Molchanov I. (1999), [Central limit theorem for a class of random measures associated with germ–grain models](#). *Advances in Applied Probability* **31**, 283–314.
- 3 Heinrich L. (2005), [Large deviations of the empirical volume fraction for stationary Poisson grain models](#). *Annals of Applied Probability* **15**, 1A, 392–420.
- 4 Schmidt, V., Spodarev, E. (2005), [Joint estimators for the specific intrinsic volumes of stationary random sets](#), *Stochastic Processes and their Applications*, **115**, 959 - 981
- 5 Pantle, U., Schmidt, V., Spodarev, E. (2006), [Central limit theorems for functionals of stationary germ-grain models](#), *Advances in Applied Probability* **38**, (to appear)
- 6 Pantle, U., Schmidt, V., Spodarev, E. (2006), [On the estimation of the integrated covariance function of stationary random fields](#), *Working paper* (in preparation)

# 5 Introduction

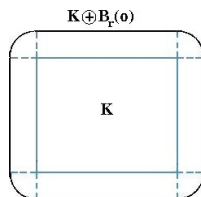
## Steiner formula

Let  $K \in \mathcal{K}$  and  $r > 0$ , then

$$|K \oplus B_r(o)| = \sum_{j=0}^d r^{d-j} \kappa_{d-j} V_j(K)$$

for functionals  $V_j : \mathcal{K} \rightarrow [0, \infty)$ , called the **intrinsic volumes**.

**Figure:** Steiner formula in  $\mathbb{R}^2$



$$\begin{aligned} |K \oplus B_r(o)| &= \pi r^2 V_0(K) + 2r V_1(K) + V_2(K) \\ &= \pi r^2 + r S(K) + A(K). \end{aligned}$$

A: area, S: boundary length



## 5 Introduction

Let  $\Xi$  be a **stationary RACS** in  $\mathbb{R}^d$  with  $P((\Xi \cap K) \in \mathcal{R}) = 1$ .

Let  $\{W_n\}$  be a sequence of **compact and convex observation windows**  $W_n = nW_0$  with  $|W_0| > 0$  and  $o \in \text{int}(W_0)$ .

If  $\mathbb{E} 2^{\mathcal{N}(\Xi \cap [0,1]^d)} < \infty$  then the limit

$$\bar{V}_j(\Xi) = \lim_{n \rightarrow \infty} \frac{\mathbb{E} V_j(\Xi \cap W_n)}{|W_n|}$$

exists for each  $j = 0, \dots, d$  and is called the

**$j$ -th specific intrinsic volume.**