## Geometric and topological functionals of smooth Gaussian fields

Michael McAuley Technological University Dublin

IMS 2024, Queens University Belfast, 29th August

Slides available at https://michael-mcauley.github.io



# Gaussian fields Motivation: cosmology

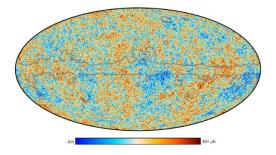


Figure: Fluctuations of the Cosmic Microwave Background Radiation (CMBR) (Source: Planck 2018).

- Physical theory and evidence confirm that the CMBR is well modelled as a realisation of a Gaussian field on the sphere [6].
- Deviations from this model provide insight about the early universe.
- Geometric properties of excursion sets can be used to test for such deviations [7].



#### Gaussian fields

Motivation: medical imaging

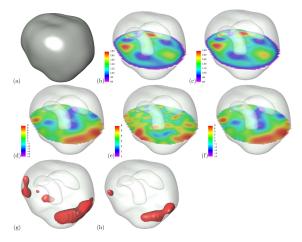


Figure: Measurements from a PET study of brain activity during a reading task. (Source: [14]). See [15] for a technical account.



## Gaussian fields Further applications

#### Quantum chaos

It is conjectured that for any Riemannian 2-manifold with 'chaotic' dynamics, the high-energy eigenfunctions of the Laplacian are well modelled by Gaussian random fields [4]. (See [8] for a recent overview.)

#### Atmospheric/climate modelling

Time-dependent models of smooth Gaussian fields on the sphere have recently been used to model global temperatures [5] and air pollution [12].



## Gaussian fields Basic setting

- ▶ Let M be a smooth manifold and  $f: M \to \mathbb{R}$  be a  $C^2$  Gaussian field with mean zero and variance one (at each point).
- ▶ The distribution of the field is specified by its covariance function  $K: M^2 \to [-1,1]$  defined as

$$K(x,y) = \mathbb{E}[f(x)f(y)] \quad \forall x,y \in M.$$

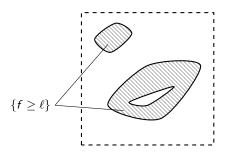
▶ We are interested in the geometry of the *excursion sets* 

$$\{f \ge \ell\} := \{x \in M \mid f(x) \ge \ell\}$$

for  $\ell \in \mathbb{R}$ .



#### A rough definition



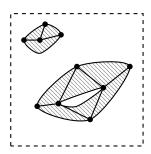


Figure: A simple excursion set in  $\mathbb{R}^2$  (left) and a triangulation of the same set (right).

- The Euler characteristic is an integer valued topological invariant of 'nice' sets in Euclidean space
- 2. The Euler characteristic of a planar set is the number of components minus the number of 'holes'
- This coincides with the graphical definition (#Vertices #Edges + #Faces) for a triangulation of the set



#### Application to Gaussian fields

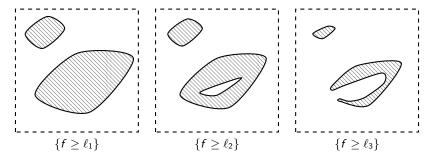


Figure: Excursion sets for a function f above levels  $\ell_1 < \ell_2 < \ell_3$ .

1. The Euler characteristic of an excursion set for a 'nice' planar function can be decomposed as

Euler characteristic = #Maxima - #Saddles + #Minima.

The expectation of this quantity for a Gaussian field can be calculated using a generalisation of Kac's counting formula.



Application to Gaussian fields

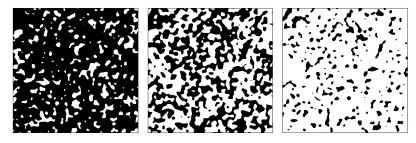


Figure: Excursion sets  $\{f \geq \ell\}$  in black for  $\ell = -1$  (left),  $\ell = 0$  (middle) and  $\ell = 1$  (right) where  $f: \mathbb{R}^2 \to \mathbb{R}$  has covariance  $K(x,y) = \exp(-|x-y|^2/2)$ .

For a stationary, planar Gaussian field

$$\mathbb{E}[\mathrm{EC}(\{f \geq \ell\} \cap [-R, R]^2)] = \sqrt{\det \nabla^2 K(0)} \frac{(2R)^2}{(2\pi)^{3/2}} \ell e^{-\ell^2/2} + O(R).$$



Cosmological data

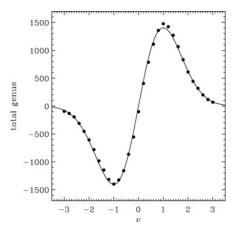


Figure: The observed Euler characteristic of the CMBR restricted to intensities above the level  $\nu$  (dots) and the expected value for a Gaussian field (solid curve). Source: [7].



Medical imaging

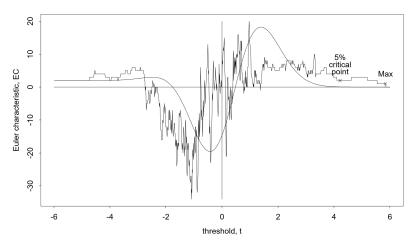


Figure: The observed Euler characteristic for PET data (jagged) and the expected value for a Gaussian field (smooth) at different thresholds. Source: [15].

References

This type of analysis results from a rich interplay between mathematical theory and applications!

For more details, see

- ▶ [14] for a non-technical overview of different applications;
- [1] for theoretical development of the Euler characteristic for Gaussian fields;
- [9] for a mathematical development of Gaussian fields with applications in cosmology.



### Geometry vs Topology

A functional of a random field is **local** if it can be represented as an integral of a pointwise function of the field and its derivatives.

#### **Geometric Functionals**

- Typically local.
- Examples:
  - Volume of the excursion set
  - Boundary length of the excursion set
  - Euler characteristic of the excursion set
- Statistics of these functionals are well understood.

#### **Topological Functionals**

- Typically non-local.
- Examples:
  - Number of components of the excursion set
  - Betti numbers of the excursion set
  - Volume of the unbounded component of the excursion set
- Occur naturally in applications [13] but are much less understood theoretically.



#### The component count

Law of large numbers

- Let  $f: \mathbb{R}^d \to \mathbb{R}$  be a stationary, centred, smooth Gaussian field.
- ▶ Given  $\ell \in \mathbb{R}$  and R > 0 we let  $N_{ES}(\ell, R)$  be the number of connected components of  $\{f \geq \ell\} \cap [-R, R]^d$ .

### Theorem (Nazarov-Sodin[10])

If f is ergodic, then there exists  $c(\ell) \ge 0$  such that

$$\lim_{R\to\infty}\frac{N_{\mathrm{ES}}(\ell,R)}{(2R)^d}=c(\ell)$$

almost surely and in  $L^1$ .

- It is straightforward to verify ergodicity using the Fourier transform of the covariance function.
- The result is extremely general: in particular, there is no requirement of fast correlation decay.
- The proof shows that the component count is 'semi-local': its value on a macroscopic domain can be well approximated by summing its value on mesoscopic domains.

#### The component count

#### Central limit theorem

Assume that f=q\*W where W is a Gaussian white noise process on  $\mathbb{R}^d$  and q satisfies some regularity conditions, including

$$\sup_{|\alpha| \le 2} |\partial^{\alpha} q(x)| \le c|x|^{-\beta}$$

for some c > 0 and  $\beta > 9d$  and all  $x \in \mathbb{R}^d$ .

Theorem (Beliaev-M.-Muirhead[3])

Given  $\ell \in \mathbb{R}$ , there exists  $\sigma^2(\ell) > 0$  such that as  $R \to \infty$ 

$$\frac{\operatorname{Var}[N_{\mathrm{ES}}(\ell,R)]}{(2R)^d} \to \sigma^2(\ell)$$

and

$$\frac{N_{\mathrm{ES}}(\ell,R) - \mathbb{E}[N_{\mathrm{ES}}(\ell,R)]}{(2R)^{d/2}} \xrightarrow{d} \mathcal{N}(0,\sigma^2(\ell)).$$



## The component count Proof of CLT

- ▶ The proof adapts a martingale CLT argument from discrete probability [11].
- ▶ Let  $(\mathcal{F}_{\nu})_{\nu \in \mathbb{Z}^d}$  be a 'lexicographic' filtration generated by the white noise W and

$$S_n := \frac{N_{\mathrm{ES}}(\ell, n) - \mathbb{E}[N_{\mathrm{ES}}(\ell, n)]}{(2n)^{d/2}}.$$

Then  $S_{n,v} := \mathbb{E}[S_n | \mathcal{F}_v]$  defines a 'lexicographic martingale array'.

- ▶ A generalisation of the classical martingale CLT states that  $S_n \to \mathcal{N}(0, \sigma^2)$  provided that the martingale differences  $U_{n,v}$  satisfy certain moment bounds and  $\sum_{v \in \mathbb{Z}^d} U_{n,v}^2 \to \sigma^2$  in  $L^1$ .
- ▶ The latter property follows from an elegant ergodic argument due to Penrose [11].
- ▶ The moments bounds follow from relating  $U_{n,v}$  to the change in the component count when the white noise W is resampled on a cube of unit length centred at v.



## Open questions

- How are the statistics of topological functionals affected by long-range dependence?
- Can a similar theory be developed for non-Gaussian (e.g. shot-noise) fields?
- ► There are many related open questions regarding the **percolation** properties of smooth Gaussian fields [2].

## Thank you for listening!



### Bibliography I

- R. J. Adler and J. E. Taylor. Random fields and geometry. Springer Monographs in Mathematics. Springer, New York, 2007. ISBN: 978-0-387-48112-8.
- [2] D. Beliaev. "Smooth Gaussian fields and percolation". In: *Probability Surveys* (2023). URL: https://doi.org/10.1214/23-PS24.
- [3] D. Beliaev, M. McAuley, and S. Muirhead. "A central limit theorem for the number of excursion set components of Gaussian fields". In: *The Annals of Probability* (2024). URL: https://doi.org/10.1214/23-A0P1672.
- [4] M. V. Berry. "Regular and irregular semiclassical wavefunctions". In: Journal of Physics A: Mathematical and General (1977). URL: https://dx.doi.org/10.1088/0305-4470/10/12/016.
- [5] A. Caponera, D. Marinucci, and A. Vidotto. "MultiScale CUSUM Tests for Time-Dependent Spherical Random Fields". In: arXiv preprint arXiv:2305.01392 (2023). URL: https://doi.org/10.48550/arXiv.2305.01392.
- [6] R. Durrer. The cosmic microwave background. Cambridge University Press, 2020.

#### Bibliography II

- [7] I. Gott J. Richard et al. "Genus topology of the cosmic microwave background from the WMAP 3-year data". In: Monthly Notices of the Royal Astronomical Society (2007). URL: https://doi.org/10.1111/j.1365-2966.2007.11730.x.
- [8] S. R. Jain and R. Samajdar. "Nodal portraits of quantum billiards: Domains, lines, and statistics". In: Rev. Mod. Phys. (4 2017). URL: https://link.aps.org/doi/10.1103/RevModPhys.89.045005.
- [9] D. Marinucci and G. Peccati. Random fields on the sphere: representation, limit theorems and cosmological applications. Cambridge University Press, 2011.
- [10] F. Nazarov and M. Sodin. "Asymptotic Laws for the Spatial Distribution and the Number of Connected Components of Zero Sets of Gaussian Random Functions". In: Journal of Mathematical Physics, Analysis, Geometry (2016). URL: https: //jmag.ilt.kharkiv.ua/index.php/jmag/article/view/jm12-0205e
- [11] M. D. Penrose. "A Central Limit Theorem With Applications to Percolation, Epidemics and Boolean Models". In: *The Annals of Probability* (2001). URL: https://doi.org/10.1214/aop/1015345760.

## Bibliography III

- [12] E. Porcu, A. Alegria, and R. Furrer. "Modeling Temporally Evolving and Spatially Globally Dependent Data". In: *International Statistical Review* (2018). URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/insr.12266.
- [13] P. Pranav et al. "Topology and geometry of Gaussian random fields I: on Betti numbers, Euler characteristic, and Minkowski functionals". In: Monthly Notices of the Royal Astronomical Society (2019). URL: https://doi.org/10.1093/mnras/stz541.
- [14] K. J. Worsley. "The Geometry of Random Images". In: CHANCE (1996). URL: https://www.math.mcgill.ca/keith/chance/chance3.pdf.
- [15] K. J. Worsley et al. "A unified statistical approach for determining significant signals in images of cerebral activation". In: Human brain mapping (1996). URL: https://doi.org/10.1002/(SICI)1097-0193(1996)4:1%3C58::AID-HBM4%3E3.0.C0;2-0.