

سید محمد سید محمد



Geometrical and Topological properties of Stochastic fields: Perturbation Theory Approach

Seyed Mohammad Sadegh Movahed

Department of Physics- Shahid Beheshti University, Tehran IRAN

Computational Cosmology Group (CCG-SBU)

School of Physics (IPM), Tehran IRAN

www.smovahed.ir

<http://faculties.sbu.ac.ir/~movahed>



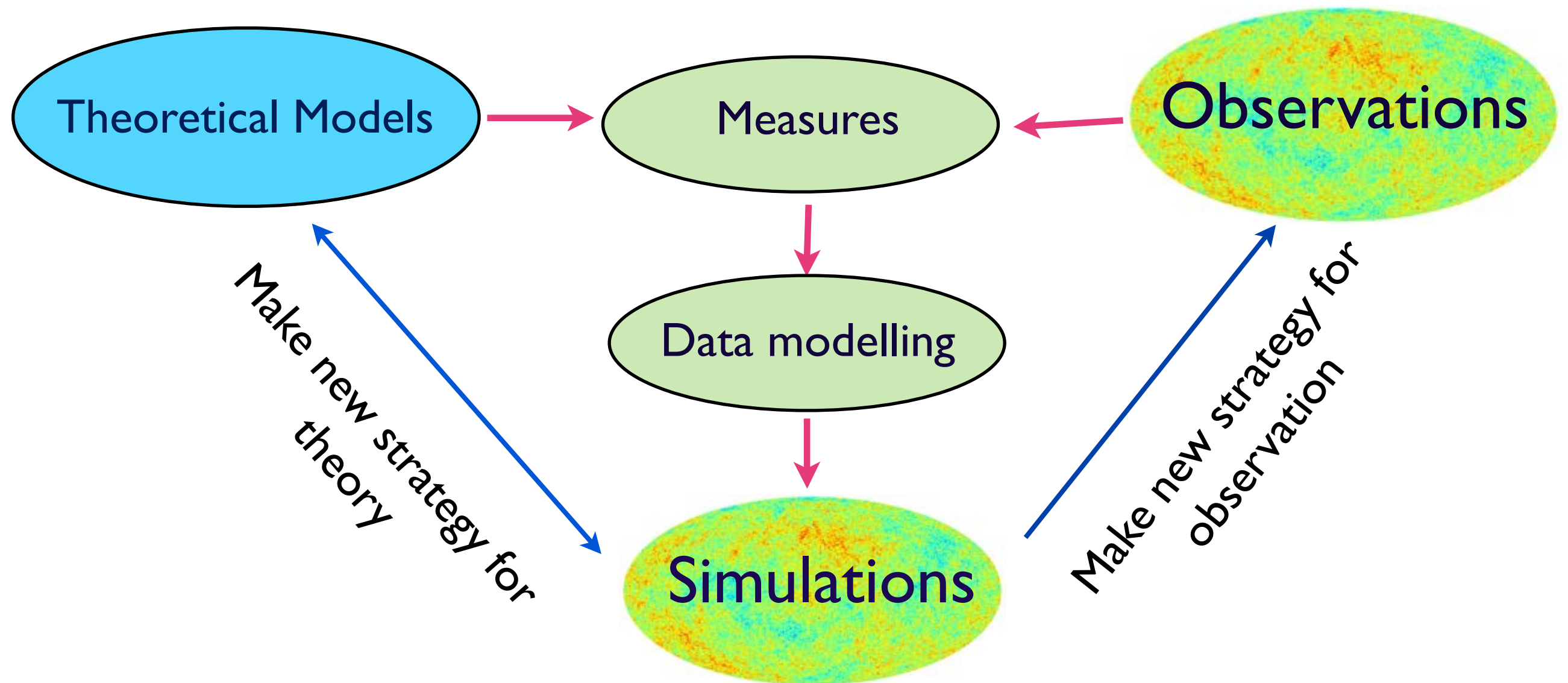
Outline



- 1) Stochastic fields in Various fields of researches
- 2) Perturbative expansion of Statistics
- 3) Excursion and Critical sets in a 2D stochastic field
- 4) Clustering of Peaks and Up-crossing
- 5) Results and researches in progress

My road map

Model - Observation & Experiments - Statistical analysis

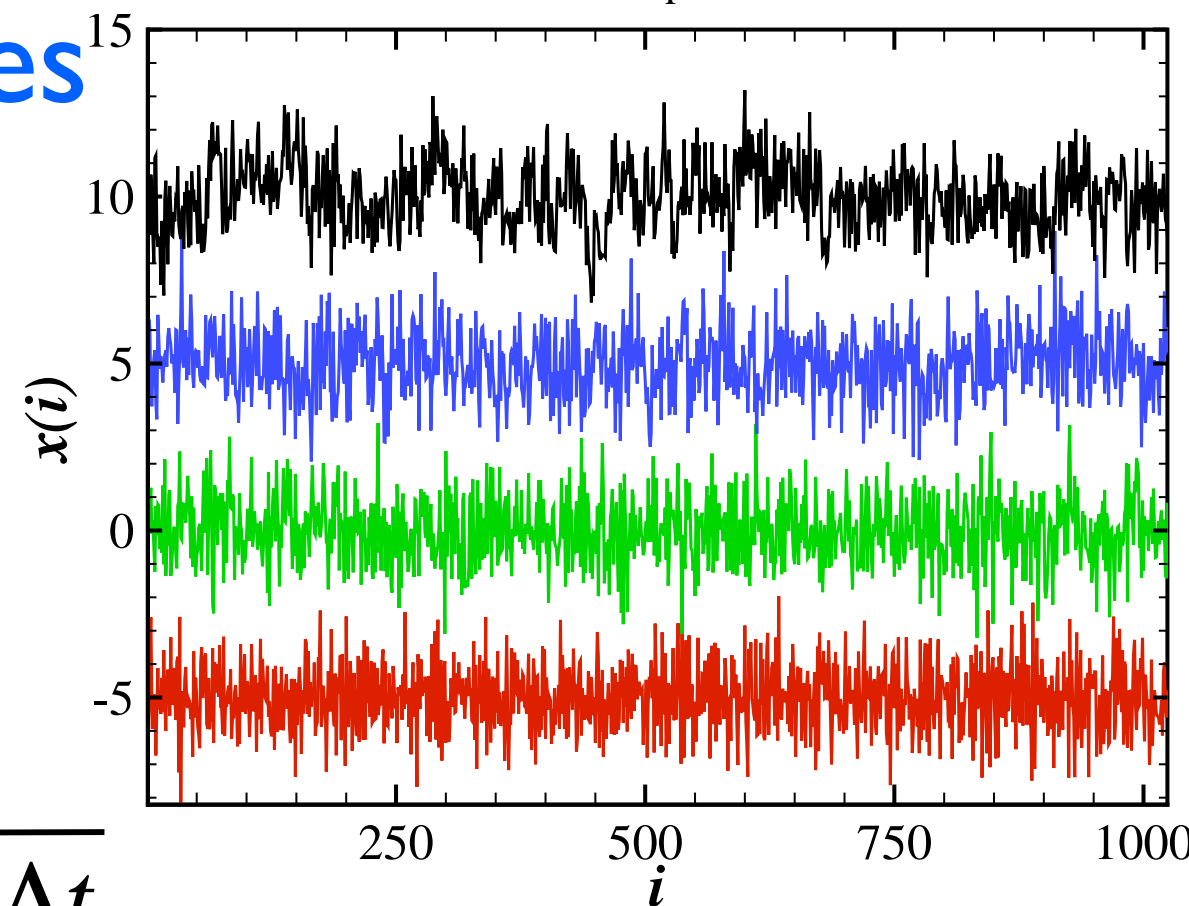
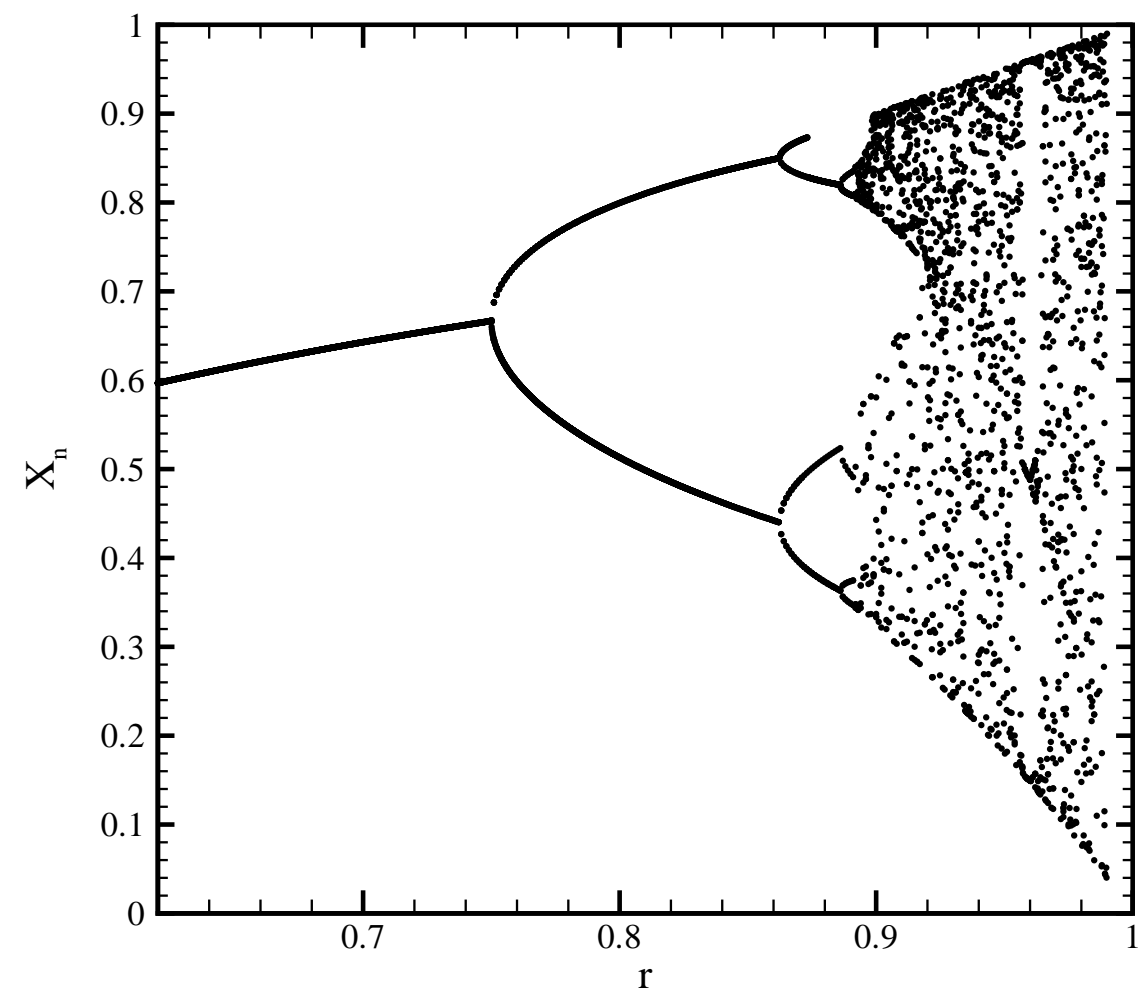


Classification of processes

- Deterministic processes
- Chaotic processes
- Stochastic Processes
 - 1) Purely Random processes
 - 2) Dependent processes
 - 3) Markov processes

$$x_{n+1} = 4rx_n(1 - x_n)$$

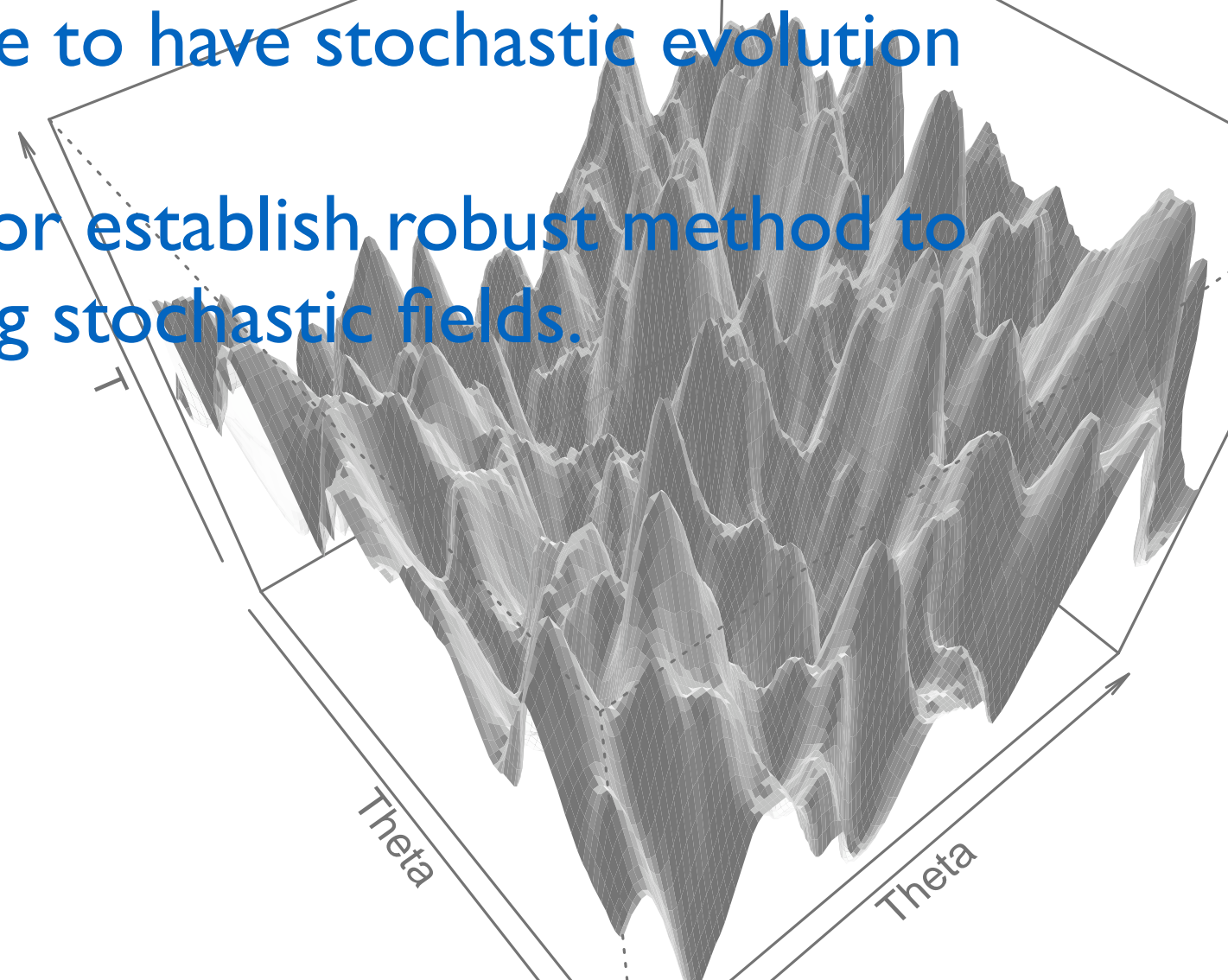
$$x(t + \Delta t) = x(t) - \gamma x(t)\Delta t + \eta(t)\sqrt{\Delta t}$$



Why stochastic field?



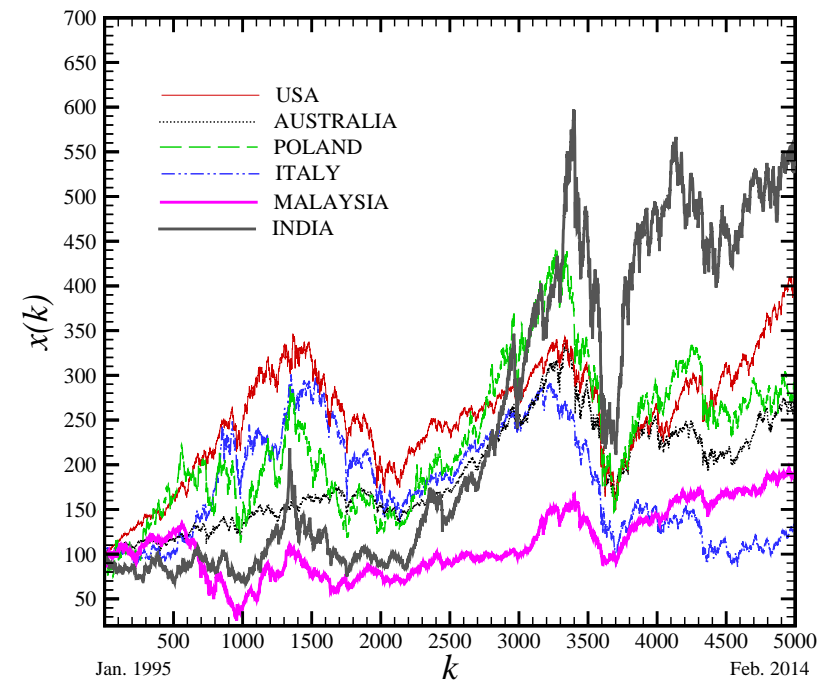
- 1) Random fields are ubiquitous in physics.
- 2) In the nature, there are many reasons to produce initial conditions in the random frameworks, e.g. Initial fluctuations are produced randomly in the position coordinate (due to quantum uncertainties)
- 2) In addition, it could be possible to have stochastic evolution (temporal and/or spatial)
- 3) Consequently, we should use or establish robust method to find reliable results for underlying stochastic fields.



Some examples

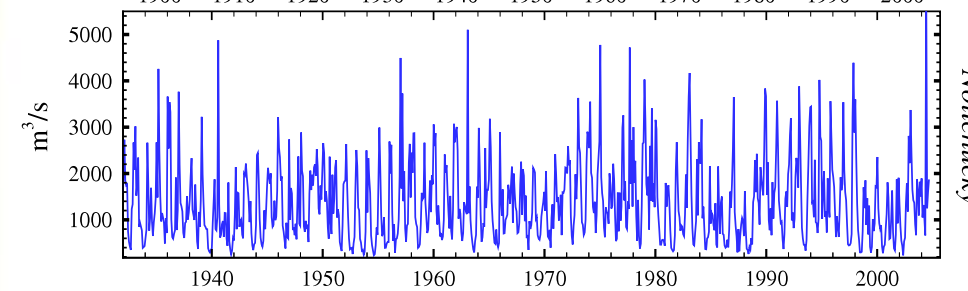
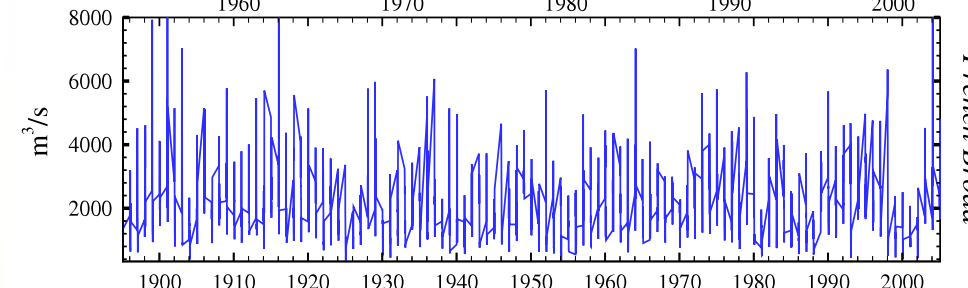
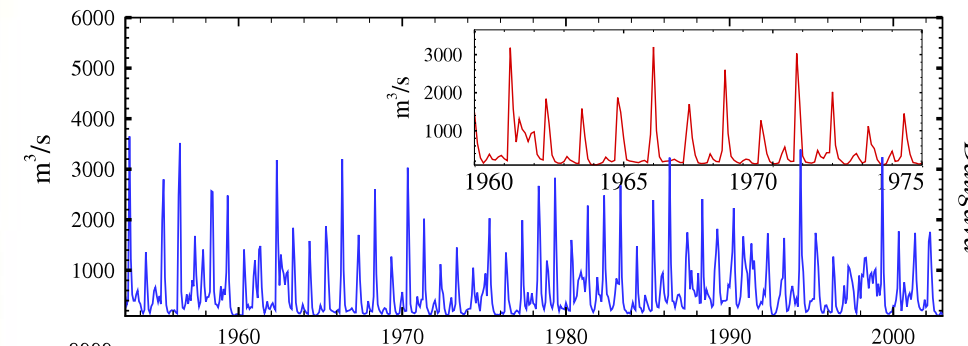
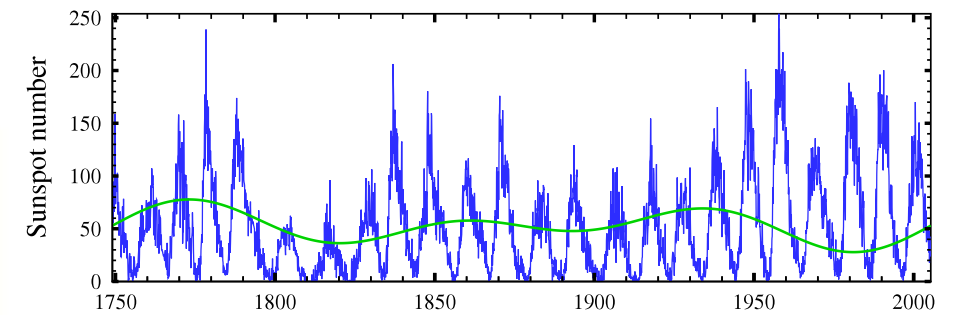
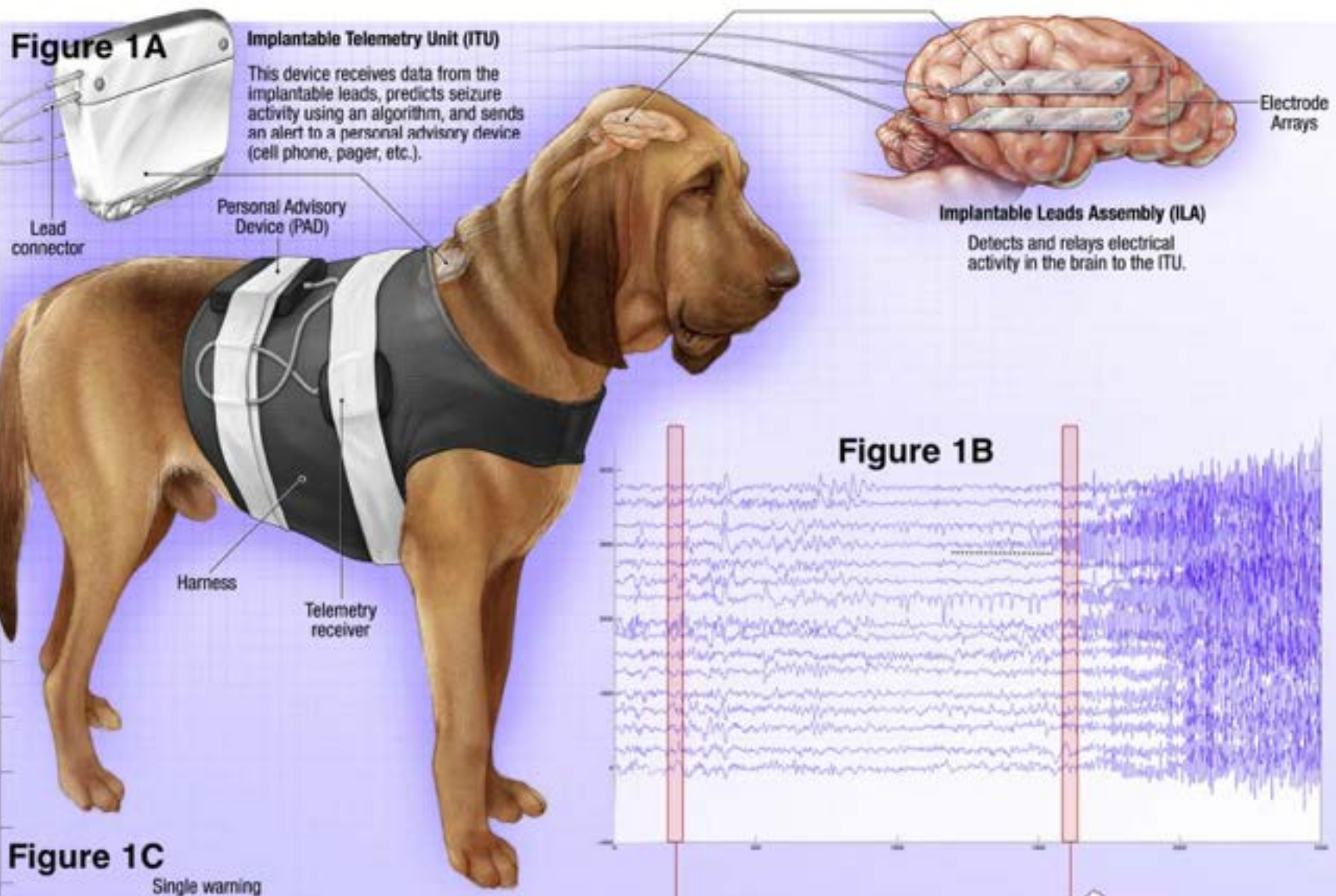
- I + ID fields

(Earthquake, Heartbeat, Epilepsy, Stock index, Climate indexes, ...)



S. Hajian, M.S. Movahed / Physica A 389 (2010) 4942–4957

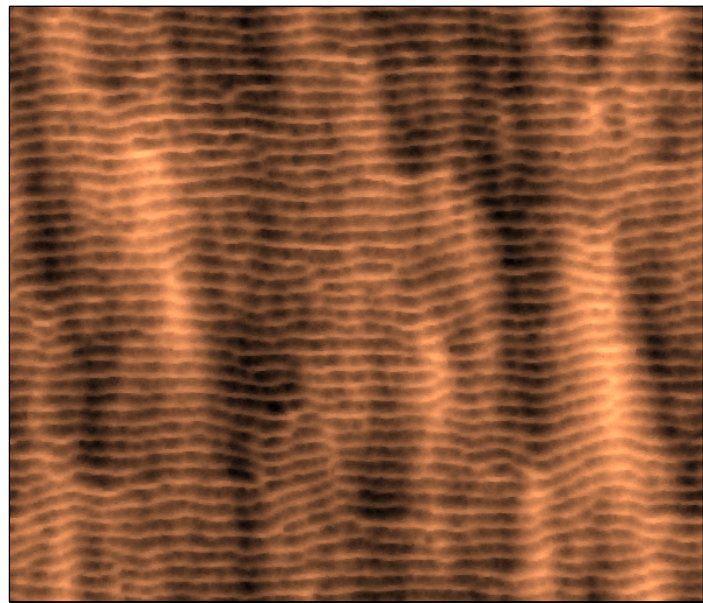
<https://www.kaggle.com/c/seizure-prediction>



Some examples

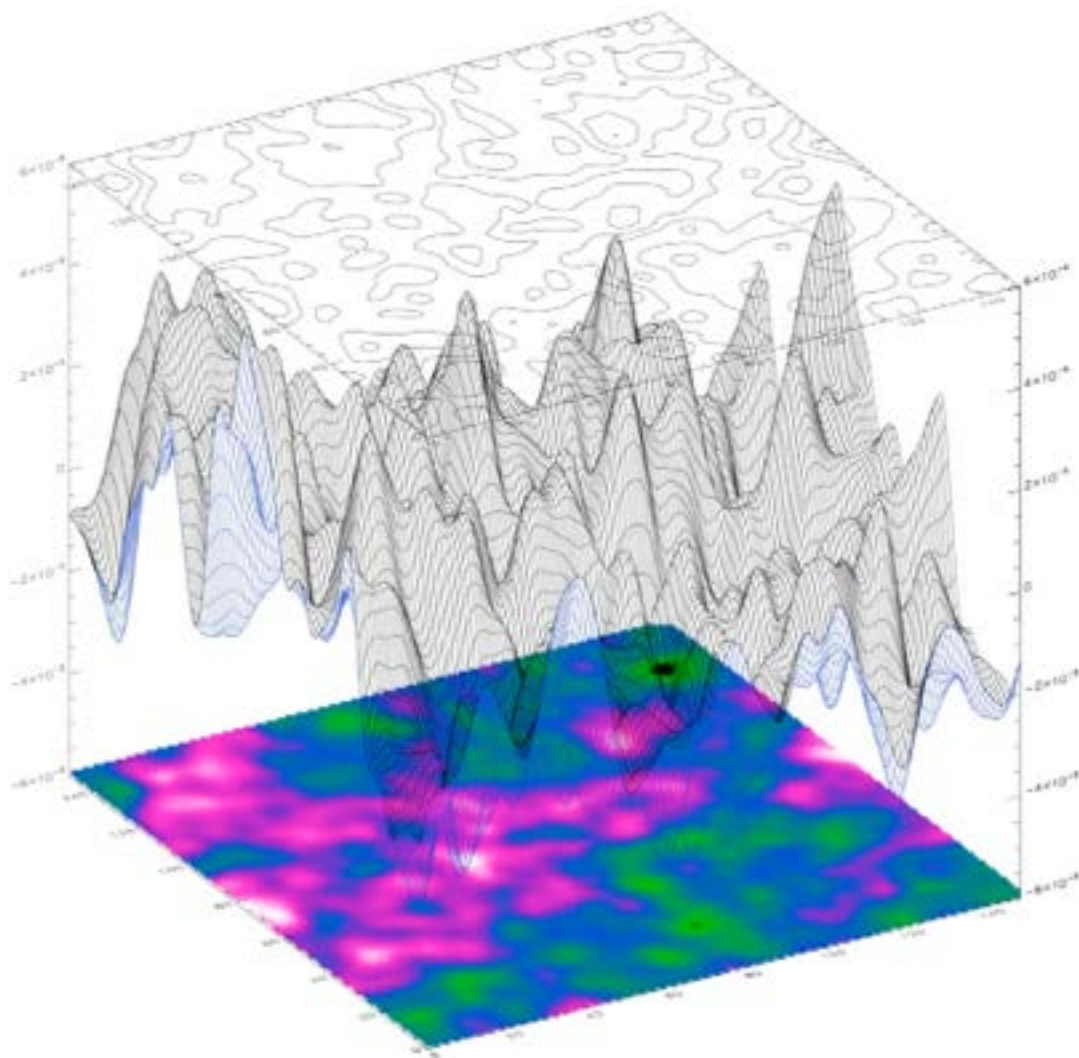
- 2D (1+2D) fields
(CMB, Rough surfaces, ...)

Anisotropic surface



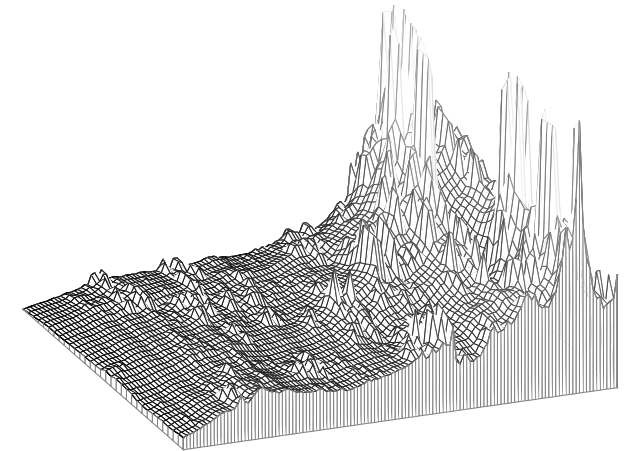
S.M.Vaez Allaei et al., (in progress)

Gaussian stochastic field
primordial quantum fluctuations

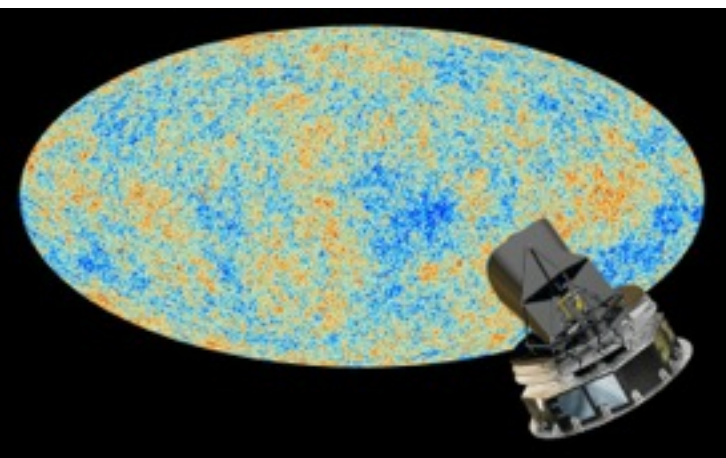


S.M.S. Movahed et. al., MNRAS 2013
S.M.S. Movahed et. al., JCAP 2011

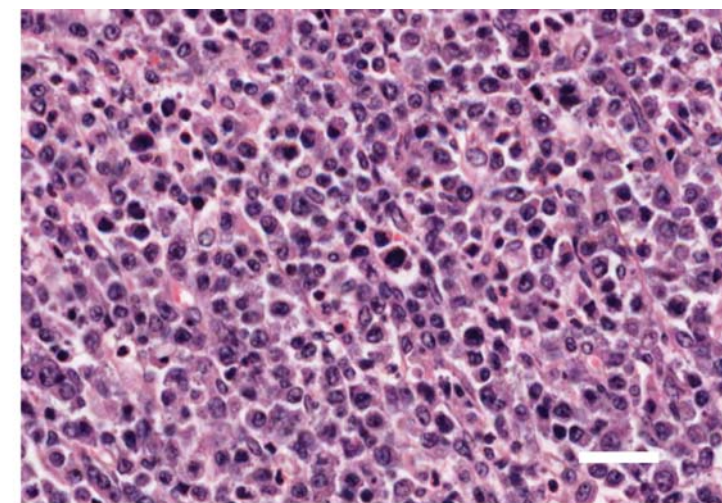
Multifractal singular and
smoothed surfaces



S. Hosseinabadi et al., PRE 2012



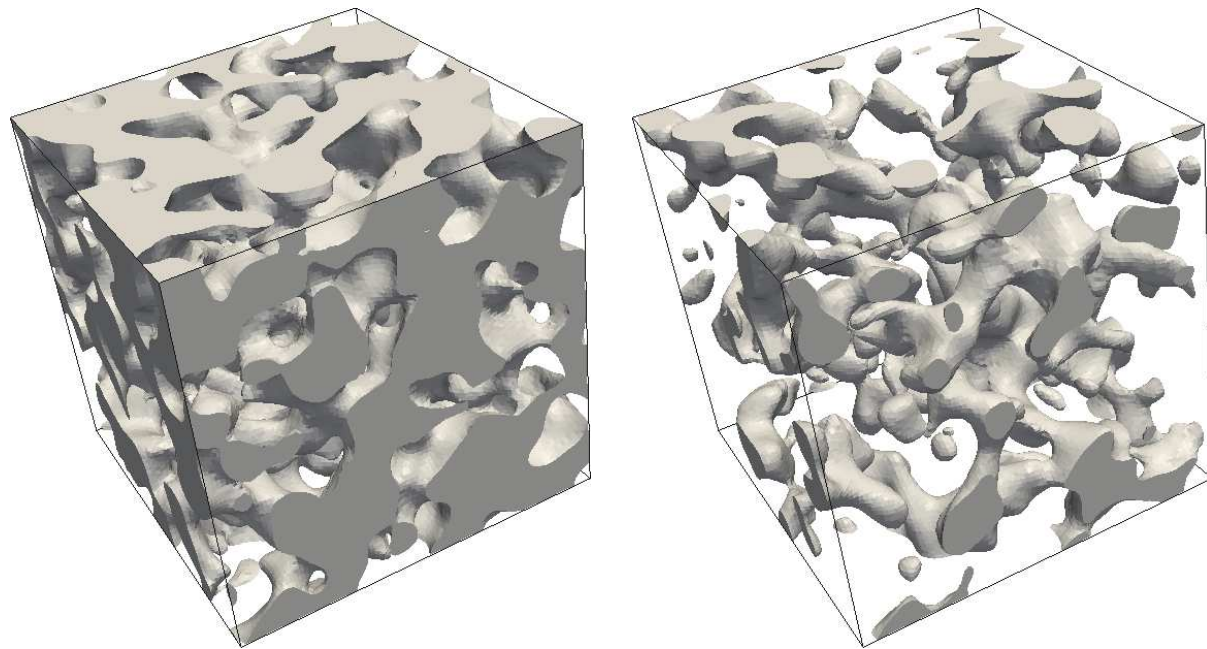
Planck Satellite results (2013)



Magnetic Resonance in Medicine 71:402–410 (2014)

Some examples

- 3D (I+3D) fields:
(Large scale structure, ...)

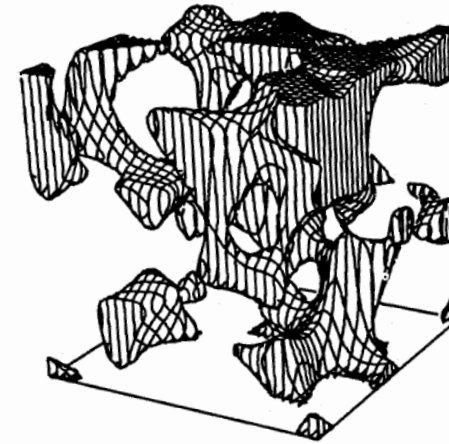


Emmanuel Roubin Thesis, 2013

THE ASTROPHYSICAL JOURNAL, 465:499–514, 1996 July 10

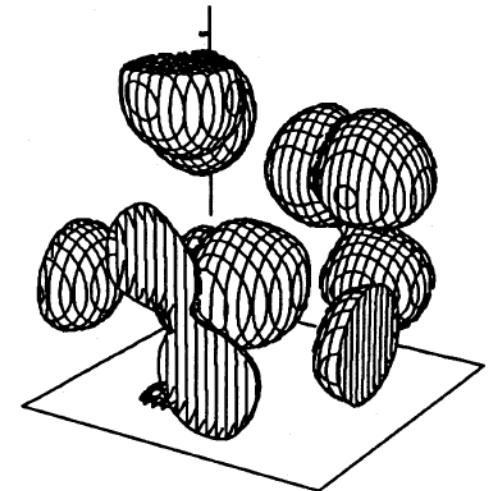
J. RICHARD GOTT III, RENYUE CEN,¹ AND JEREMIAH P. OSTRICKER

16% high

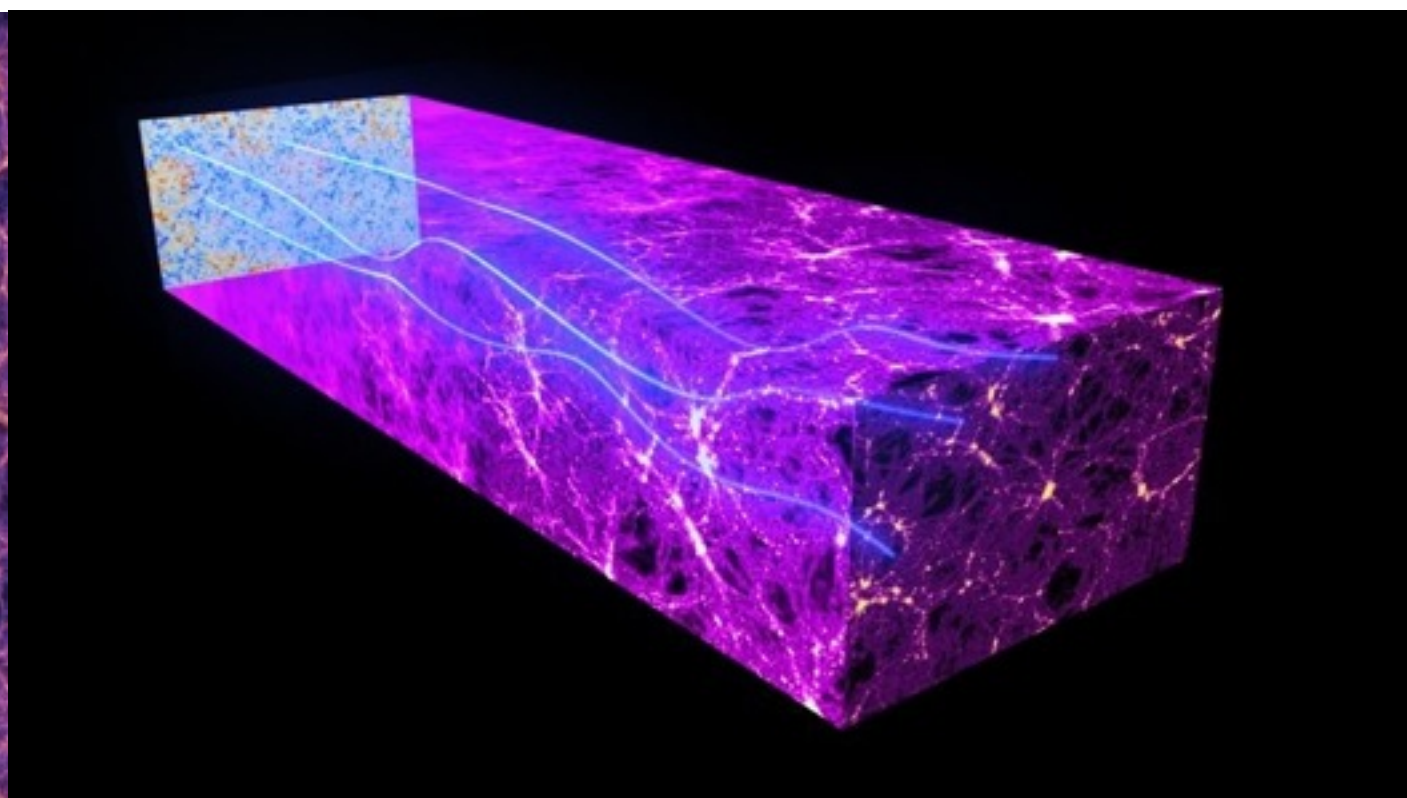
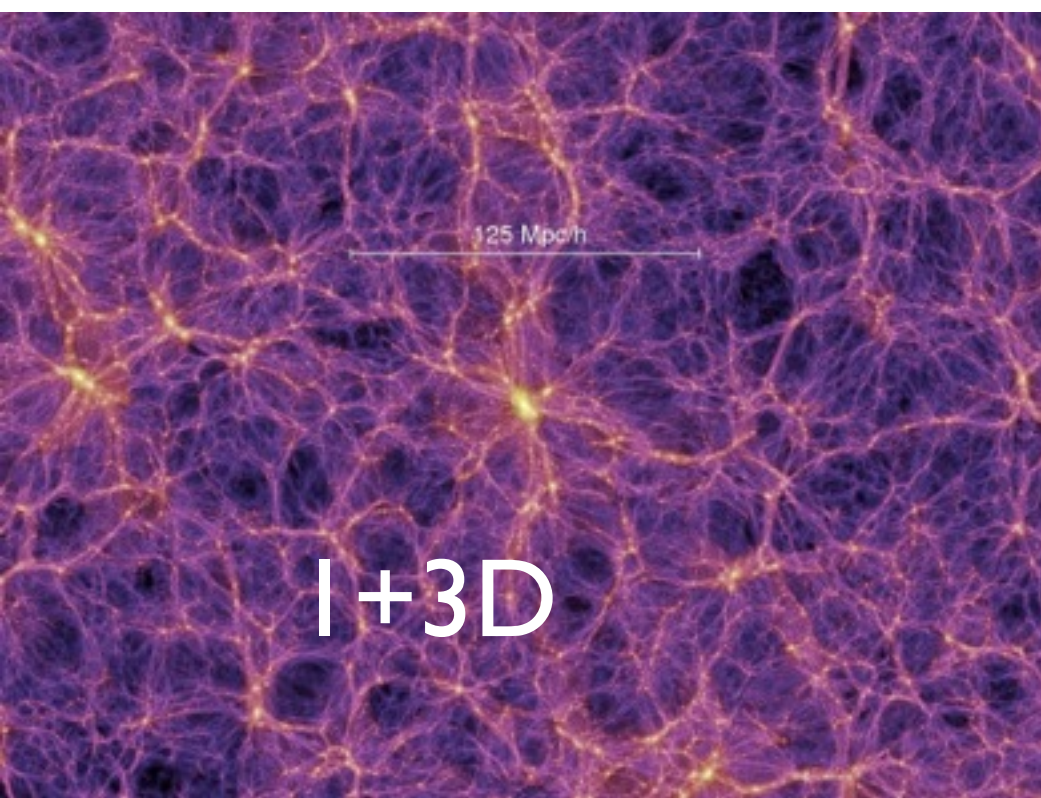


Swiss cheese: isolated voids surrounded on all sides by walls

16% high

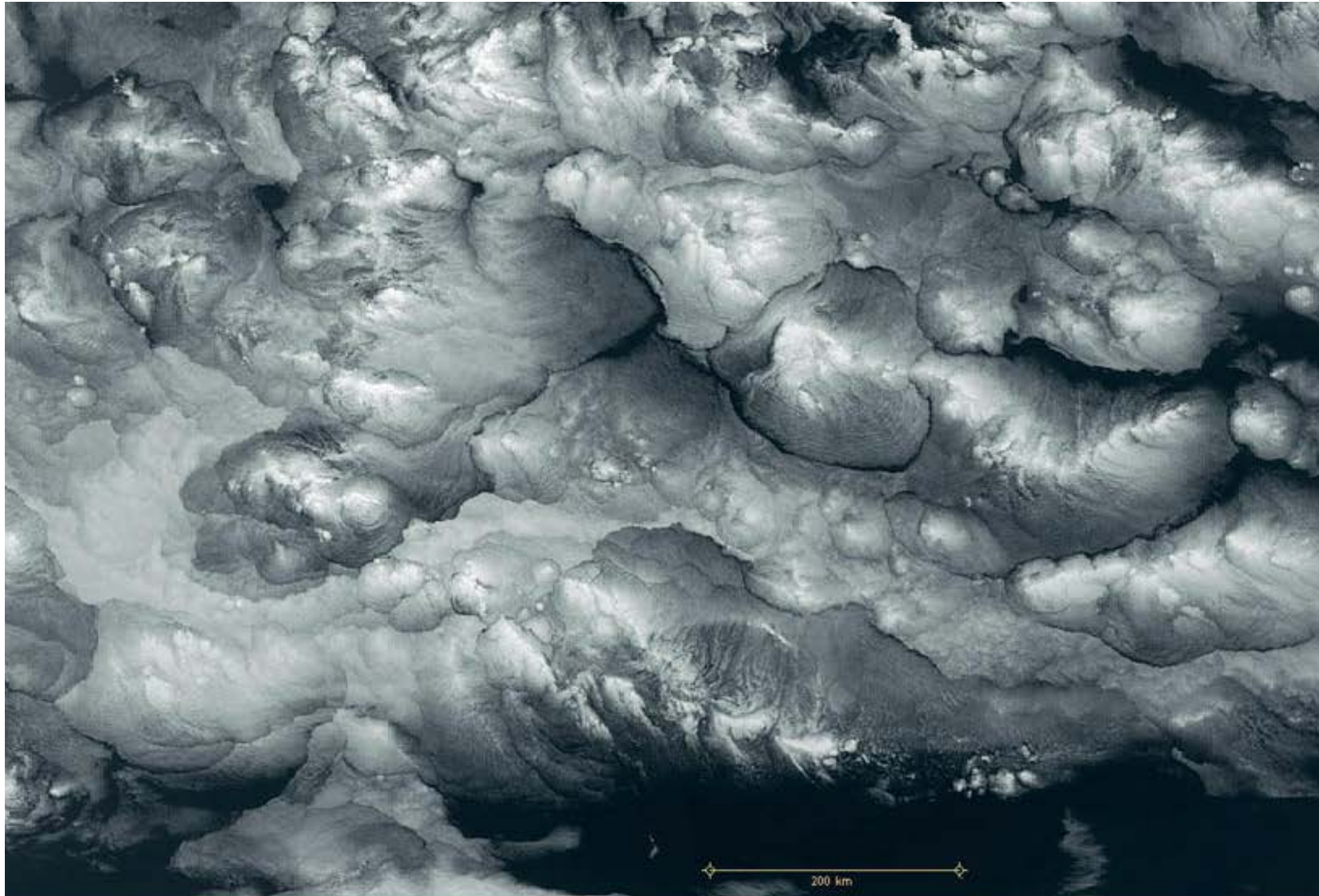


Meatball: isolated clusters in low density connected background



<http://www.esa.int>

Cloud structure



<http://www.brockmann-consult.de/>

Feature of Stochastic fields by mathematics



Density contrast field
I+4D

$$\delta(t; \bar{X}) \equiv \frac{\rho(t; \bar{X}) - \langle \rho(t; \bar{X}) \rangle}{\langle \rho(t; \bar{X}) \rangle}$$

Velocity contrast field
I+4D

$$\delta \vec{V}(t; \bar{X}) \equiv \frac{\vec{V}(t; \bar{X}) - \langle \vec{V}(t; \bar{X}) \rangle}{\langle \vec{V}(t; \bar{X}) \rangle}$$

Gravitational field
I+4D

$$\delta \Phi(t; \bar{X}) \equiv \frac{\Phi(t; \bar{X}) - \langle \Phi(t; \bar{X}) \rangle}{\langle \Phi(t; \bar{X}) \rangle}$$

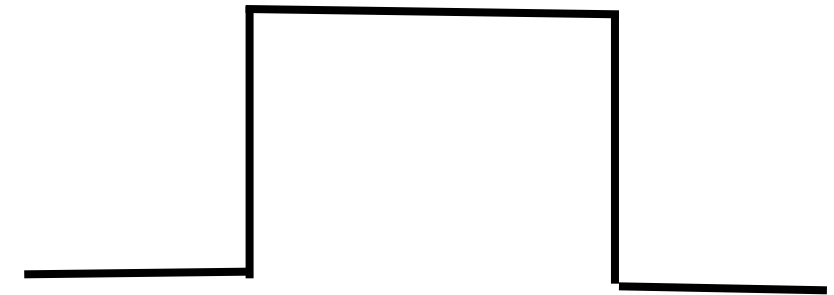
Height or Temperature
fields I+3D and I+2D

$$\delta T(t; \bar{X}) \equiv \frac{T(t; \bar{X}) - \langle T(t; \bar{X}) \rangle}{\langle T(t; \bar{X}) \rangle}$$

Preparing real field: Smoothed stochastic field

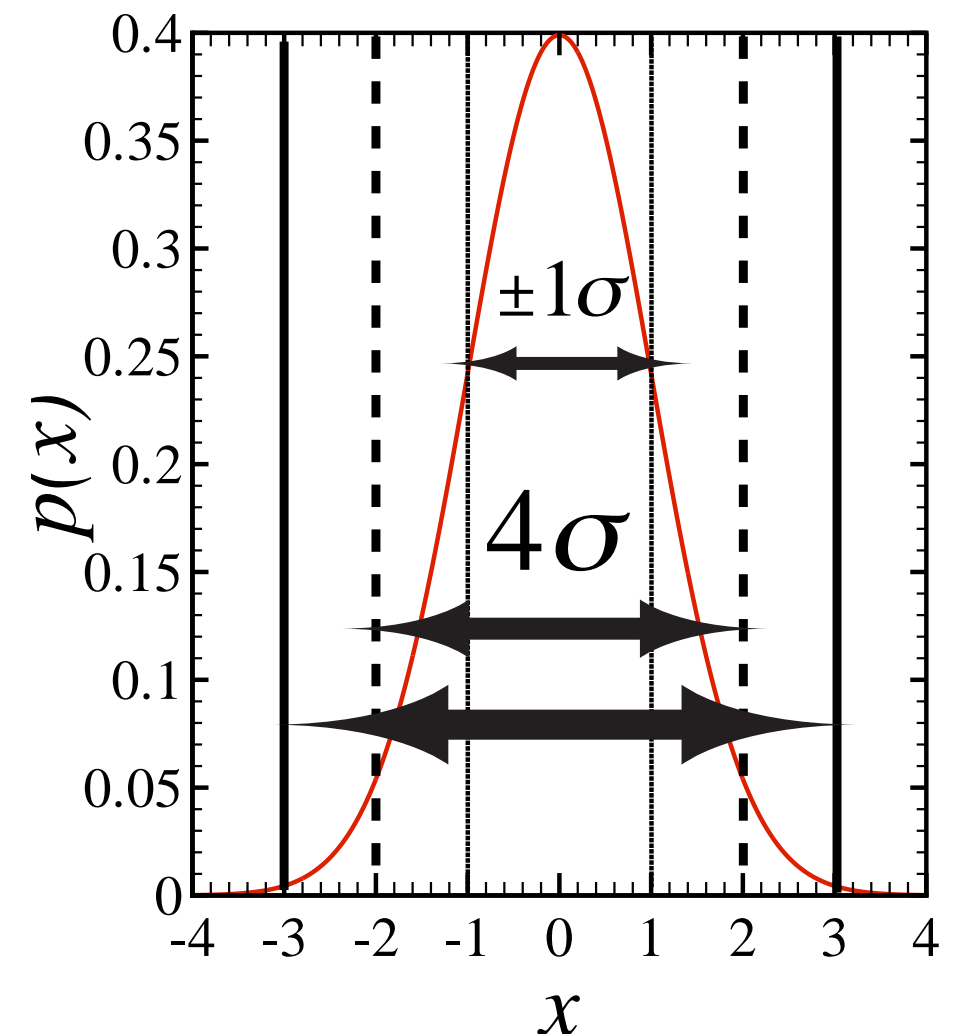
To cut the high-frequency fluctuations (Low-pass filter)

$$f_{smoothed}(\vec{r}) = \int d^d \vec{r}' W_R(|\vec{r} - \vec{r}'|) f(\vec{r}')$$



$$W_R(r) \sim \Theta(R - r)$$

$$W_R(r) \sim \exp\left(-\frac{r^2}{2R^2}\right)$$



Probability density function of features in an arbitrary smoothed stochastic field

Perturbative expansion of Statistics I

$$f \rightarrow f' \equiv f - \langle f \rangle \rightarrow \langle f' \rangle = 0 \quad \sigma_0^2 = \langle f^2 \rangle = \frac{1}{(2\pi)^{d/2}} \int d^d k P(k) \quad \alpha \equiv \frac{f}{\sigma_0}$$

$$A_{\mu\nu\eta\dots} = \left(\alpha(r_\mu), \alpha(r_\mu)_{;1}, \alpha(r_\mu)_{;2}, \alpha(r_\mu)_{;3}, \alpha(r_\mu)_{;11}, \alpha(r_\mu)_{;22}, \alpha(r_\mu)_{;33}, \alpha(r_\mu)_{;12}, \alpha(r_\mu)_{;13}, \alpha(r_\mu)_{;23}, \right. \\ \left. \alpha(r_\nu), \alpha(r_\nu)_{;1}, \alpha(r_\nu)_{;2}, \alpha(r_\nu)_{;3}, \alpha(r_\nu)_{;11}, \alpha(r_\nu)_{;22}, \alpha(r_\nu)_{;33}, \alpha(r_\nu)_{;12}, \alpha(r_\nu)_{;13}, \alpha(r_\nu)_{;23}, \dots \right)$$

$$Z_A(\lambda) \equiv \langle \exp(i\lambda \cdot A) \rangle_A = \int_{-\infty}^{+\infty} d^N A P(A) \exp(i\lambda \cdot A)$$

Moment

$$= 1 + \sum_{n=1} \frac{i^n}{n!} \left(\sum_{\mu_1=1}^N \sum_{\mu_2=1}^N \dots \sum_{\mu_a=1}^N \sum_{\nu_1=1}^N \sum_{\nu_2=1}^N \dots \sum_{\nu_b=1}^N M_{\mu_1 \mu_2 \dots \mu_a; \nu_1, \nu_2 \dots \nu_b}^{(a+b=n)} \lambda_{\mu_1} \lambda_{\mu_2} \dots \lambda_{\mu_a} \lambda_{\nu_1} \lambda_{\nu_2} \dots \lambda_{\nu_b} \right)$$

$$\ln(Z_A(\lambda)) = \sum_{n=1} \frac{i^n}{n!} \left(\sum_{\mu_1=1}^N \sum_{\mu_2=1}^N \dots \sum_{\mu_a=1}^N \sum_{\nu_1=1}^N \sum_{\nu_2=1}^N \dots \sum_{\nu_b=1}^N K_{\mu_1 \mu_2 \dots \mu_a; \nu_1, \nu_2 \dots \nu_b}^{(a+b=n)} \lambda_{\mu_1} \lambda_{\mu_2} \dots \lambda_{\mu_a} \lambda_{\nu_1} \lambda_{\nu_2} \dots \lambda_{\nu_b} \right)$$

Free energy

Cumulant

Perturbative expansion of Statistics II



$$Z_A(\lambda) \equiv \langle \exp(i\lambda \cdot A) \rangle_A = \int_{-\infty}^{+\infty} d^N A P(A) \exp(i\lambda \cdot A)$$

$$Z_A(\lambda) = \exp\left(-\frac{1}{2} \lambda^T \cdot K^{(2)} \cdot \lambda\right)$$

$$\times \sum_{n=3} \frac{i^n}{n!} \left(\sum_{\mu_1=1}^N \sum_{\mu_2=1}^N \cdots \sum_{\mu_a=1}^N \sum_{\nu_1=1}^N \sum_{\nu_2=1}^N \cdots \sum_{\nu_b=1}^N K_{\mu_1 \mu_2 \dots \mu_n; \nu_1, \nu_2 \dots \nu_n}^{(a+b=n)} \lambda_{\mu_1} \lambda_{\mu_2} \cdots \lambda_{\mu_a} \lambda_{\nu_1} \lambda_{\nu_2} \cdots \lambda_{\nu_b} \right)$$

$$K^{(2)} \equiv \langle A \otimes A \rangle$$

$$= \begin{pmatrix} K_{\mu_{11}} & K_{\mu_{12}} & \cdots & K_{\mu_{1n}} & K_{\mu_{1\nu_1}} & \cdots & K_{\mu_{1\nu_n}} \\ \vdots & & & & & & \cdots \\ K_{\nu_n \mu_1} & K_{\nu_n \mu_2} & \cdots & K_{\nu_n \mu_n} & K_{\nu_n \nu_1} & \cdots & K_{\nu_n \nu_n} \end{pmatrix}_{2n \times 2n = N \times N}$$

$$Z_A(\lambda) \equiv \langle \exp(i\lambda \cdot A) \rangle_A = \int_{-\infty}^{+\infty} d^N A P(A) \exp(i\lambda \cdot A)$$

$$P(\vec{A}) = \frac{1}{(2\pi)^N} \int_{-\infty}^{+\infty} d^N \lambda Z_A(\lambda) \exp(-i\lambda \cdot A)$$

$$= \exp \left(\sum_{n=3}^{\infty} \frac{(-1)^n}{n!} \left(\sum_{\mu_1=1}^N \sum_{\mu_2=1}^N \dots \sum_{\mu_a=1}^N \sum_{\nu_1=1}^N \sum_{\nu_2=1}^N \dots \sum_{\nu_b=1}^N K_{\mu_1 \mu_2 \dots \mu_a; \nu_1 \nu_2 \dots \nu_b}^{(a+b=n)} \frac{\partial^n}{\partial A_{\mu_1} \dots \partial A_{\mu_a} \partial A_{\nu_1} \dots \partial A_{\nu_b}} \right) \right) \times P_G(\vec{A})$$

$$P_G(\vec{A}) = \frac{\exp \left(-\frac{1}{2} \vec{A}^T \cdot (K^{(2)})^{-1} \cdot \vec{A} \right)}{(2\pi)^{N/2} \sqrt{\text{Det} |K^{(2)}|}}$$

Covariance matrix or
The inverse of Fisher
information matrix

$$\langle F \rangle_A = \int_{-\infty}^{+\infty} d^N A P(A) F$$

$$\langle F \rangle_A = \left\langle \exp \left(\sum_{n=3}^{\infty} \frac{(-1)^n}{n!} \left(\sum_{\mu_1=1}^N \sum_{\mu_2=1}^N \dots \sum_{\mu_a=1}^N \sum_{\nu_1=1}^N \sum_{\nu_2=1}^N \dots \sum_{\nu_b=1}^N K_{\mu_1 \mu_2 \dots \mu_a; \nu_1, \nu_2 \dots \nu_b}^{(a+b=n)} \frac{\partial^n}{\partial A_{\mu_1} \dots \partial A_{\mu_a} \partial A_{\nu_1} \dots \partial A_{\nu_b}} \right) \right) F \right\rangle_G$$

$$\langle F \rangle_A = \langle F \rangle_G + \frac{1}{3!} \sum_{\mu_1=1}^N \sum_{\mu_2=1}^N \sum_{\mu_3=1}^N K_{\mu_1 \mu_2 \mu_3}^{(3)} \langle F_{;\mu_1 \mu_2 \mu_3} \rangle_G + \dots$$

$$F \equiv \delta(\alpha - \beta) \quad \alpha \equiv \frac{f}{\sigma_0}$$

$$P(\alpha) = \int dA_{\mu_2} dA_{\mu_3} \dots dA_{\mu_N} \delta(\alpha - \beta) P(\vec{A})$$

$$P(f) = \frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left(-\frac{\alpha^2}{2}\right) + \frac{1}{3!} K_{111}^{(3)} \left\langle \frac{\partial^3 \delta(\alpha - \beta)}{\partial \beta^3} \right\rangle_G + \dots$$

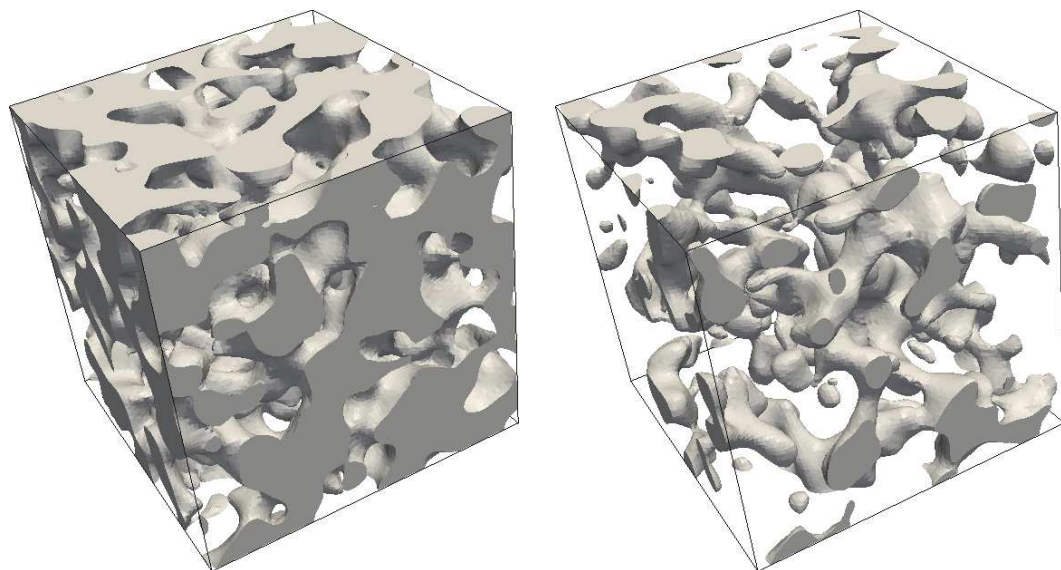
$$P(f) = \frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left(-\frac{\alpha^2}{2}\right) \left[1 + \frac{1}{6} K_{111}^{(3)} H_3(\alpha) + O(\sigma_0^3) \right]$$

Skewness

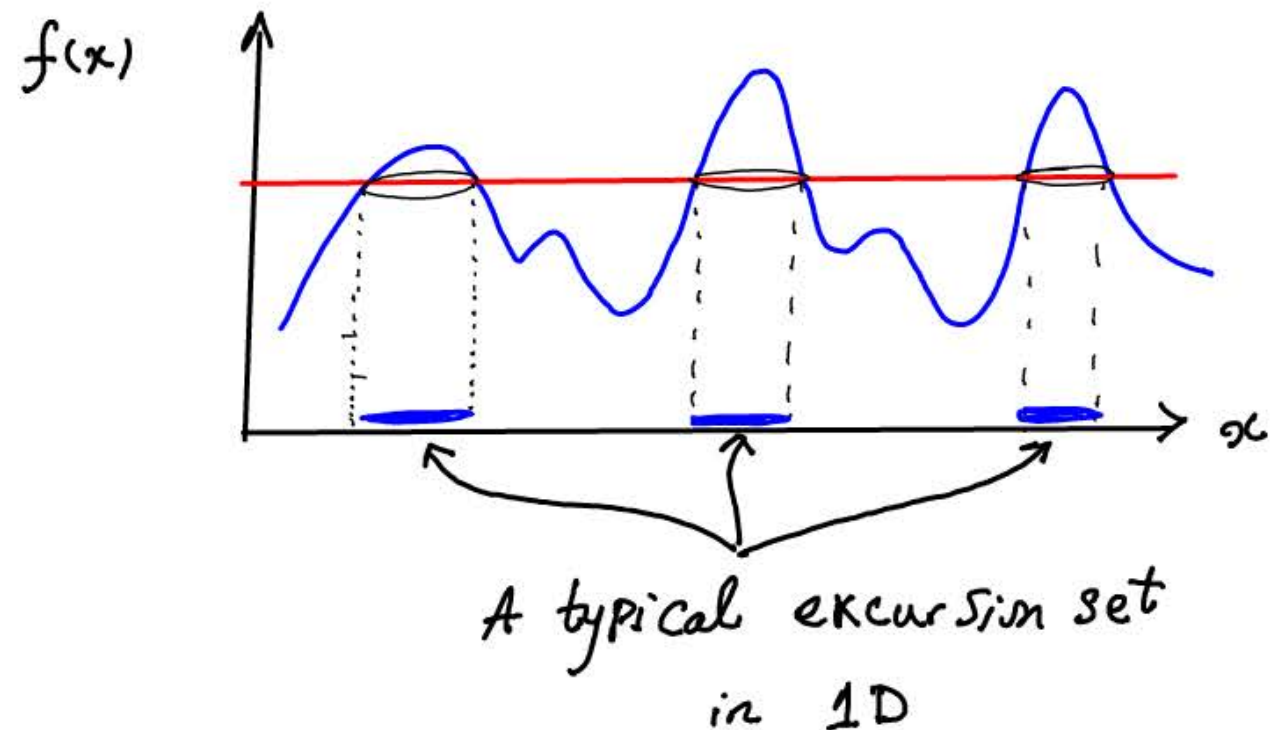
Hermit polynomial

Excursion sets:

In principle, an excursion set is defined as an arbitrary feature considered in an arbitrary condition in the underlying stochastic field



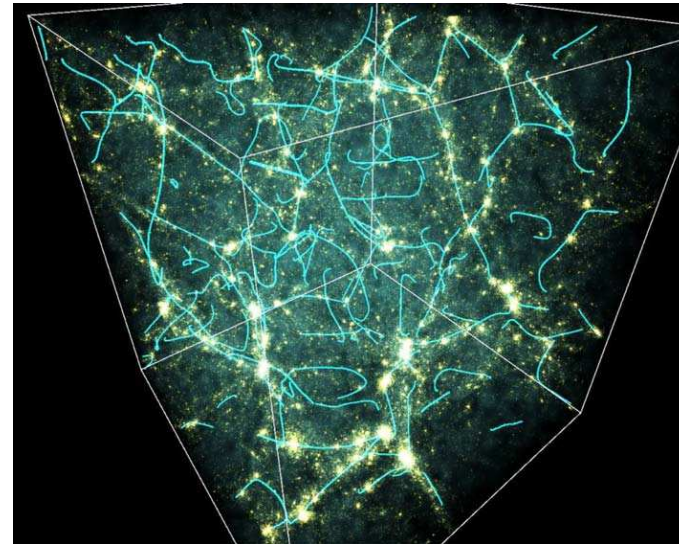
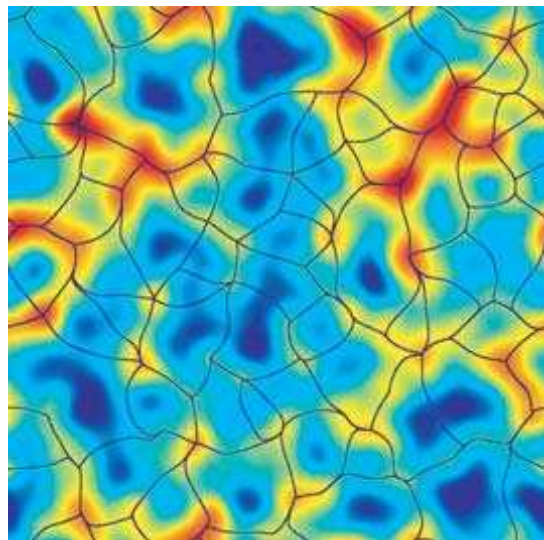
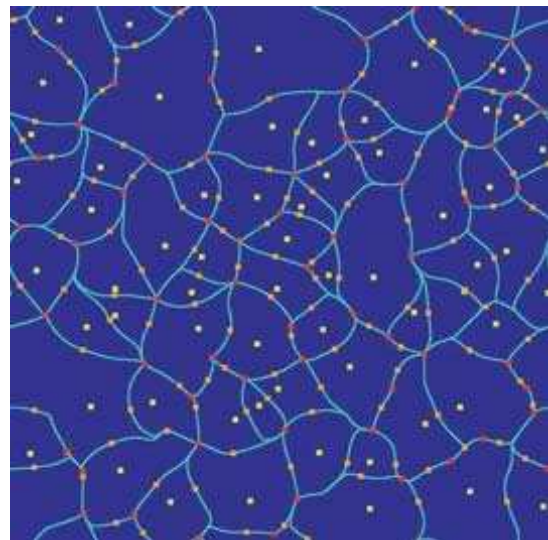
Emmanuel Roubin Thesis, 2013



Critical sets

In principle, a critical set is defined as extrema point or path in the underlying stochastic field

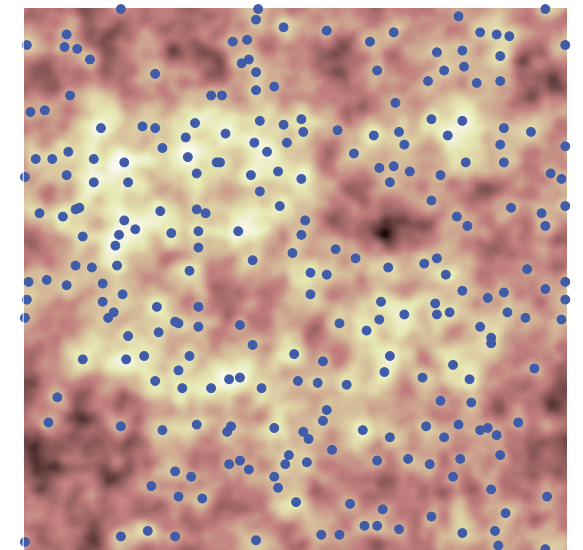
Skeleton as a probe of filamentary 2D & 3D



Mon. Not. R. Astron. Soc. **366**, 1201–1216 (2006)

Mon. Not. R. Astron. Soc. **383**, 1655–1670 (2008)

Peaks



S.M.S. Movahed et. al., (2013)

Skeleton is given by the set of points where the gradient is aligned with local curvature major axis and simultaneously, second component of local curvature is negative

Statistical measures for Excursion and Critical sets



- **Topological measures**

- **Genus** # of handles - # of isolated regions ($C \equiv \int k dA = 4\pi(1 - g)$)
- **Minkowski Functionals** (T. Matsubara et.al. 2013)
- **Euler characteristics** # of maxima + # of minima - # of saddle points
- **Gaussian curvature**

- **Geometrical measures**

- **Crossing statistics** (Rieck 1944, 1945, Ryden 1988, Rahimitabar et. al., 2001-2012, S.M.Vaez Allaei et. al., (2014) in progress, S.M.S. Movahed et. al. (2014), in progress)

- **Peaks theory** (BBBKS (1986), Matsubara (2003-2013), S.M.S. Movahed, Javanmardi, R.K. Sheth.

MNRAS 2013)

- **Skeletons and saddles** (Novikov et. al., 2006; Pogosyan et. al. 2012)

- **Contour analysis** (Kondev et. al., PRE 2000; A.A Saberi et. al. PRL, 2008; S. Hosseinabadi et.al., PRE 2012)

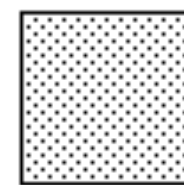
A brief about Topology

Topology is (roughly) the study of properties invariant under "continuous transformation"

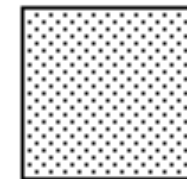
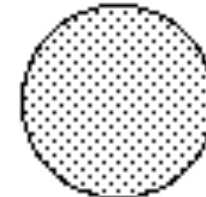
- Two shapes are topologically equivalent if and only if one shape can continuously deform to the other shape.

e.g. Sphere, cube, pyramid are all topologically equivalent.

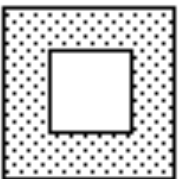
On the other hands, Sphere and torus are different from topological point of view.



|||



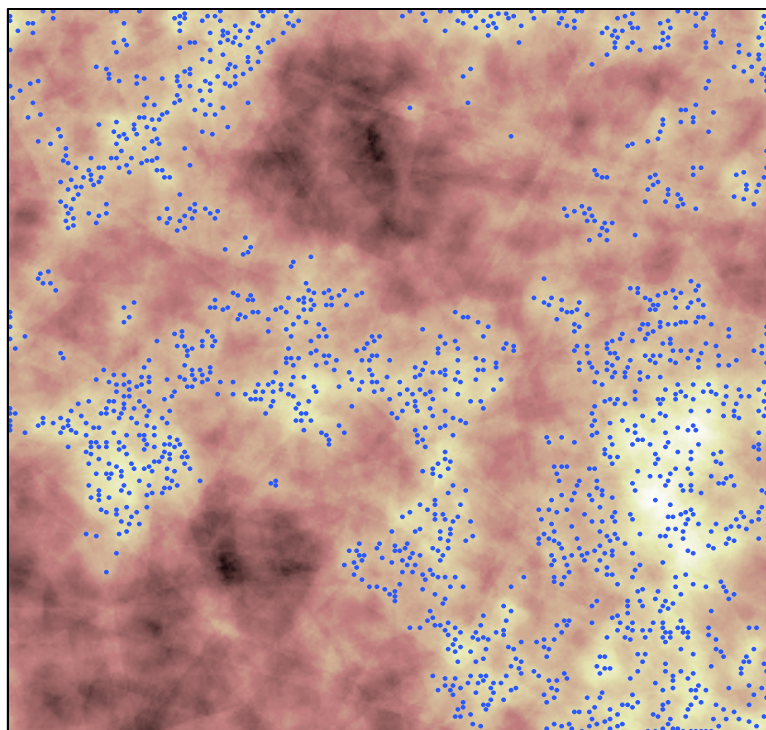
-||-



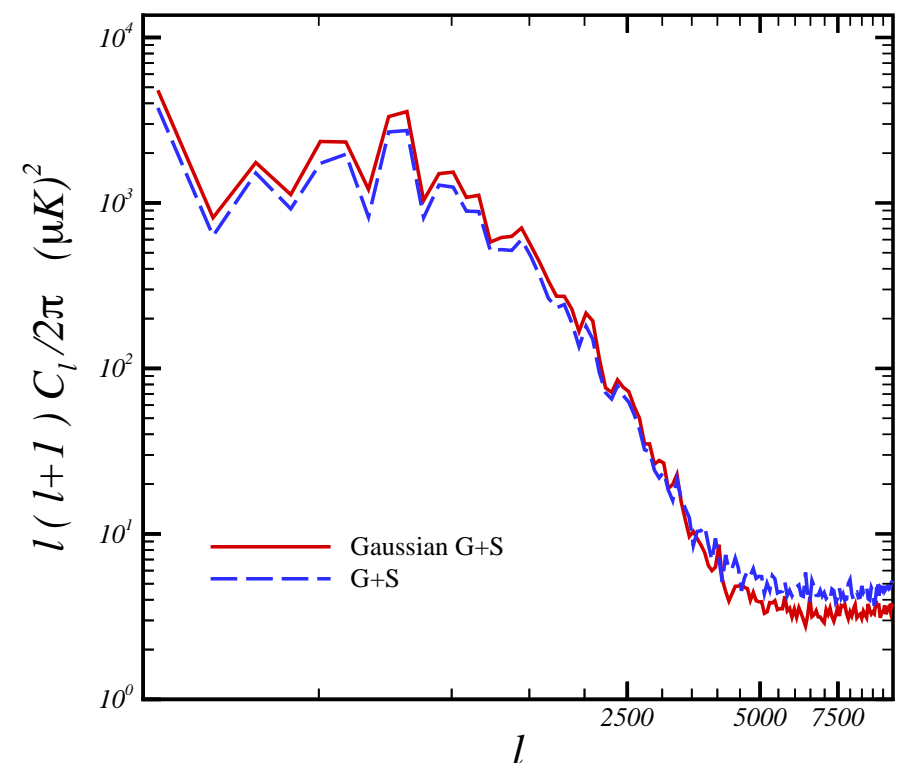
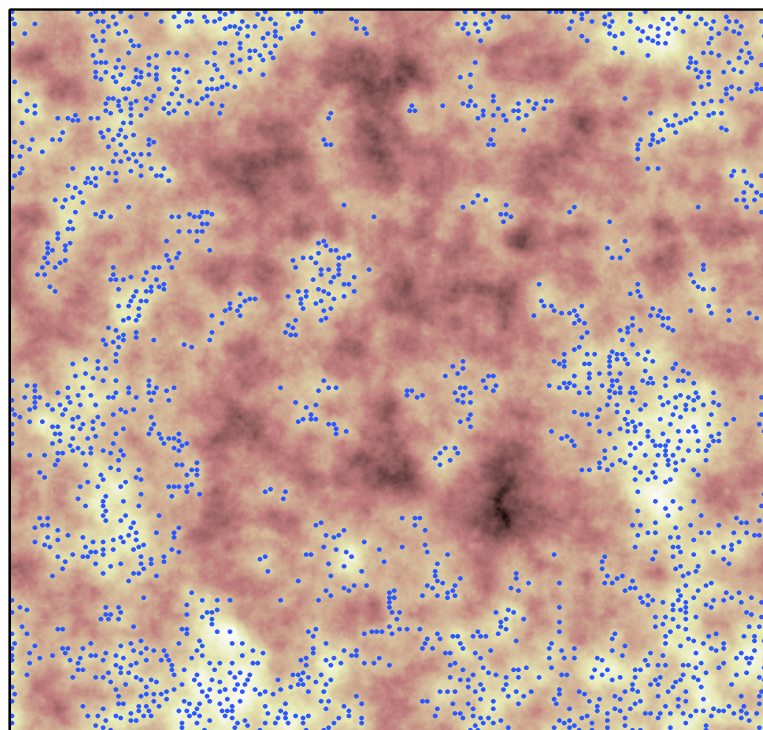
An important motivation:

Both of these fields have same power spectrum
 But their textures are completely different

GS



Gaussian-GS



Why is topology so important?

To answer to this question let me explain PDF and correlation function

- PDF shows the abundance of features while

- correlation corresponds to probability of finding features with a condition

To distinguish between various stochastic fields mentioned tools are not enough

Probabilistic frameworks

- Beside the mathematical definition of some criteria, in principle, it is possible to derive them in probabilistic frameworks
- One most relevant motivation for such approaches is that, it facilitates to compare computational and theoretical predictions

Theoretical approach



One-point statistics

$$\langle f \rangle = \langle \text{Conditions correspond to feature} \rangle$$

$$= \langle f \rangle_{\text{Gaussian}} + \text{Perturbative Parts} \Big|_{\text{NG + Anisotropy}}$$

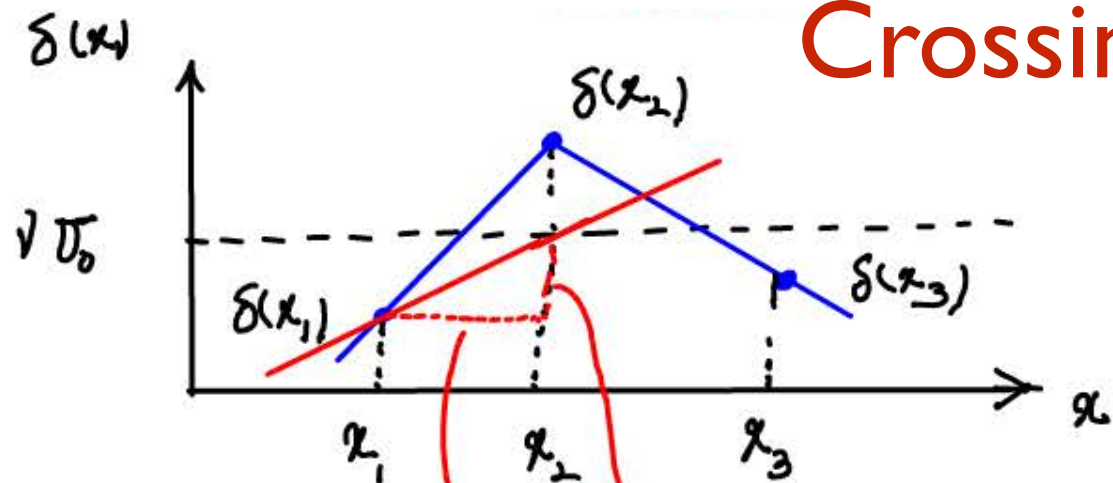
Two-point statistics

$$\langle f(r_1) g(r_2) \rangle = \int dA_1 dA_2 P(A_1, A_2) f(r_1) g(r_2)$$

$$P(\vec{A}_1, \vec{A}_2) = \left[\frac{1}{2\pi^N \text{Det}(K)} \right]^{\frac{1}{2}} \exp\left(- \frac{\vec{A}_1^\dagger \cdot \vec{K}^{-1} \cdot \vec{A}_2}{2} \right)$$



Crossing from Mathematics



① $\delta(x_1) < \nu\sigma_0$

② $\frac{\nu\sigma_0 - \delta(x_1)}{\Delta x} < \eta_x \Rightarrow \delta(x_1) > \nu\sigma_0 - |\eta_x| \Delta x$

$$\Delta x N_1(\nu) = \lim_{\Delta x \rightarrow 0} \int d\eta_x \int_{\nu\sigma_0 - |\eta_x|}^{\nu\sigma_0} d\delta P(\eta_x, \delta)$$

1D = no. of crossing

$$= \int d\eta_x \Delta x |\eta_x| P(\eta_x, \delta = \nu\sigma_0) = \langle \delta_D(\alpha - \nu) |\eta_x| \theta(\eta_x) \rangle$$

2D = mean length of iso-density contour

$$N_2(\nu) = \int d\eta_x d\eta_y (\eta_x^2 + \eta_y^2)^{1/2} P(\vec{\eta}, \nu\sigma_0) = \langle \delta_D(\alpha - \nu) |\eta_x^2 + \eta_y^2|^{1/2} \rangle$$

3D = mean surface of iso-density region

$$N_3(\nu) = \int d\eta_x d\eta_y d\eta_z |\vec{\eta}| P(\vec{\eta}, \nu\sigma_0) = \langle \delta_D(\alpha - \nu) |\eta_x^2 + \eta_y^2 + \eta_z^2|^{1/2} \rangle$$

Homogeneous and Isotropic field



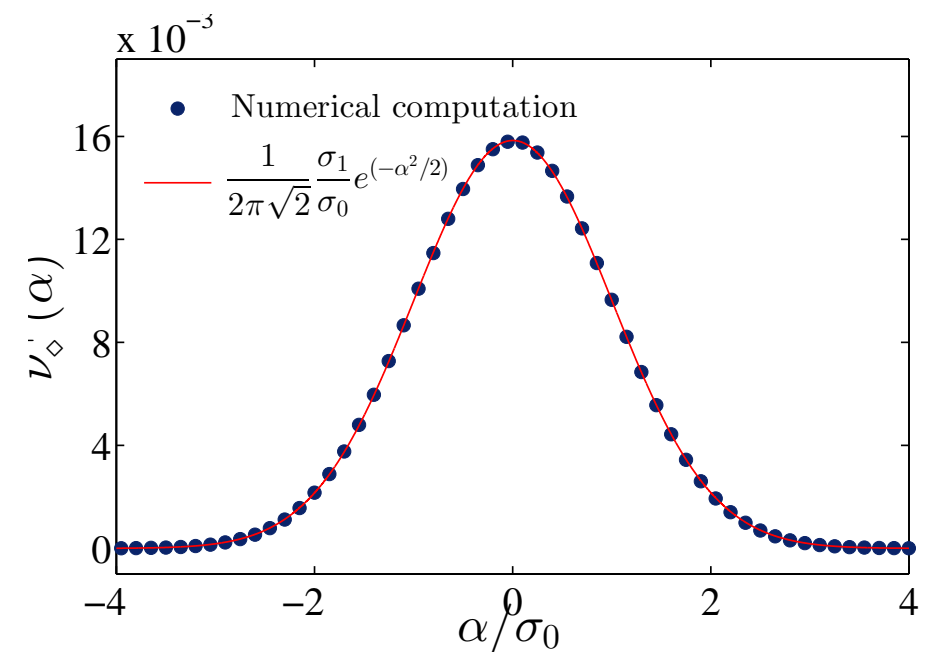
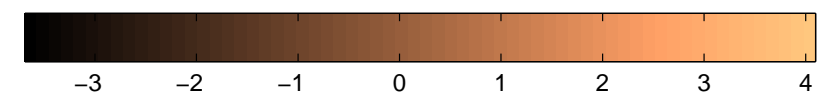
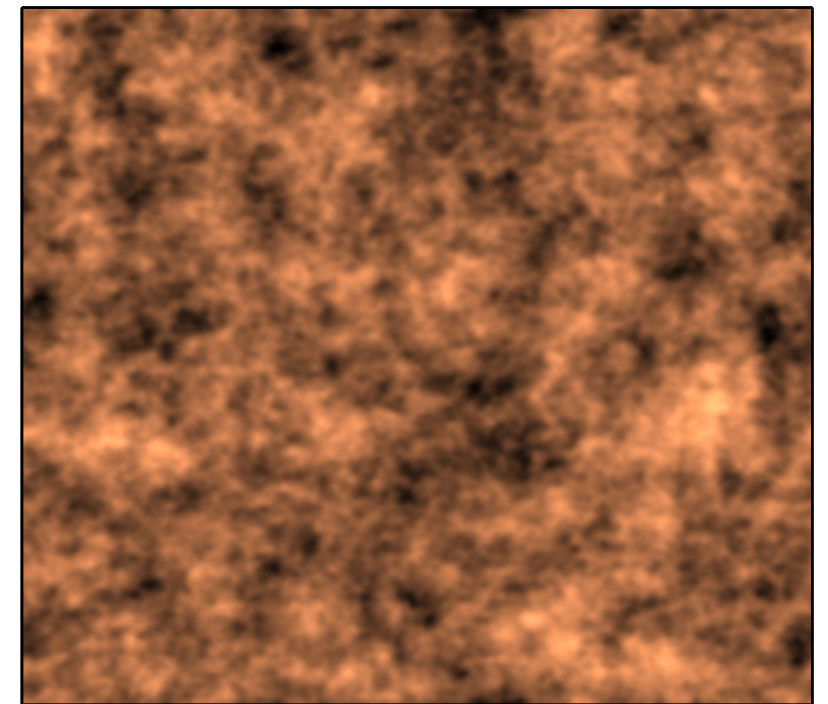
$$N_3(\nu) = \langle |\vec{\eta}| \rangle P_G(\nu\sigma_0) = \frac{1}{\sqrt{2\pi}\sigma_0} e^{-\nu^2/2} \langle |\vec{\eta}| \rangle_{\nu\sigma_0}$$

$$N_3(\nu) = \frac{4}{\pi} N_2(\nu) = 2 N_1(\nu)$$

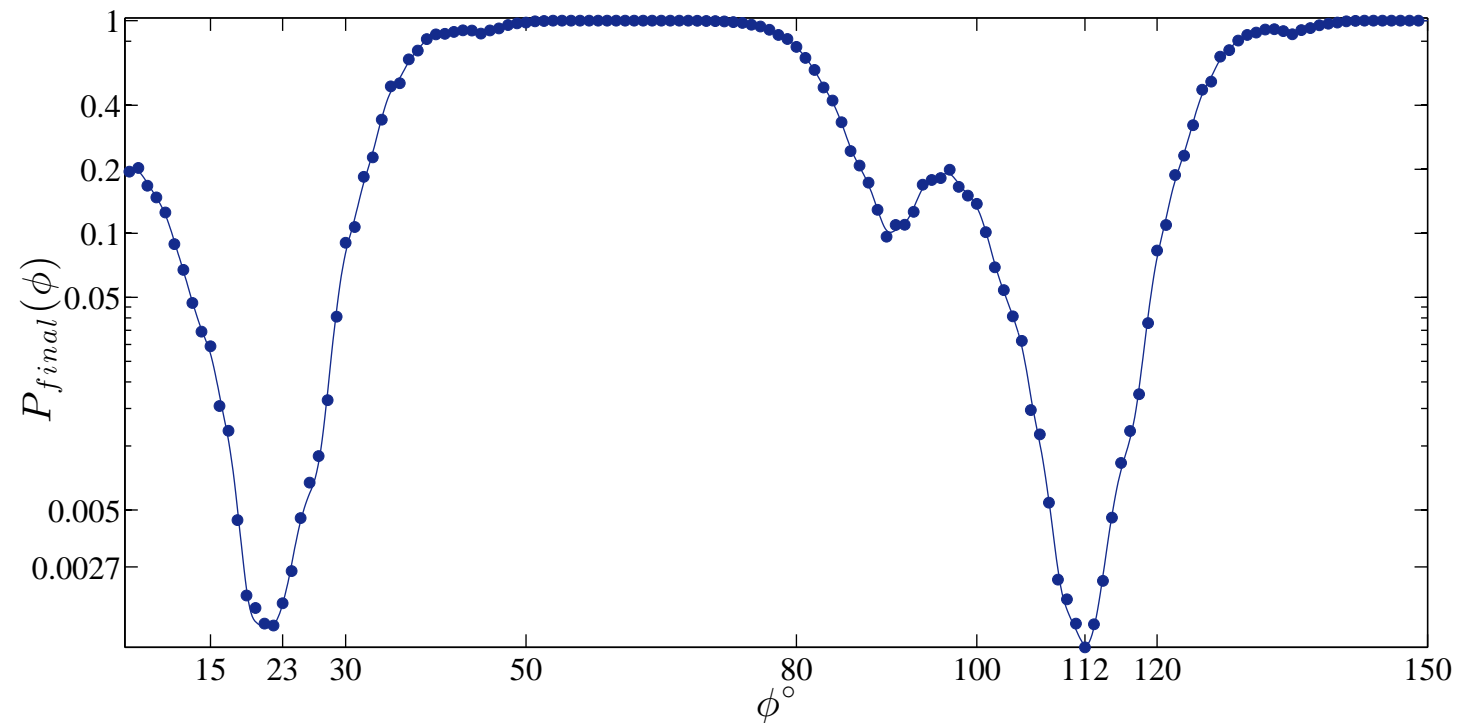
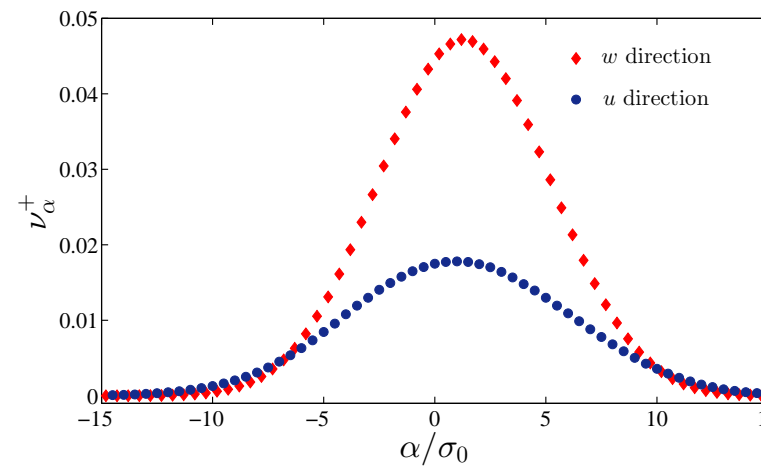
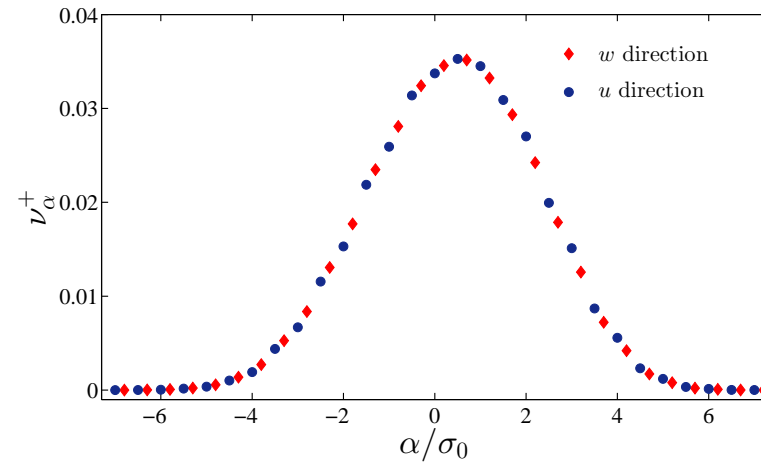
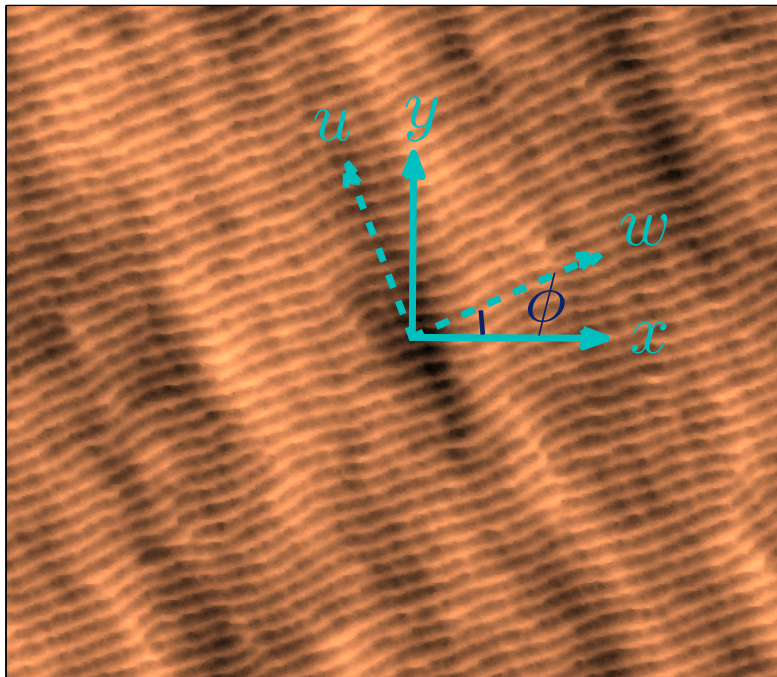
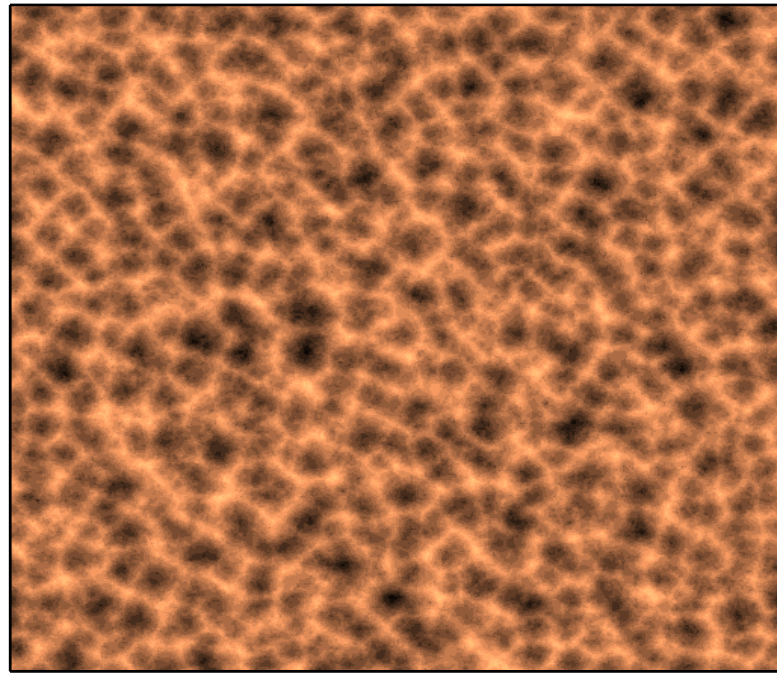
$$\langle |\vec{\eta}| \rangle = 2 \left(\frac{2}{3\pi} \right)^{1/2} \sigma_1$$

$$\sigma_0^2 \equiv \langle \delta^2(r) \rangle = \frac{L^D}{(2\pi)^D} \int d^D k S^D(\vec{k})$$

$$\sigma_2^2 \equiv \left\langle \left(\frac{\partial^n \delta}{\partial x^n} \right)^2 \right\rangle = \frac{L^D}{(2\pi)^D} \int d^D k k^{2n} S^D(\vec{k})$$



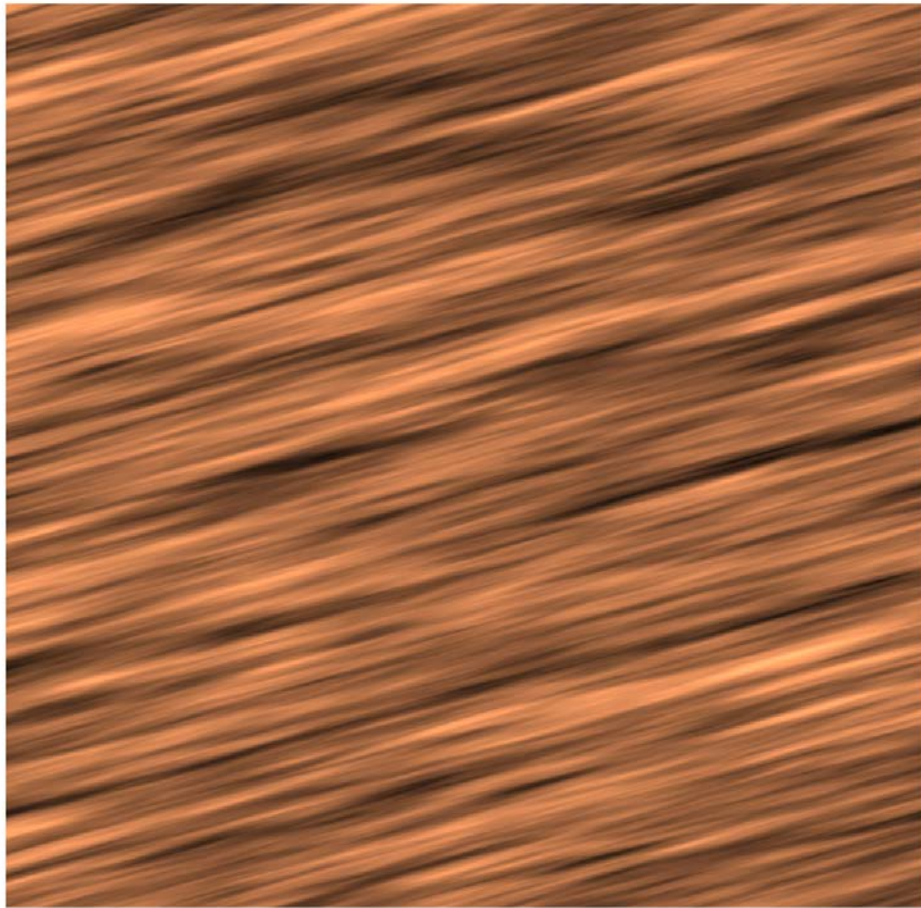
Application for anisotropic surface



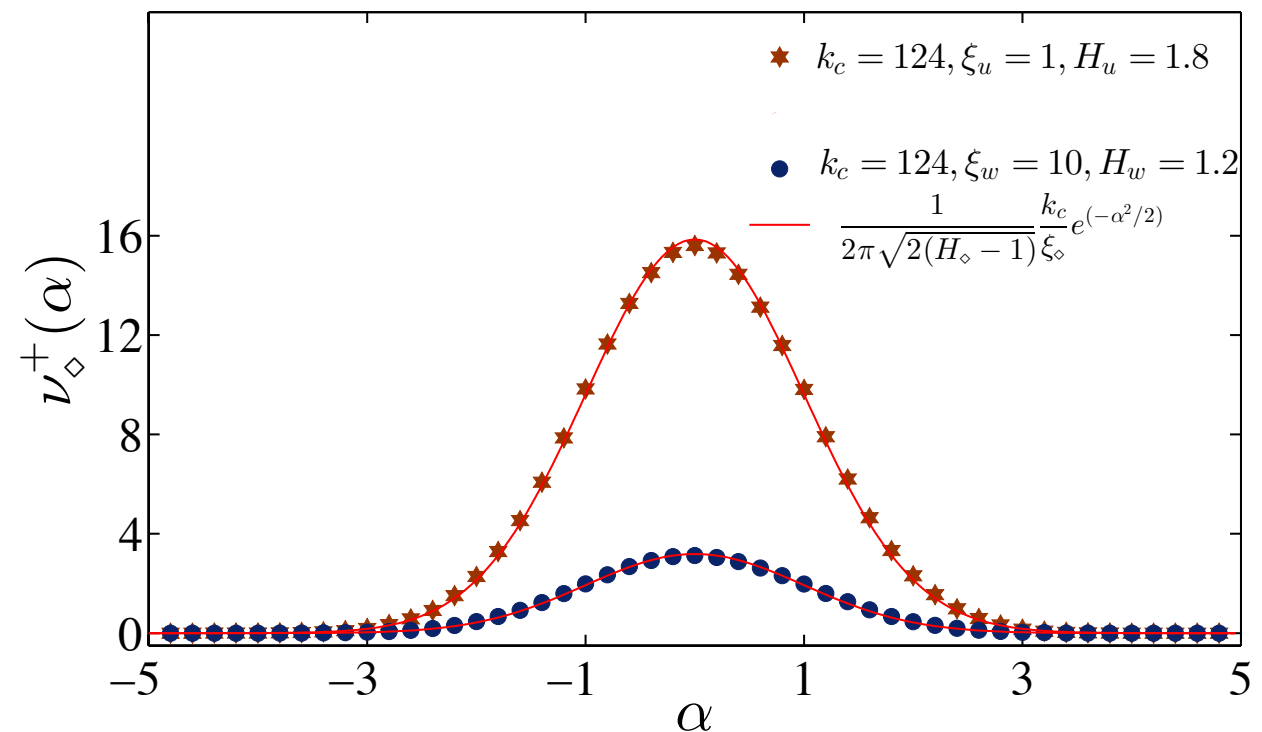
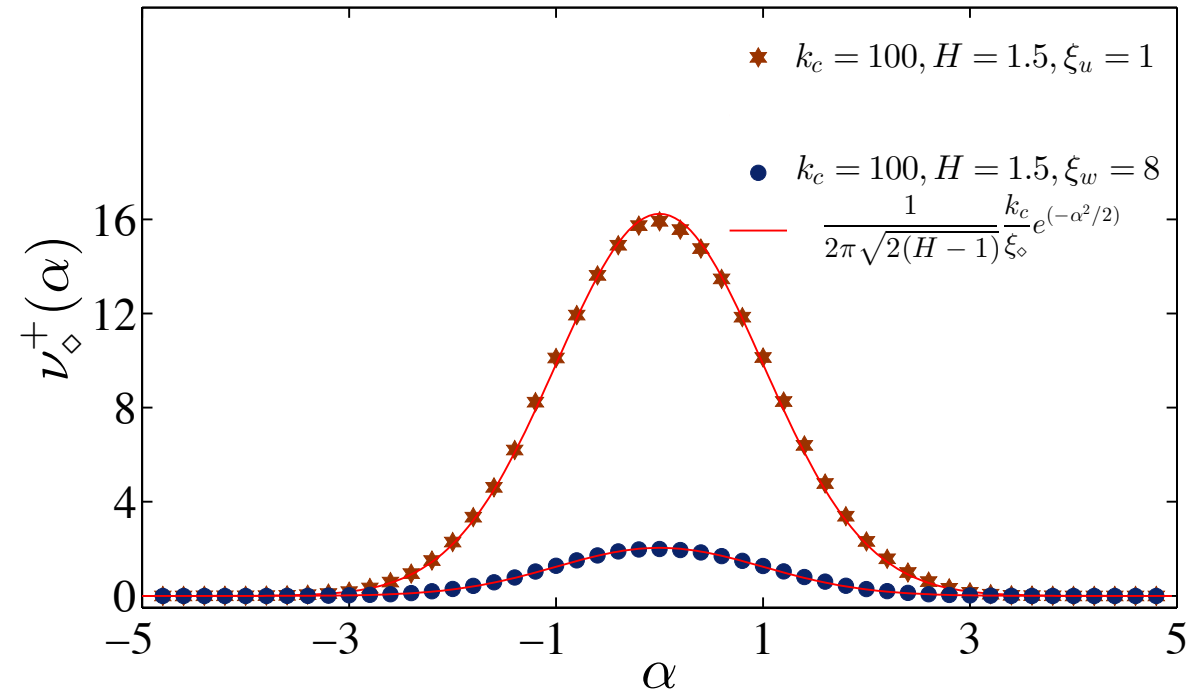
$$t(\phi, q) = [N_{tot}^u(\phi, q) - N_{tot}^w(\phi, q)] \times \sqrt{\frac{N_{run}}{\sigma_u^2(\phi, q) + \sigma_w^2(\phi, q)}}$$

$$P_{final}(\phi) = 1 - \frac{1}{2^{\mu/2} \Gamma(\mu/2)} \int_0^{\chi^2(\phi)} e^{-x/2} x^{\mu/2-1} dx$$

Application for anisotropic surface



Model 1: correlation length
 anisotropy
 Model 2: Scaling anisotropy





Perturbative parts in D-dimension Isotropic field

$$N_1(\nu) = \langle \delta_D(\alpha - \nu) | \eta_1 | \Theta(\eta_1) \rangle$$
$$= N_1^G + \text{Perturbative Parts}$$

$$= \frac{1}{\pi} \frac{\sigma_1}{\sqrt{D} \sigma_0} e^{-\nu^2/2} + N_1^{NG}$$

$$= N_1^G(\nu) \left[1 + A \sigma_0 + B \sigma_0^2 + \mathcal{O}(\sigma_0^3) \right]$$

$$A = \frac{S}{6} H_3(\nu) + \frac{S^{(1)}}{3} H_1(\nu)$$

$$B = \frac{1}{24} (K - S S^{(1)}) H_4(\nu) - H_2(\nu) \left(\frac{1}{12} K^{(1)} + \frac{1}{96} S^{(1)2} \right) + \frac{1}{72} S^2 H_6(\nu) + \frac{1}{8} (-K^{(3)})$$

$$S = \frac{\langle \alpha^3 \rangle}{\sigma_0} \quad , \quad S^{(1)} = -\frac{3}{4} \frac{\langle \alpha^2 \nabla \alpha \rangle}{\sigma_0^2 \sigma_1^2} \quad , \quad K^{(3)} = \frac{\langle \nabla f^4 \rangle}{2 \sigma_0^2 \sigma_1^4}$$

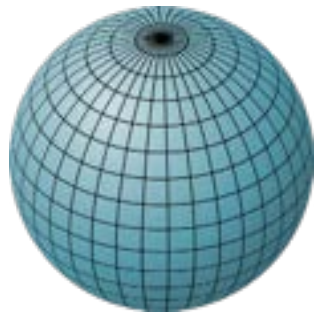
Genus from Mathematics

1) In principle Genus is

$G3 = \#$ of handles to the surface - $\#$ of holes enclosed by the surface

$G3 = \#$ of handles of contours - $\#$ of isolated contours

$G2 = \#$ of contours around higher dense region - $\#$ of contours around lower dense region



$G=0$



$G=1$

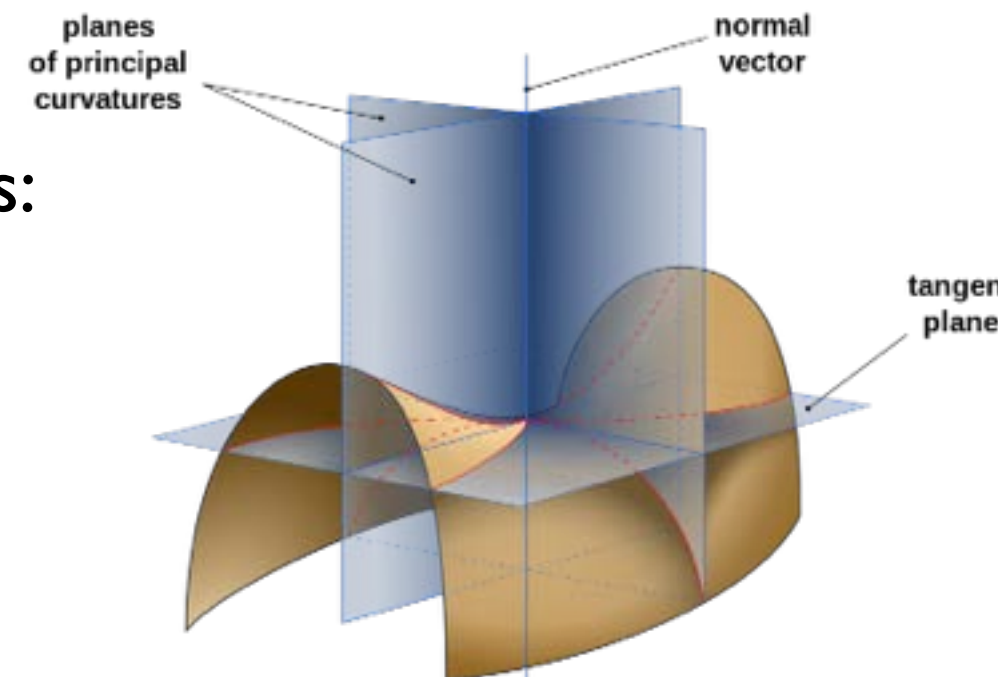


$G=3$

2) It is related to Gaussian curvature of surface as:

$$G = 1 - \frac{1}{4\pi} \int \frac{dA}{R_1 R_2}$$

Global Property Local Property



Genus from Mathematics



3) If there is no information about Gaussian curvatures, Euler characteristic can be used for determining Genus as:

$$\chi \equiv \# \text{ of faces} + \# \text{ of vertices} - \# \text{ of edges}$$

$$\chi \equiv \# \text{ of Maxima} + \# \text{ of Minima} - \# \text{ of Saddle Points}$$

$$G = 1 - \frac{\chi}{2}$$

Multi-connected field has $G > 0$



Euler-Poincaré characteristic χ

$$\chi^{3D}(\nu) = \langle \delta_D(\alpha-\nu) \delta_D(\eta_1) \delta_D(\eta_2) |\eta_3| (\xi_{11} \xi_{22} - \xi_{12}^2) \rangle$$

$$\chi^{2D}(\nu) = \langle \delta_D(\alpha-\nu) \delta_D(\eta_1) |\eta_2| \xi_{11} \rangle \quad \text{Intuitive definition}$$

$$\chi^{1D}(\nu) = \langle \delta_D(\alpha-\nu) |\eta_1| \rangle = N_1(\nu)$$

$$G = 1 - \frac{\chi}{2}$$

$$\langle G(\nu) \rangle = \langle G(\nu) \rangle_G + \text{Perturbation parts} \quad \Big| \quad \text{Non-Gaussian, Anisotropic}$$

Genus from Statistics



$$G^{3D}(\nu) = \frac{2}{(2\pi)^2} \left(\frac{\sigma_1}{\sqrt{D}\sigma_0} \right)^3 e^{-\nu^2/2} \left[H_2(\nu) + \left(\frac{S^0}{6} H_5(\nu) + S^{(1)} H_3(\nu) + S^{(2)} H_1(\nu) \right) \sigma_0 + \mathcal{O}(\sigma_0^2) \right]$$

$$G^{2D}(\nu) = \frac{-2}{(2\pi)^{3/2}} \left(\frac{\sigma_1}{\sqrt{D}\sigma_0} \right)^2 e^{-\nu^2/2} \left[H_1(\nu) + \left(\frac{S^0}{6} H_4(\nu) + \frac{2S^{(1)}}{3} H_2(\nu) + \frac{S^{(2)}}{3} \right) \sigma_0 + \mathcal{O}(\sigma_0^2) \right]$$

$$G^{1D}(\nu) = \frac{N_1(\nu)}{2} = \frac{1}{\pi} \frac{\sigma_1}{\sqrt{D}\sigma_0} e^{-\nu^2/2} \left[1 + \left(\frac{S^0}{6} H_3(\nu) + \frac{S^{(1)}}{3} H_1(\nu) \right) \sigma_0 + \mathcal{O}(\sigma_0^2) \right]$$

Euler characteristic from mathematics



Leonhard Euler (1707-1783)

1) The *Euler Characteristic* is something which generalises [Euler's](#) observation of 1751 (in fact already noted by [Descartes](#) in 1639) that on "triangulating" a sphere into F regions, E edges and V vertices one has $V - E + F = 2$.

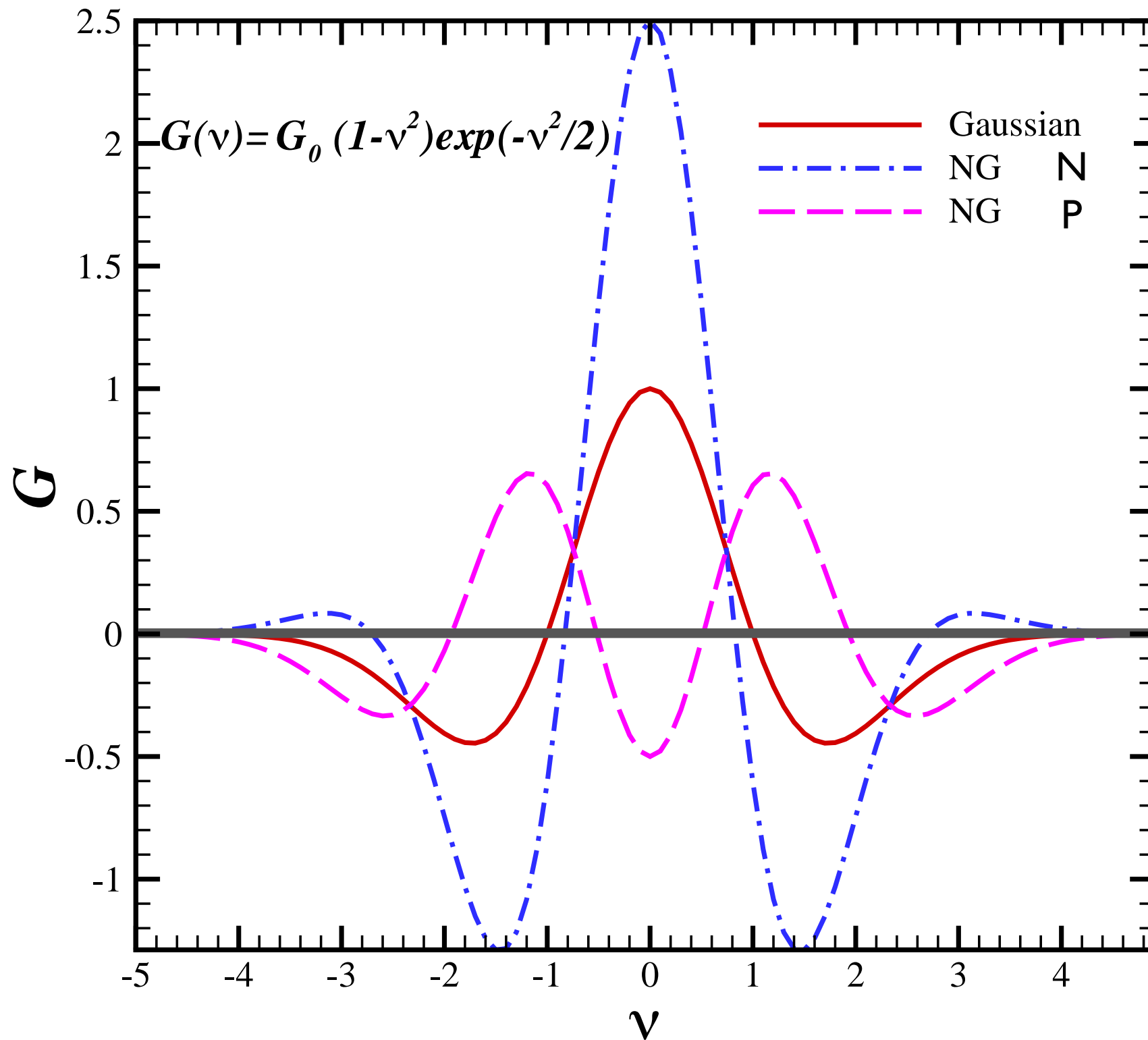
2) In addition the value of Euler characteristic does not depend on how tessellation is done

3) Euler for Sphere is equal to 2

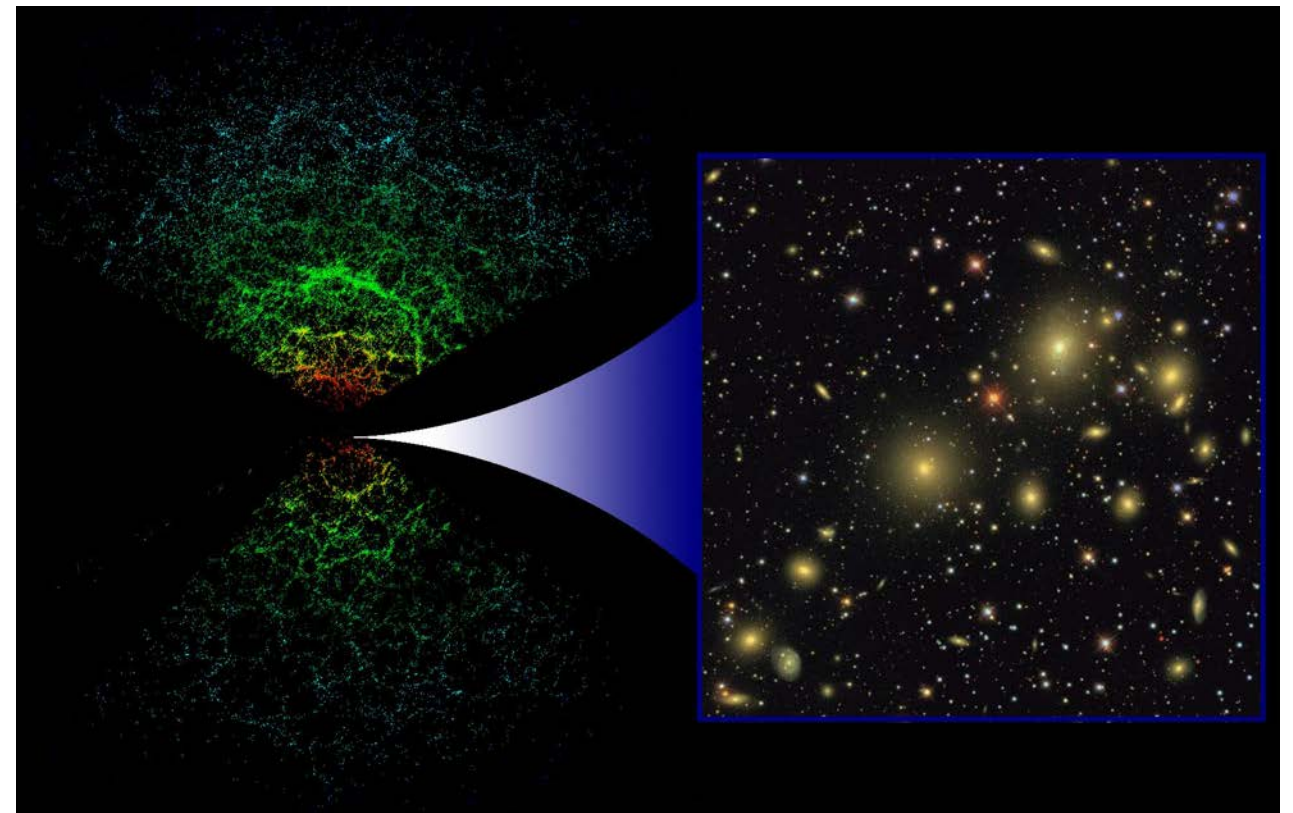
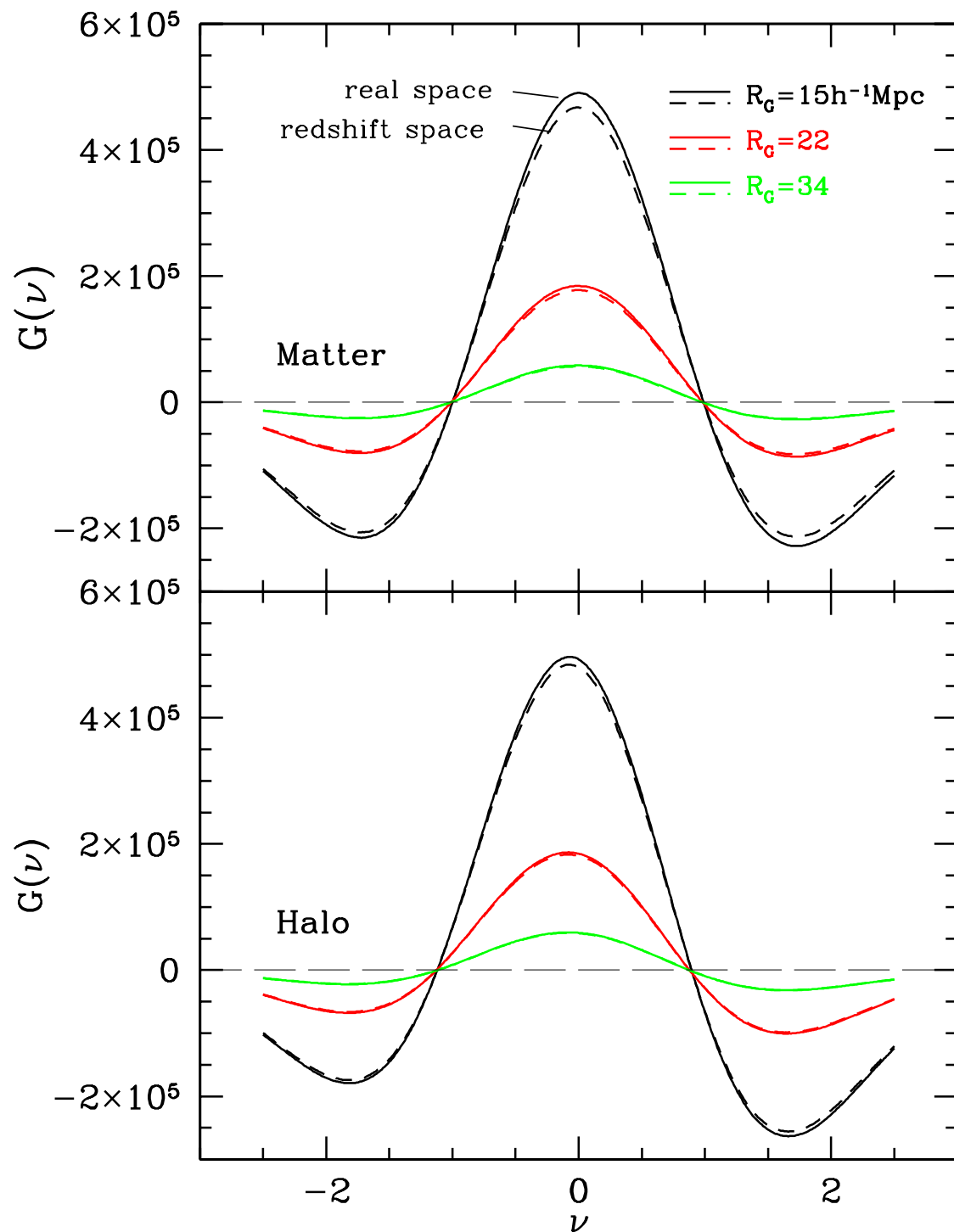
The Euler characteristic for convex polyhedra always equals 2

Name	Image	Vertices V	Edges E	Faces F	Euler characteristic $V - E + F$
Tetrahedron		4	6	4	2
Hexahedron or cube		8	12	6	2
Octahedron		6	12	8	2
Dodecahedron		20	30	12	2
Icosahedron		12	30	20	2

Genus from Gaussian and NG fields 3D



Topology of our Universe

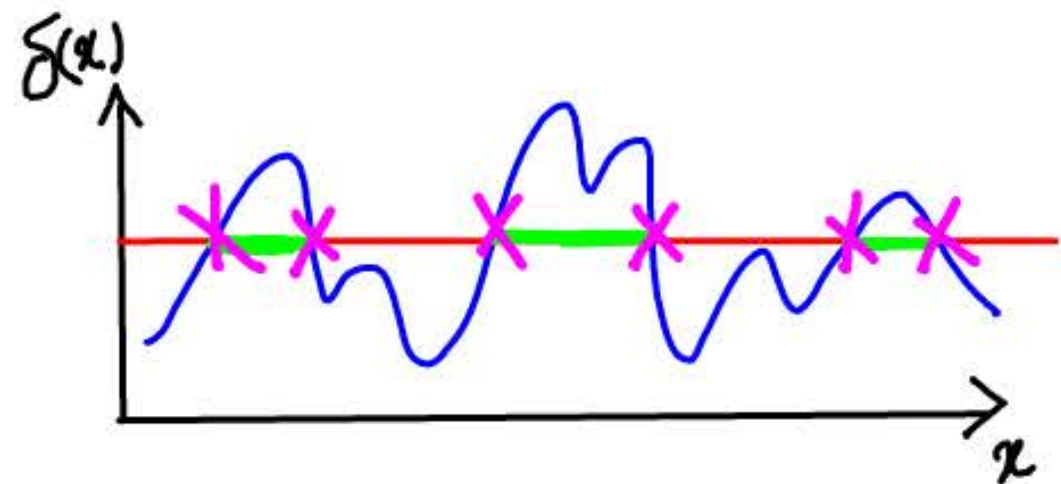


- 1) Topological consideration is consistent with Gaussian field
- 2) At median density, topology of our local universe is swiss-cheese
- 3) At large threshold, the topology belongs to meatball

1D field

$$V_0(\nu) = \int_a d\ell = \langle \theta(\alpha - \nu) \rangle$$

$$V_1(\nu) = \int_{\partial a} d\ell = \frac{1}{2} \langle \delta_D(\alpha - \nu) |\eta_1| \rangle \sim N_1(\nu)$$

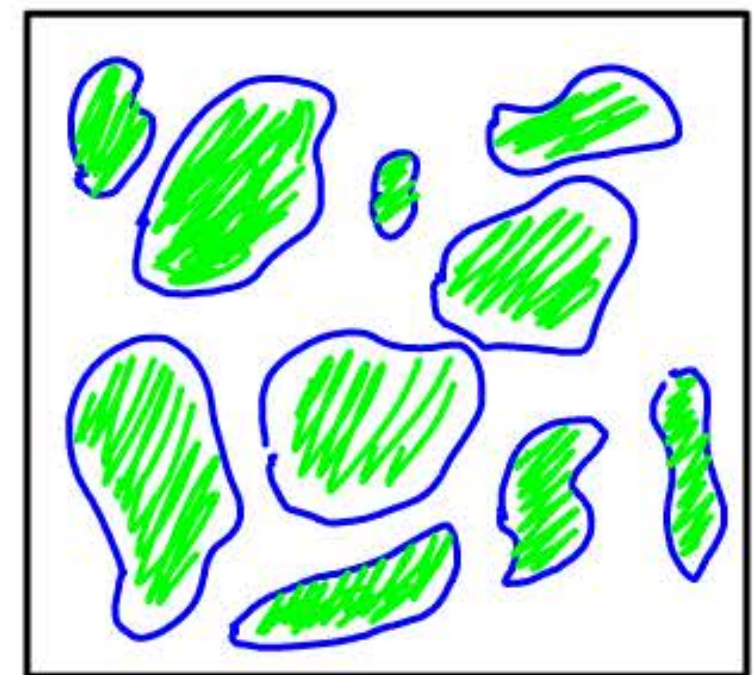


2D field

- $$V_0(\nu) = \int_a dA = \langle \theta(\alpha - \nu) \rangle$$

- $$V_1(\nu) = \frac{1}{4} \int_{\partial a} d\ell = \frac{\pi}{8} \langle \delta_D(\alpha - \nu) |\eta_1| \rangle \sim N_1(\nu)$$

$$V_2(\nu) = \frac{1}{2\pi} \int_{\partial a} K d\ell = -\frac{1}{2} \langle \delta_D(\alpha - \nu) \delta_D(\eta_1) |\eta_1| \zeta_{11} \rangle$$



Minkowski Functionals

General case



Volume fraction
of excursion set

$$\bar{V}_0^{(D)}(\nu) = \frac{1}{V} \int_K dV = \langle \theta(\nu - \alpha) \rangle$$

2D

$$\bar{V}_j^{(2)}(\nu) = \frac{1}{V} \int_{\partial K} dL(x) \nu_j^{(2)}(\nu, x)$$

$$\nu_1^{(2)}(\nu, x) \equiv \frac{1}{4}$$

$$\nu_2^{(2)}(\nu, x) \equiv \frac{1}{2\pi} \frac{1}{R_1} \quad \frac{1}{R_1} \equiv \text{Principal curvature}$$

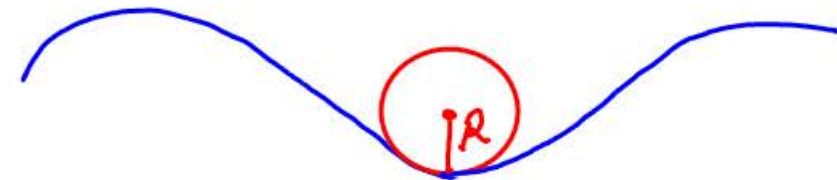
3D

$$\bar{V}_j^{(3)}(\nu) = \frac{1}{V} \int_{\partial K} d^2A(x) \nu_j^{(3)}(\nu, x)$$

$$\nu_1^{(3)}(\nu, x) \equiv \frac{1}{6}$$

$$\nu_2^{(3)}(\nu, x) \equiv \frac{1}{6\pi} \left(\frac{1}{R_1} + \frac{1}{R_2} \right)$$

$$\nu_3^{(3)}(\nu, x) \equiv \frac{1}{4\pi} \frac{1}{R_1 R_2}$$



R is radius of osculating circle

Minkowski functionals



Crofton (1868) :

$$V_3^{(D)}(\nu) = -\frac{\omega_D}{\omega_D - 3\omega_0} G_3(\nu)$$

$$V_2^{(D)}(\nu) = \frac{\omega_D}{\omega_D - 2\omega_2} G_2(\nu)$$

$$V_1^{(D)}(\nu) = \frac{\omega_D}{2\omega_D - 1\omega_1} N_1(\nu)$$

$$\omega_D \equiv \frac{\pi^{D/2}}{\Gamma(D/2 + 1)}$$

Clustering of Peaks and crossing in 2D stochastic field

To this end we should introduce peaks

Theoretical approach for clustering (1+2D)

Number density of Peaks

- We are interested in investigating local extrema on the CMB as one of most famous stochastic field
- To this end we should evaluate number density of peaks:

$$\mathcal{F}(\mathbf{r}) \equiv [T(\mathbf{r}) - \langle T(\mathbf{r}) \rangle] / \langle T(\mathbf{r}) \rangle$$

$$p(\vec{\mathcal{W}}) = \sqrt{\frac{1}{(2\pi)^6 \det \mathcal{M}}} e^{-\frac{1}{2}(\mathcal{W}^T \cdot \mathcal{M}^{-1} \cdot \mathcal{W})} \quad \mathcal{M} = \langle \mathcal{W} \otimes \mathcal{W} \rangle$$

$$\vec{\mathcal{W}} = \{\mathcal{F}, \mathcal{F}_x, \mathcal{F}_y, \mathcal{F}_{xx}, \mathcal{F}_{xy}, \mathcal{F}_{yy}\} \quad \mathcal{F}_i \equiv \frac{\partial \mathcal{F}}{\partial x_i} \quad \mathcal{F}_{ij} \equiv \frac{\partial^2 \mathcal{F}}{\partial x_i \partial x_j}$$

$$n(\vartheta) = \int p(\vec{\mathcal{W}} | \mathcal{F}_i = 0) |\det \mathcal{F}_{ij}| d\vec{\mathcal{W}}$$

$$n(\vartheta) = \frac{1}{(2\pi)^{3/2} \gamma^2} e^{-\vartheta^2/2} \mathcal{G}(\Psi, \Psi\vartheta)$$

$$\begin{aligned}
\mathcal{G}(\Psi, \Psi\vartheta) \equiv & (\Psi^2\vartheta^2 - \Psi^2) \left\{ 1 - \frac{1}{2} \operatorname{erfc} \left[\frac{\Psi\vartheta}{\sqrt{2(1-\Psi^2)}} \right] \right\} \\
& + \Psi\vartheta(1-\Psi^2) \frac{e^{-\frac{\Psi^2\vartheta^2}{2(1-\Psi^2)}}}{\sqrt{2\pi(1-\Psi^2)}} \\
& + \frac{e^{-\frac{\Psi^2\vartheta^2}{3-2\Psi^2}}}{\sqrt{3-2\Psi^2}} \left\{ 1 - \frac{1}{2} \operatorname{erfc} \left[\frac{\Psi\vartheta}{\sqrt{2(1-\Psi^2)(3-2\Psi^2)}} \right] \right\}
\end{aligned}$$

$$\Psi \equiv \frac{\sigma_1^2}{\sigma_0\sigma_2} \quad \gamma \equiv \sqrt{2} \frac{\sigma_1}{\sigma_2}$$

$$\sigma_0^2 \equiv \langle \mathcal{F}(\mathbf{r})^2 \rangle = \frac{1}{(2\pi)^2} \int S(|\mathbf{k}|) d\mathbf{k}$$

$$\sigma_n^2 \equiv \left\langle \left(\frac{\partial^n \mathcal{F}(\mathbf{r})}{\partial x^n} \right)^2 \right\rangle = \frac{1}{(2\pi)^2} \int k^{2n} S(|\mathbf{k}|) d\mathbf{k}$$

Weak non-Gaussian field

$$\frac{\partial n_{\text{ext}}}{\partial x} = \int d^3 x_{ij} P(x, x_i = 0, x_{ij}) |x_{ij}|$$

$$\begin{aligned} \frac{\partial n_{\text{max/min}}}{\partial \nu} &= \frac{1}{\sqrt{2\pi}R_*^2} \exp\left(-\frac{\nu^2}{2}\right) \left[1 \pm \text{erf}\left(\frac{\gamma\nu}{\sqrt{2(1-\gamma^2)}}\right) \right] K_1(\nu, \gamma) \pm \frac{1}{\sqrt{2\pi(1-\gamma^2)}R_*^2} \exp\left(-\frac{\nu^2}{2(1-\gamma^2)}\right) K_3(\nu, \gamma) \\ &+ \frac{\sqrt{3}}{\sqrt{2\pi(3-2\gamma^2)}R_*^2} \exp\left(-\frac{3\nu^2}{6-4\gamma^2}\right) \left[1 \pm \text{erf}\left(\frac{\gamma\nu}{\sqrt{2(1-\gamma^2)(3-2\gamma^2)}}\right) \right] K_2(\nu, \gamma), \end{aligned}$$

$$\frac{\partial n_{\text{sad}}}{\partial \nu} = \frac{2\sqrt{3}}{\sqrt{2\pi(3-2\gamma^2)}R_*^2} \exp\left(-\frac{3\nu^2}{6-4\gamma^2}\right) K_2(\nu, \gamma),$$

$$\zeta = (x + \gamma J_1) / \sqrt{1 - \gamma^2}$$

$$\gamma = -\langle x J_1 \rangle$$

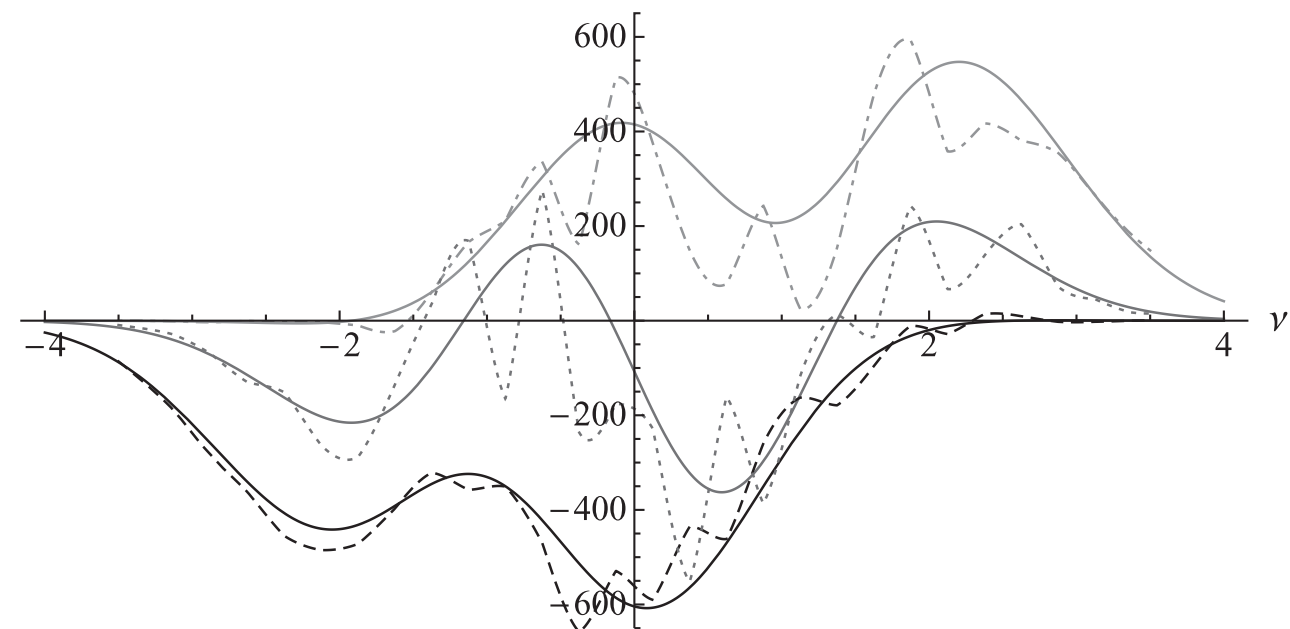
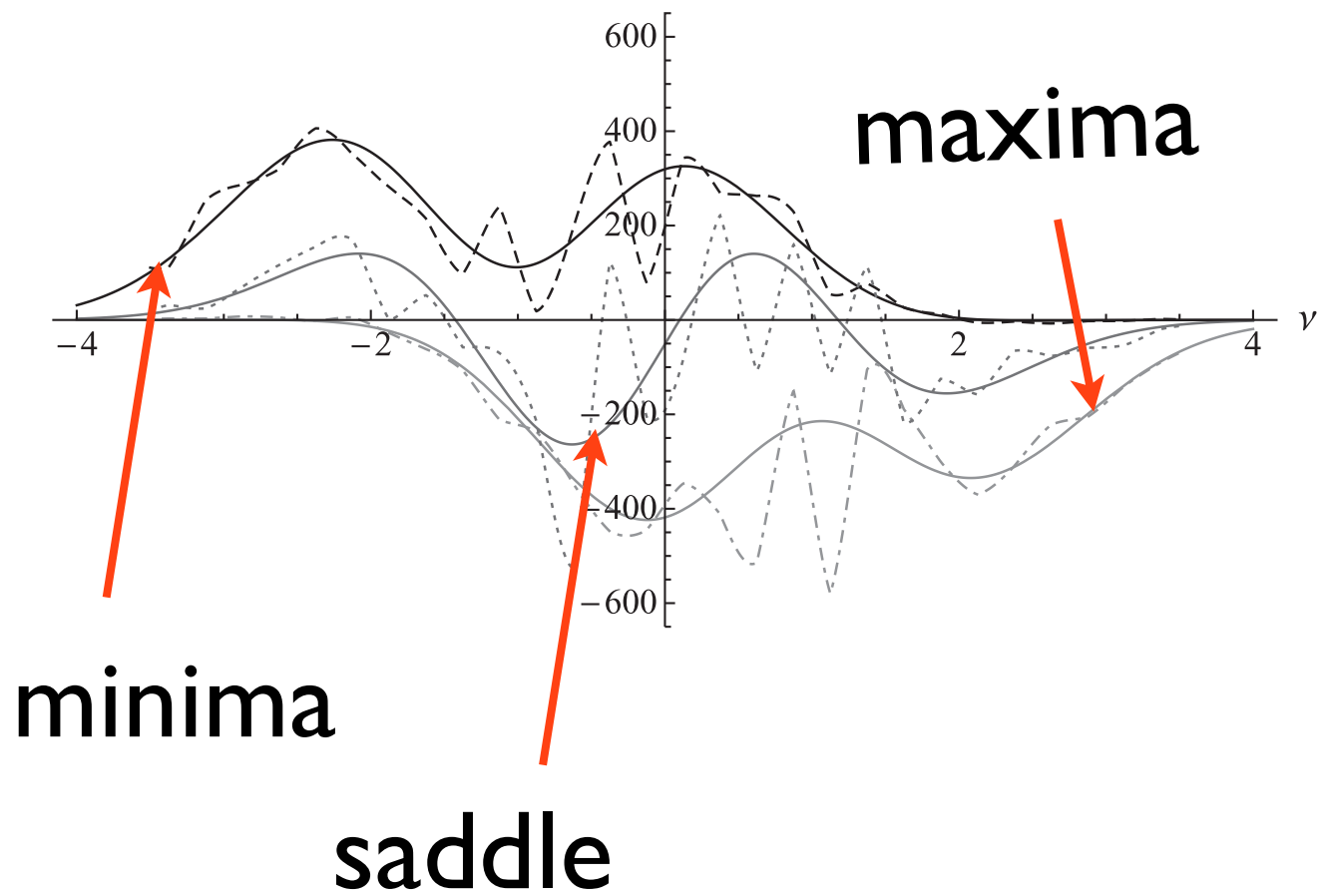
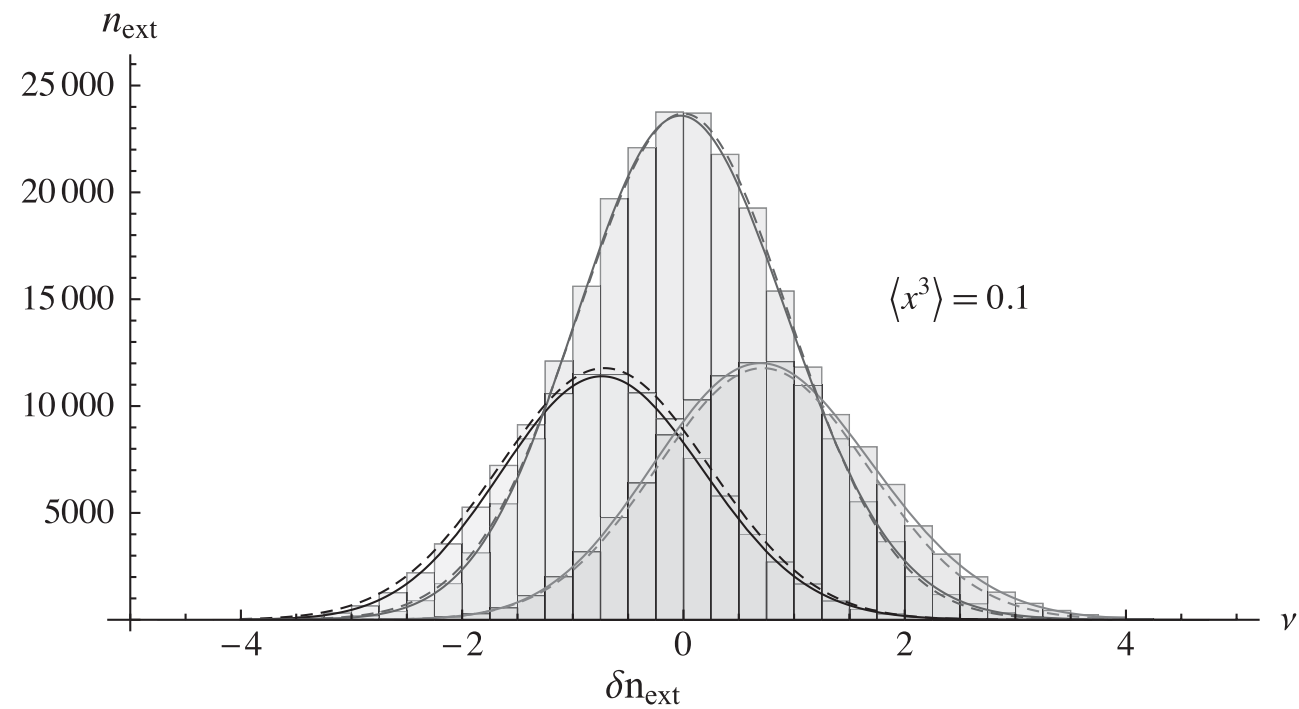
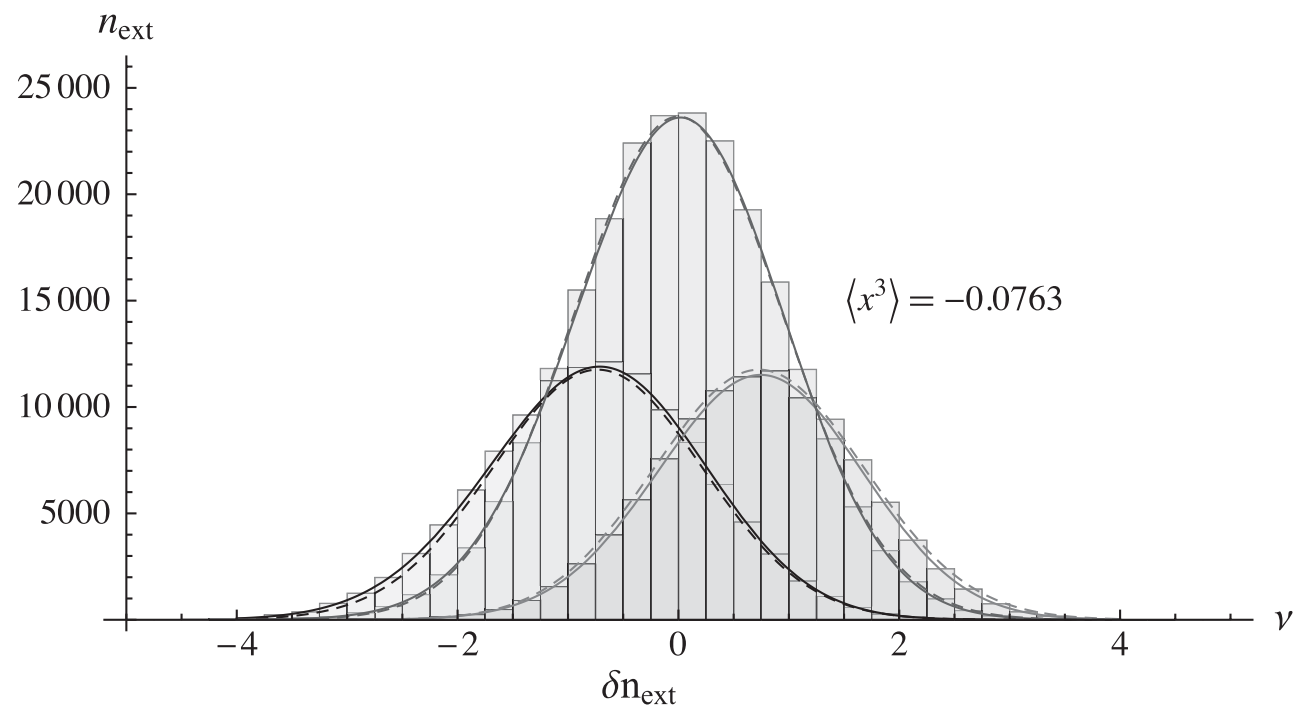
$$K_1 = \frac{\gamma^2}{8\pi} \left[H_2(\nu) + \left(\frac{2}{\gamma} \langle q^2 J_1 \rangle + \frac{1}{\gamma^2} \langle x J_1^2 \rangle - \frac{1}{\gamma^2} \langle x J_2 \rangle \right) H_1(\nu) - \left(\langle x q^2 \rangle + \frac{1}{\gamma} \langle x^2 J_1 \rangle \right) H_3(\nu) + \frac{1}{6} \langle x^3 \rangle H_5(\nu) \right]$$

$$K_2 = \frac{1}{8\pi\sqrt{3}} \left[1 - \left(\langle x q^2 \rangle + \frac{1}{3} \langle x J_1^2 \rangle - \frac{4}{3} \langle x J_2 \rangle + \frac{2}{3} \gamma \langle q^2 J_1 \rangle + \frac{2}{9} \gamma \langle J_1^3 \rangle - \frac{2}{3} \gamma \langle J_1 J_2 \rangle \right) \mathcal{H}_1^-(\nu, \sqrt{1 - 2/3\gamma^2}) \right. \\ \left. + \frac{1}{6} \left(\langle x^3 \rangle + 2\gamma \langle x^2 J_1 \rangle + \frac{4}{3} \gamma^2 \langle x J_1^2 \rangle + \frac{2}{3} \gamma^2 \langle x J_2 \rangle + \frac{8}{27} \gamma^3 \langle J_1^3 \rangle + \frac{4}{9} \gamma^3 \langle J_1 J_2 \rangle \right) \mathcal{H}_3^-(\nu, \sqrt{1 - 2/3\gamma^2}) \right]$$

$$K_3 = \frac{(1 - \gamma^2)}{2(2\pi)^{3/2}(3 - 2\gamma^2)^3} \left[\gamma(3 - 2\gamma^2)^3 \mathcal{H}_1^+(\nu, \sqrt{1 - \gamma^2}) + \left(\frac{1}{2} \gamma^3(1 + \gamma^2 - 26\gamma^4 + 28\gamma^6 - 8\gamma^8) \langle x^3 \rangle \right. \right. \\ \left. - \gamma^4(26 - 28\gamma^2 + 8\gamma^4) \langle x^2 J_1 \rangle + \gamma(1 - \gamma^2)(1 + 2\gamma^2)(3 - 2\gamma^2)^2 \langle x q^2 \rangle - \gamma(24 - 26\gamma^2 + 8\gamma^4) \langle x J_1^2 \rangle \right. \\ \left. + \gamma(15 - 23\gamma^2 + 8\gamma^4) \langle x J_2 \rangle + 4(1 - \gamma^2)(3 - 2\gamma^2)^2 \langle q^2 J_1 \rangle - (10 - 12\gamma^2 + 4\gamma^4) \langle J_1^3 \rangle + 6(1 - \gamma^2)(2 - \gamma^2) \langle J_1 J_2 \rangle \right) \\ \left. - \frac{1}{6} (\gamma(27 + 36\gamma^2 - 224\gamma^4 + 192\gamma^6 - 48\gamma^8) \langle x^3 \rangle + (108 - 324\gamma^2 + 216\gamma^4 - 48\gamma^6) \langle x^2 J_1 \rangle \right. \\ \left. + 6\gamma(3 - 2\gamma^2)^3 \langle x q^2 \rangle - 36\gamma \langle x J_1^2 \rangle - 18\gamma \langle x J_2 \rangle - 8\gamma^2 \langle J_1^3 \rangle - 12\gamma^2 \langle J_1 J_2 \rangle \right) \mathcal{H}_2^+(\nu, \sqrt{1 - \gamma^2}) \right]$$

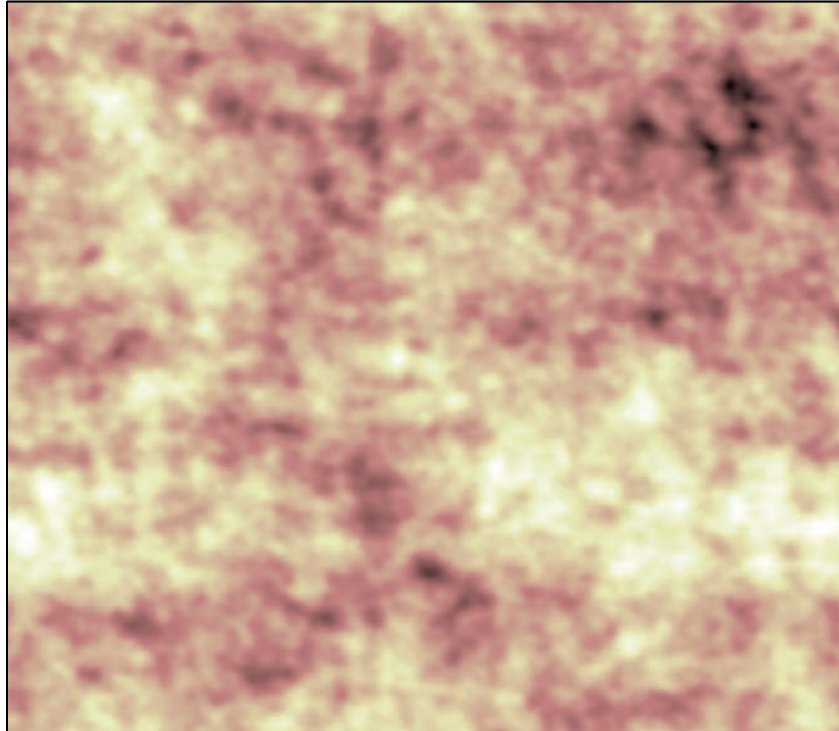
$$n_{\max/\min} = \frac{1}{8\sqrt{3}\pi R_*^2} \pm \frac{18\langle q^2 J_1 \rangle - 5\langle J_1^3 \rangle + 6\langle J_1 J_2 \rangle}{54\pi\sqrt{2\pi} R_*^2},$$

$$n_{\text{sad}} = \frac{1}{4\sqrt{3}\pi R_*^2}, \quad J_1 \equiv \lambda_1 + \lambda_2, \quad J_2 \equiv (\lambda_1 - \lambda_2)^2$$



Our Simulation

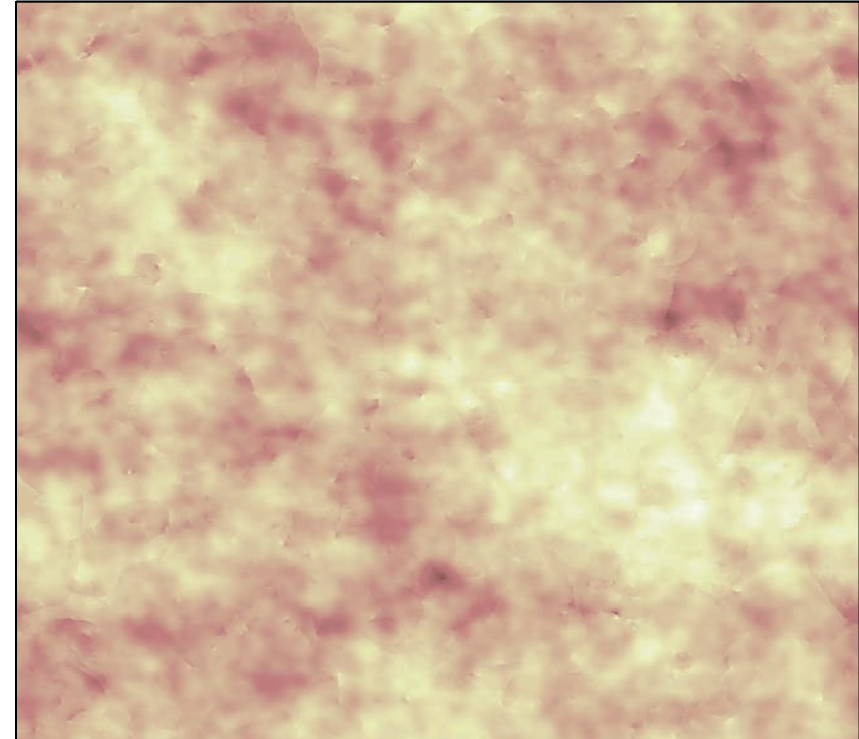
G

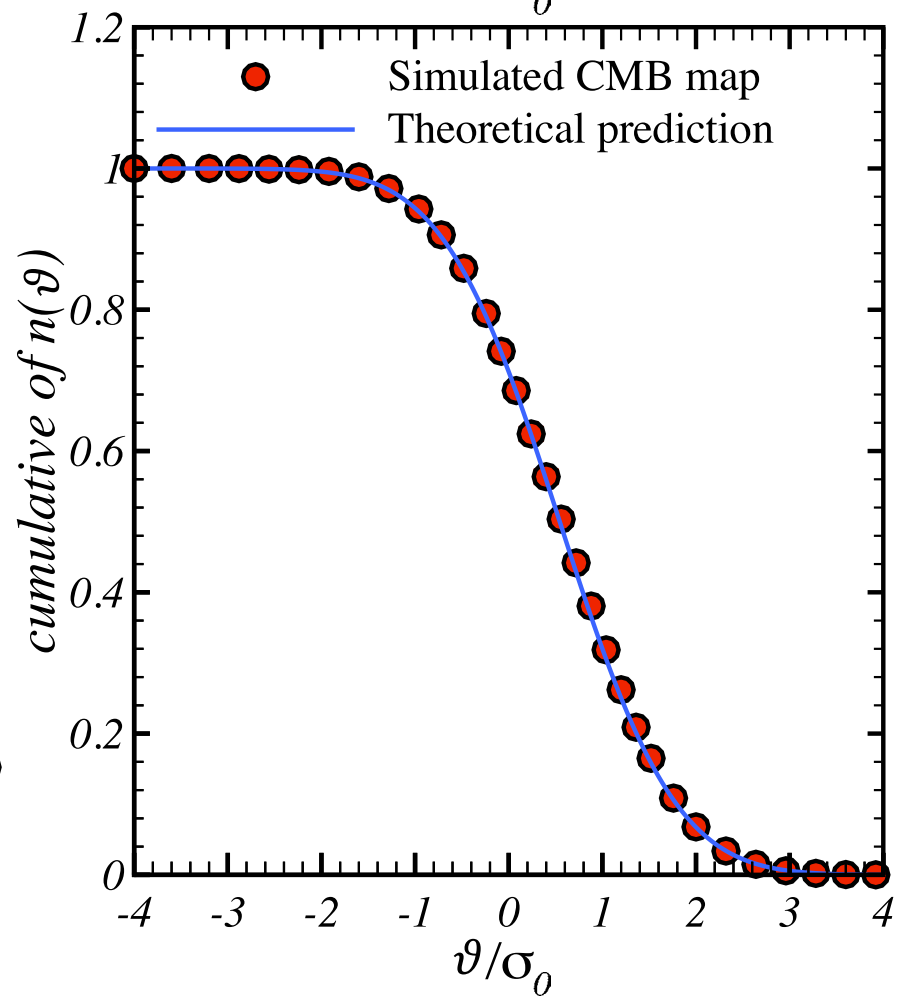
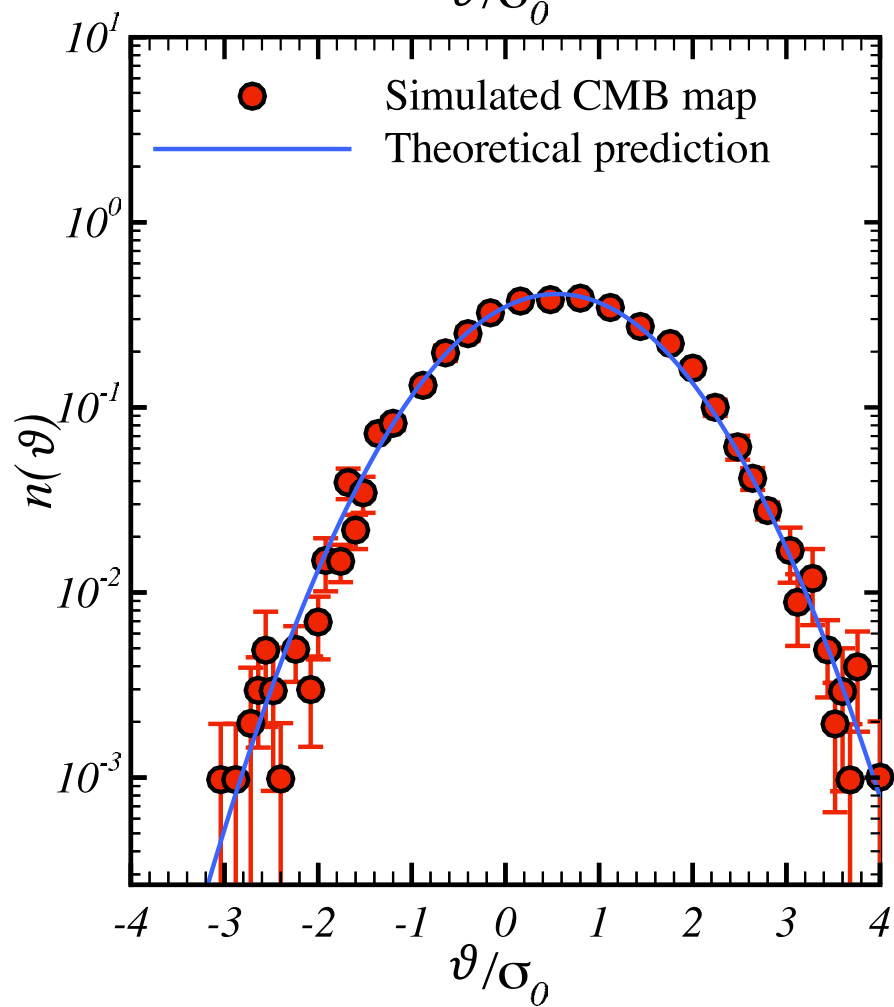
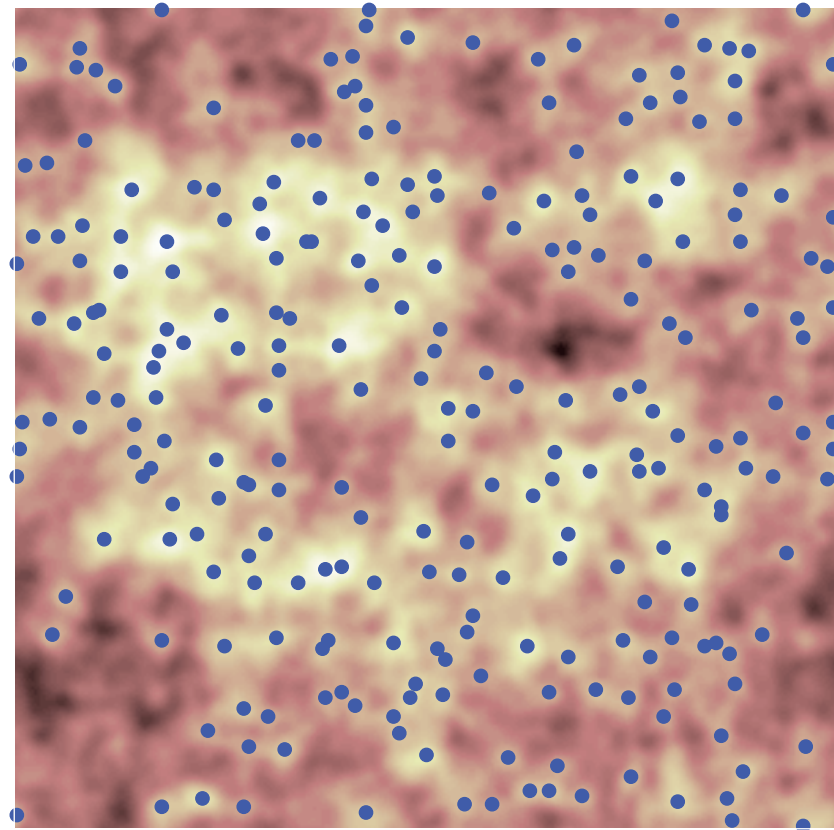
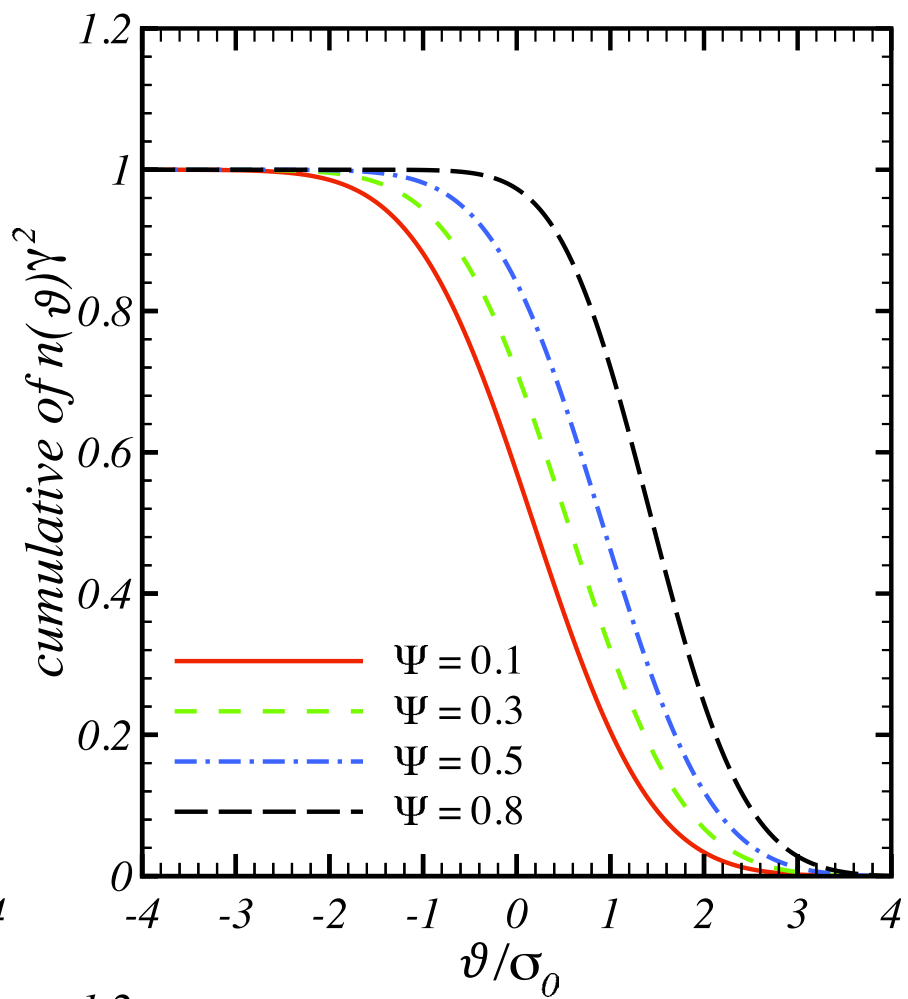
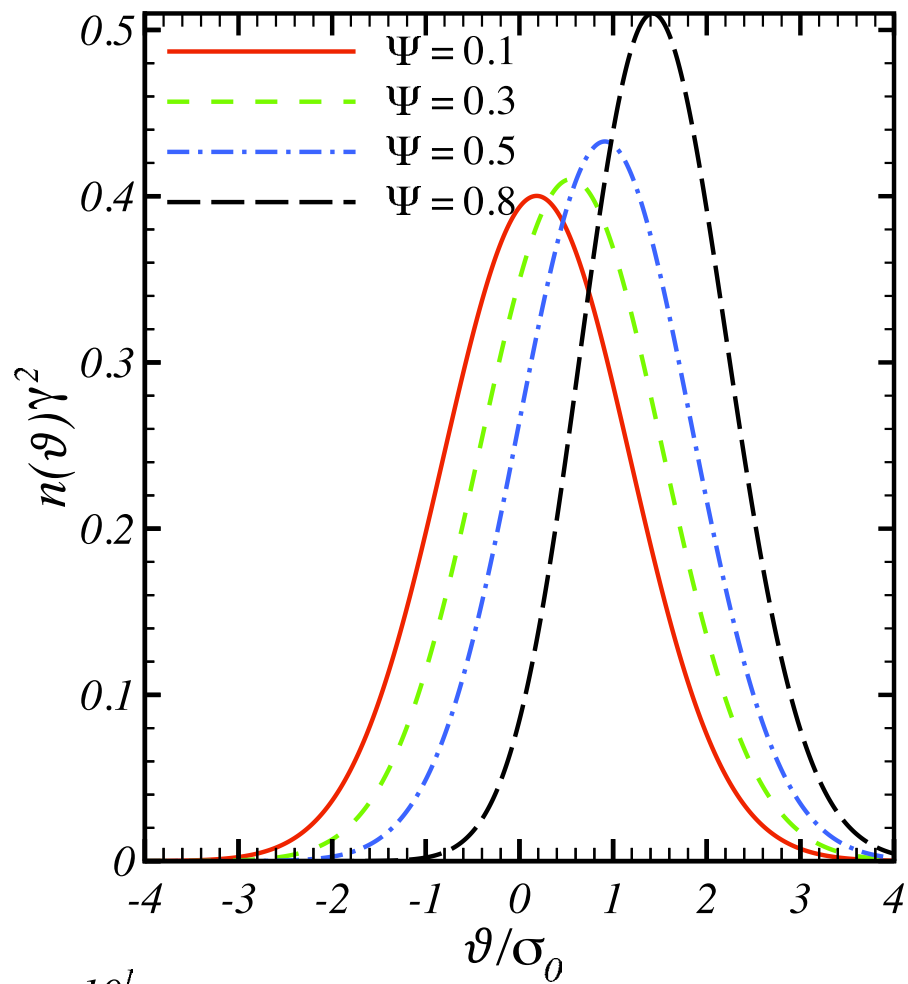


S



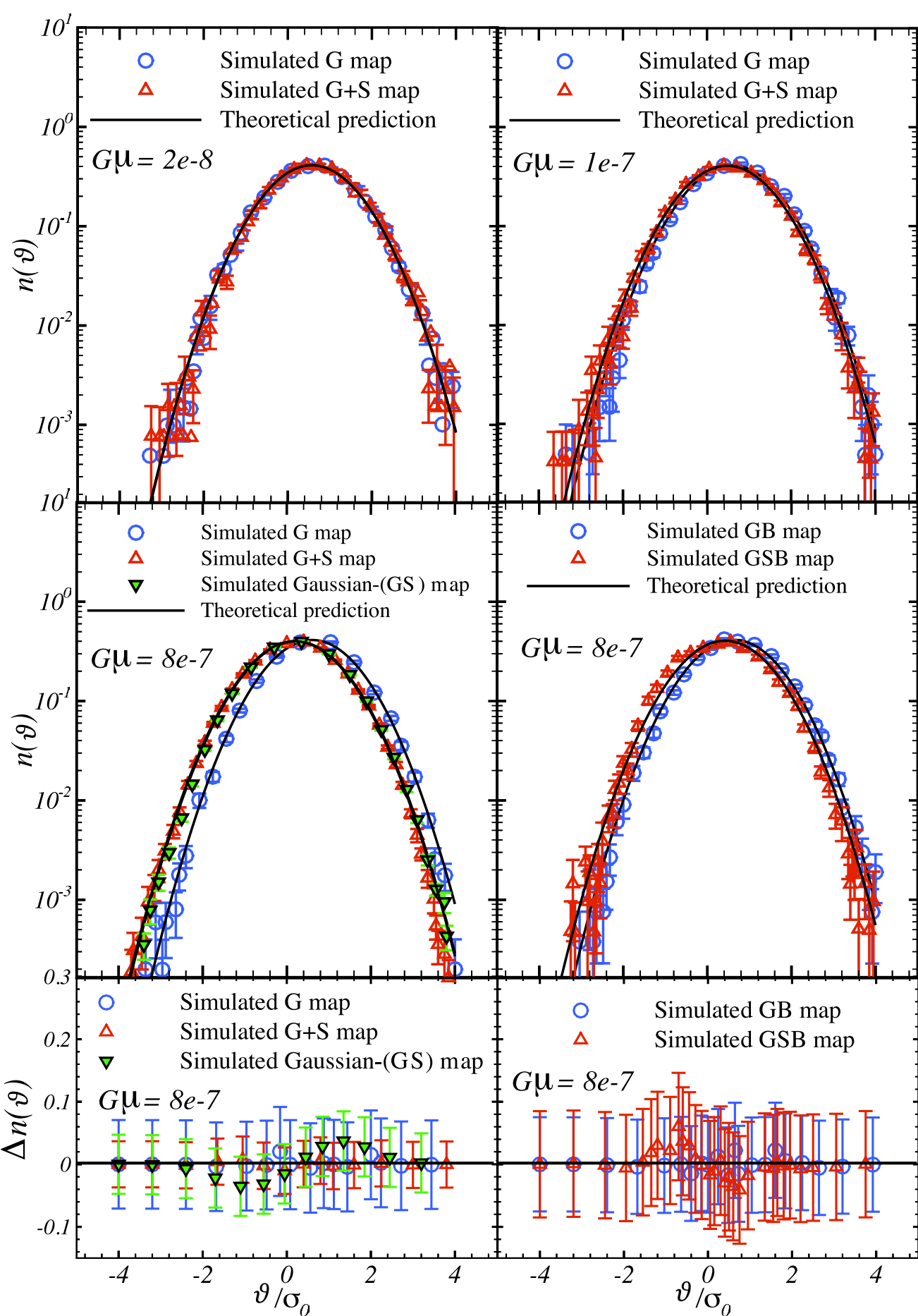
GS



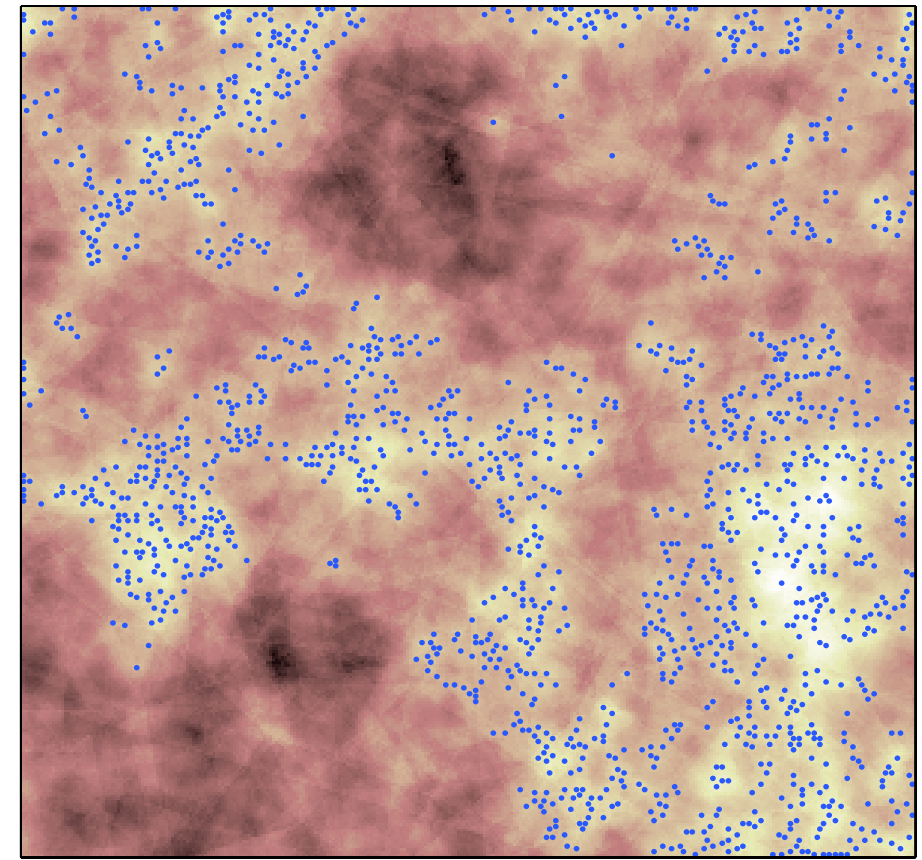


Number
density of
peaks

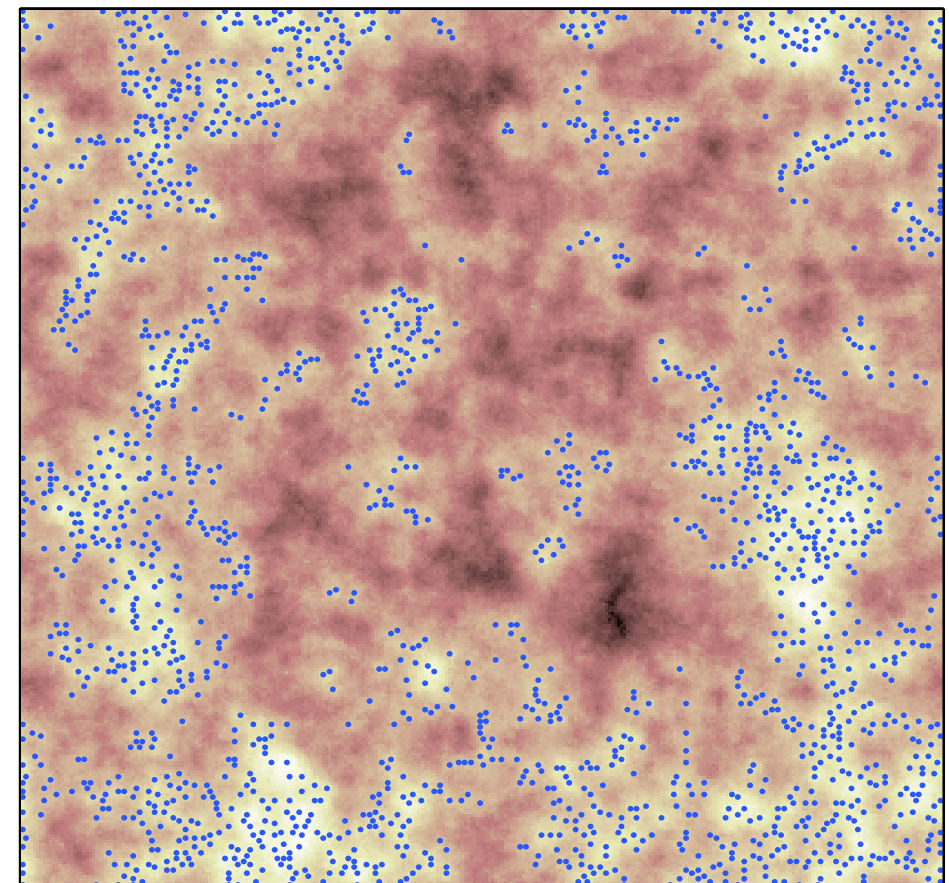
Number density analysis



$$\Delta n(\vartheta) \equiv n_{com.}(\vartheta) - n_{the.}(\vartheta)$$



Gaussian-GS



Theoretical approach for clustering (1+2D)

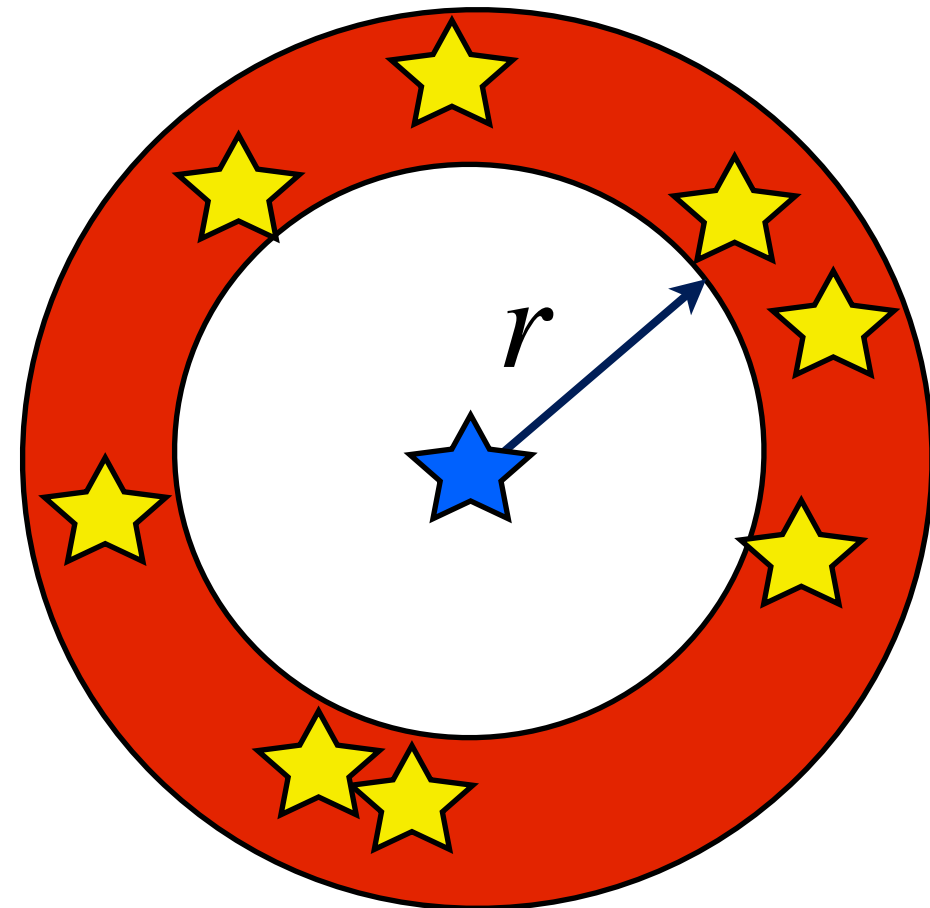
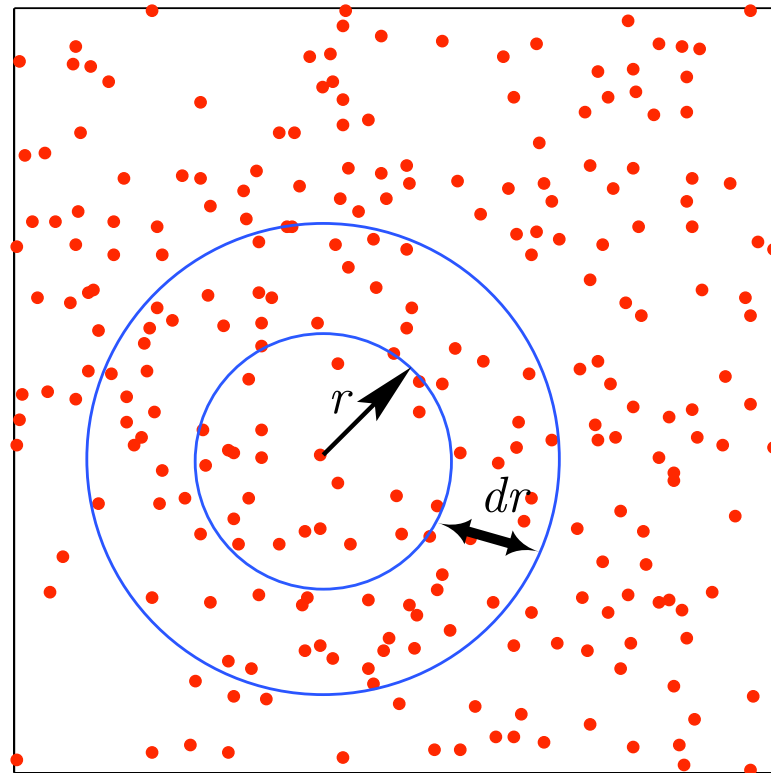
- Excess probability of finding a peak at a given distance from another relative to the probability for a uniform distribution of peaks (Peacock & Heavens and Peebles):

$$\Delta P_{12}(r) = n\Delta A_1 \times n\Delta A_2 \times (1 + \xi(r))$$

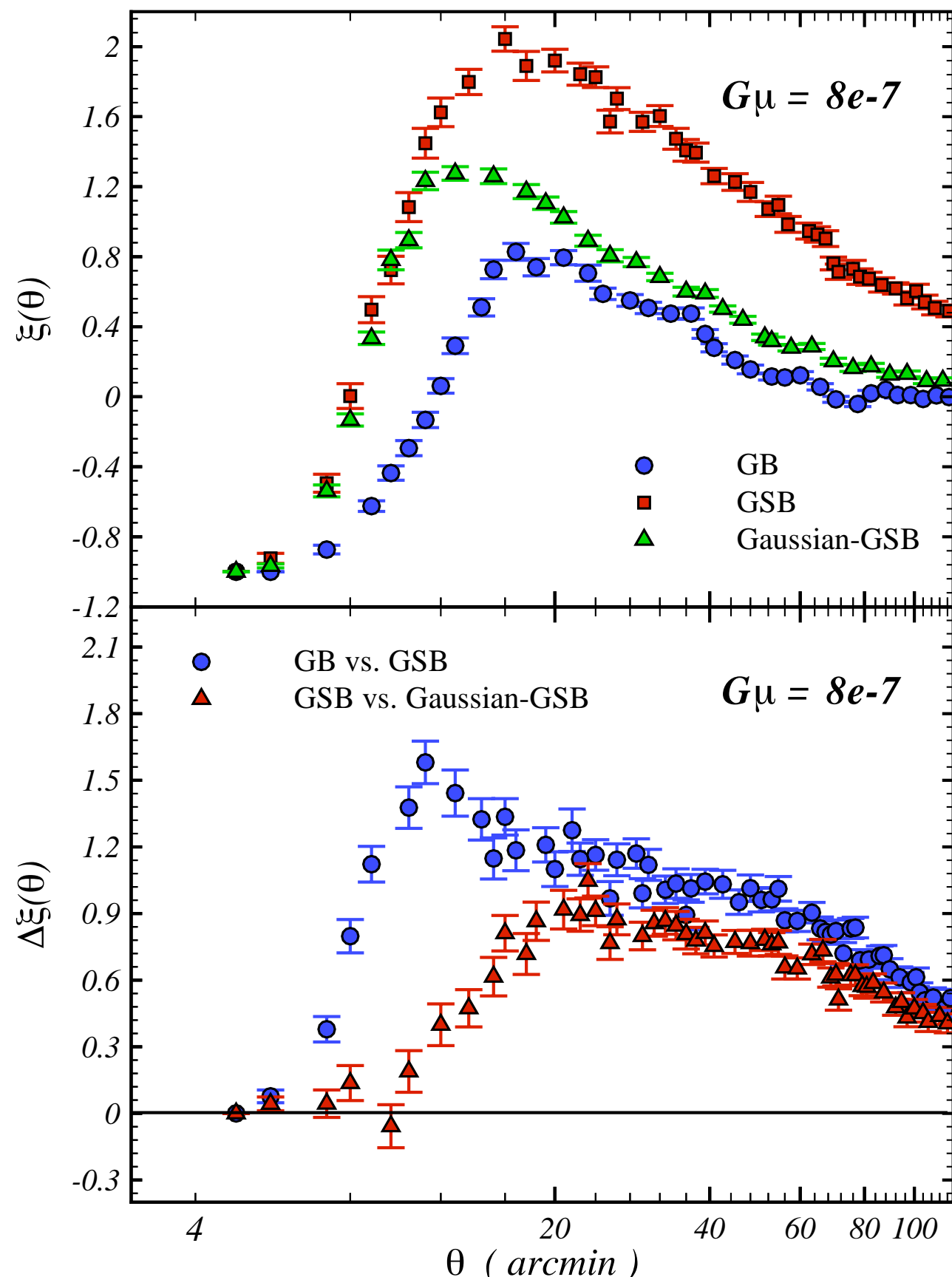
$$\Delta P_{12}(r) = n_{pair}\Delta A(r) \times (1 + \xi(r))$$

$$n_{pair} = \frac{M(M-1)}{2A} \sim \frac{M}{2}n$$

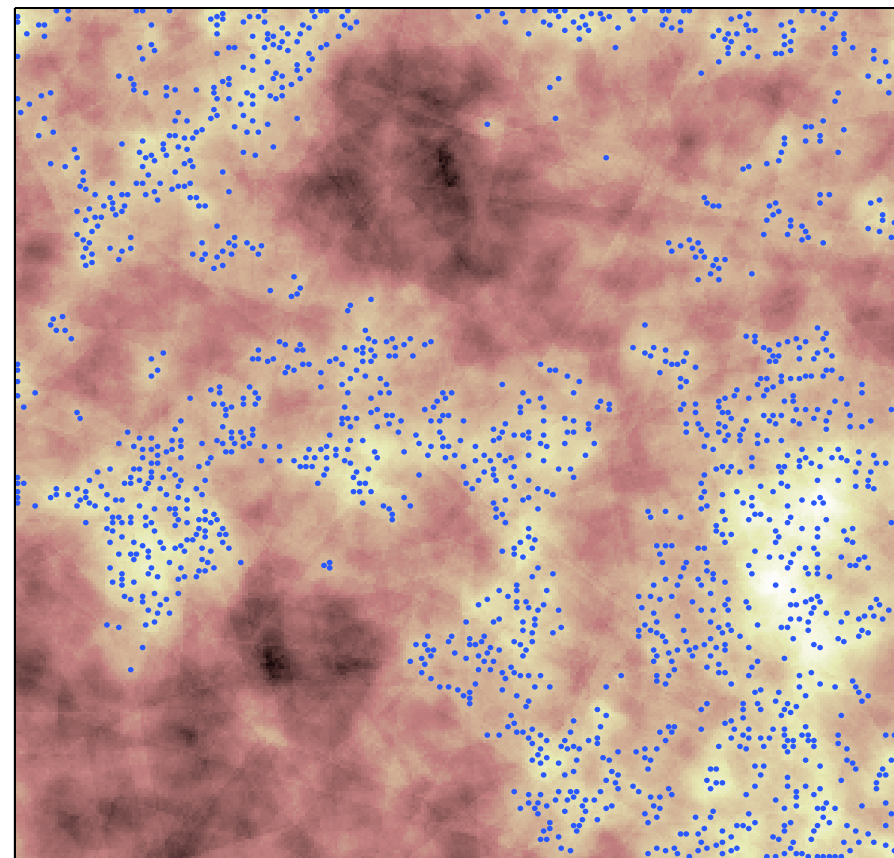
$$\xi(r) = \frac{\langle N \rangle_{pairs}}{n_{pair}2\pi r\Delta r} - 1$$



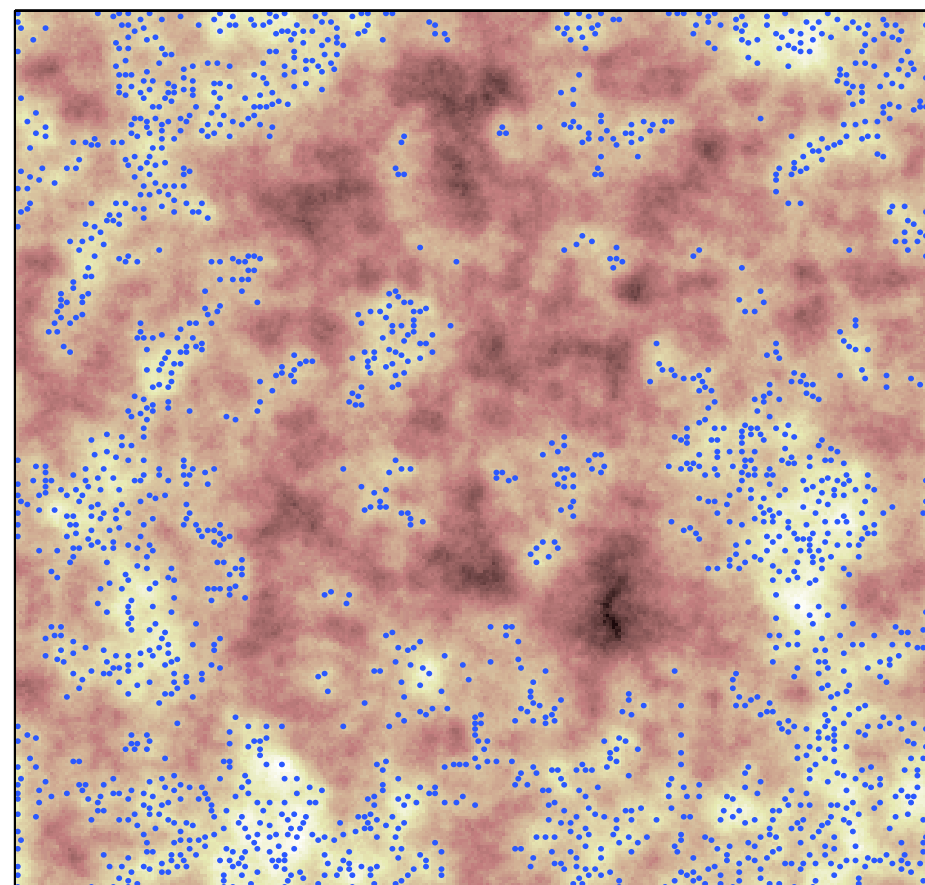
TPCF



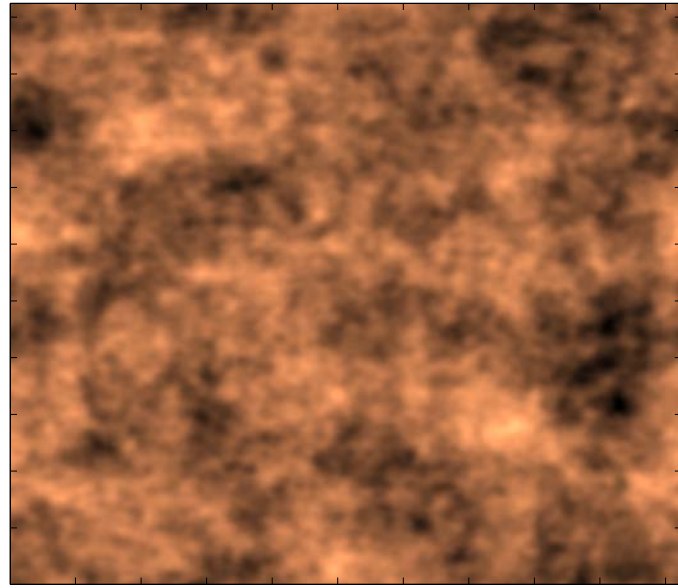
GS



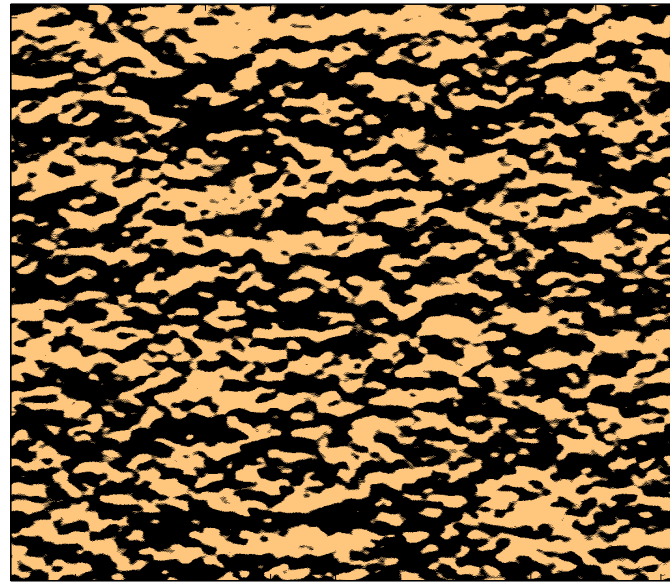
Gaussian-GS



Clustering of Up-Crossing



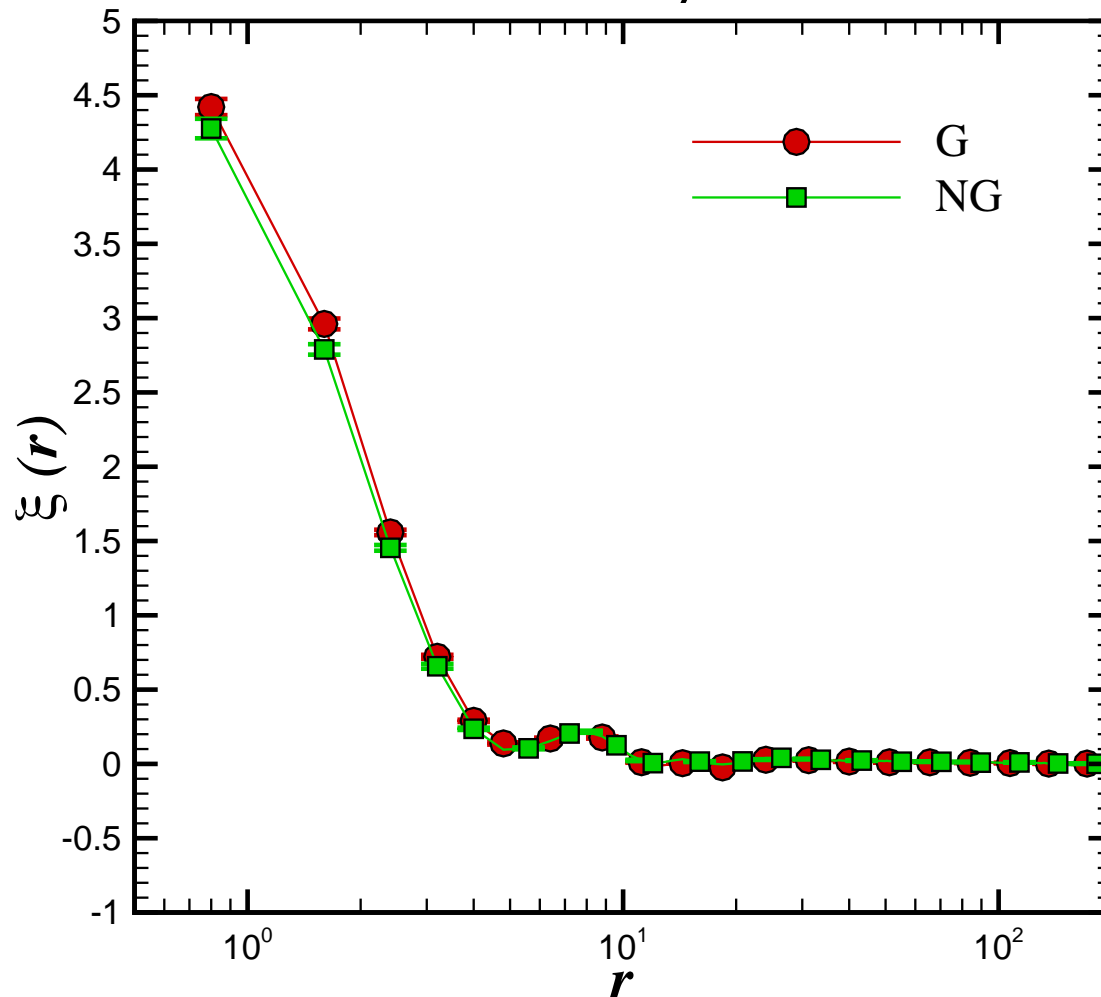
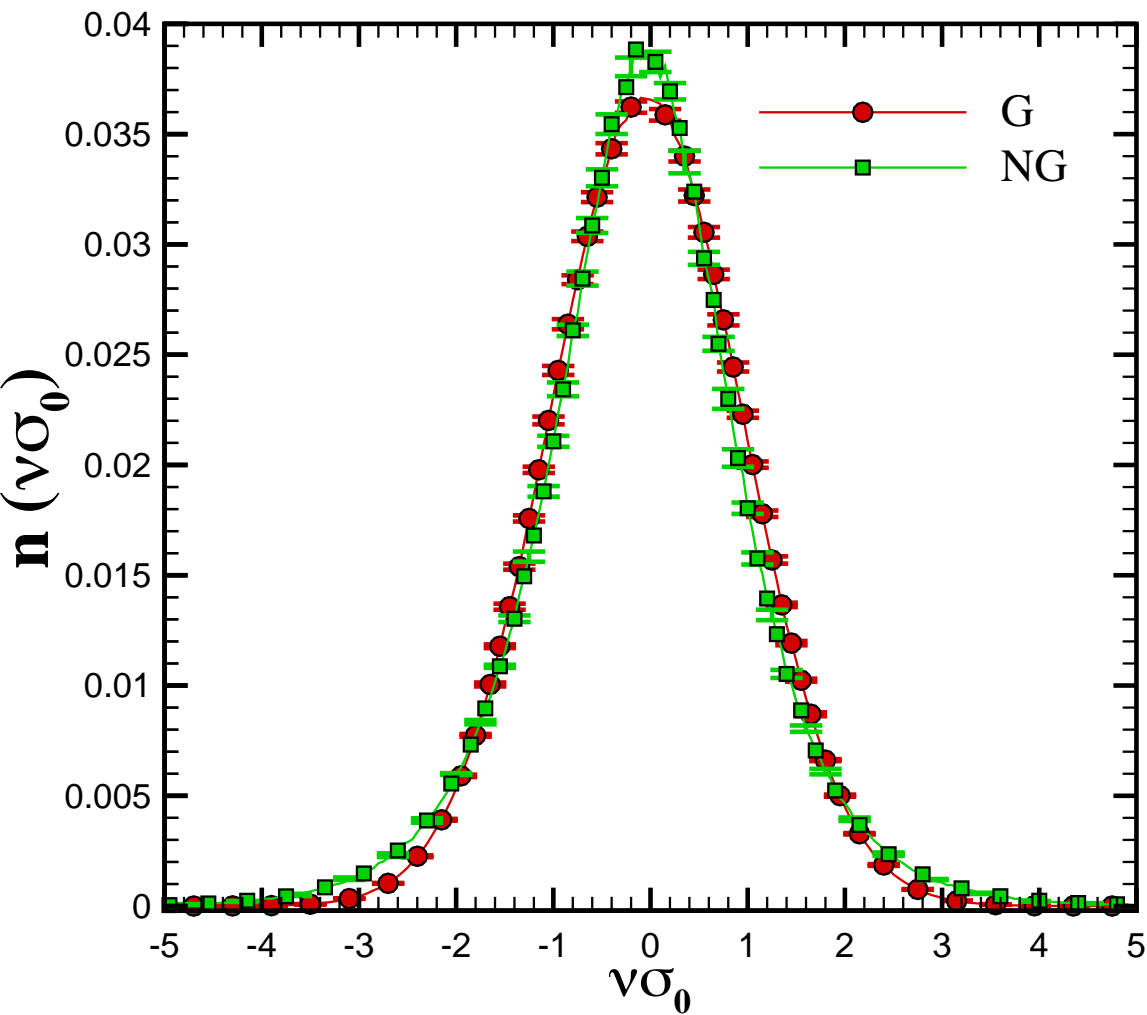
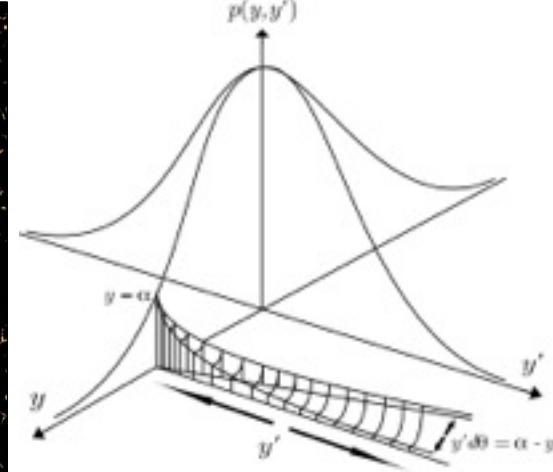
Gaussian field



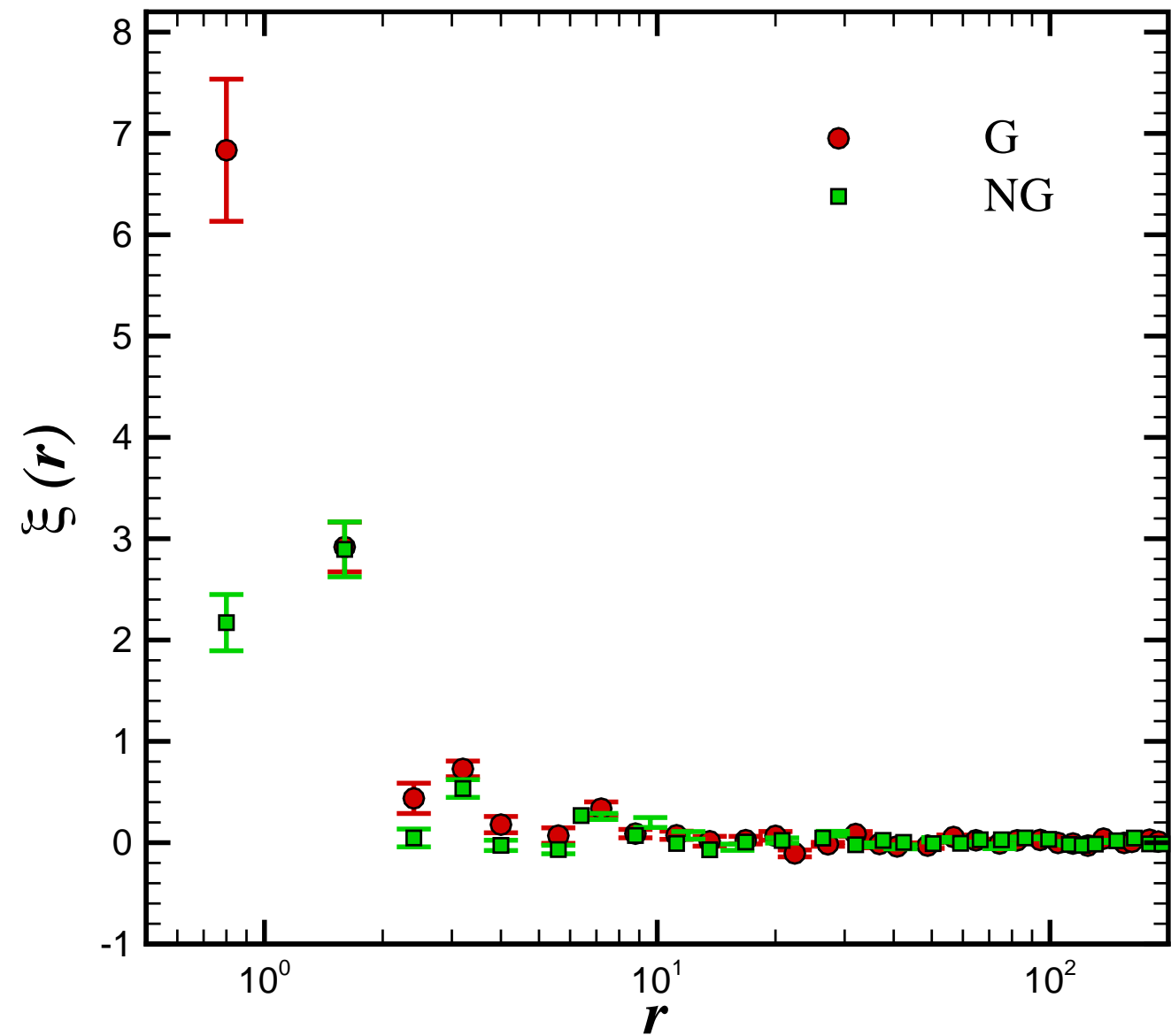
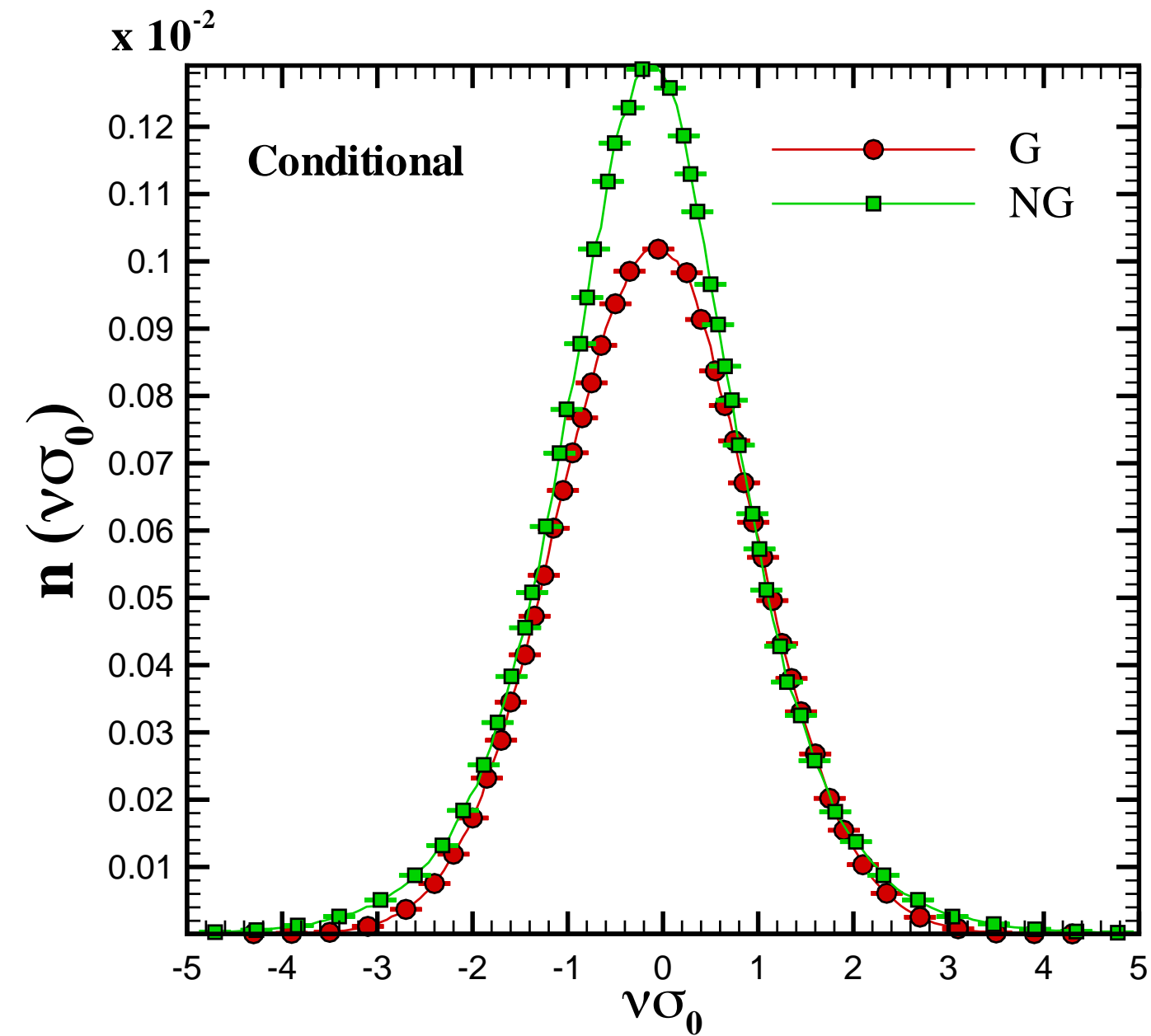
Cumulative of crossing in x



Cumulative of crossing in x with further condition in y direction



Clustering of Up-Crossing



Theoretical prediction

$$n_{up}(v) = \sum_u \delta_D(\vec{r} - \vec{r}_u)$$

$$\langle n_{up}(v) \rangle = \langle \delta_D(\vec{r} - \vec{r}_u) \rangle = \int dA_\mu P(A_\mu) \delta_D(\vec{r} - \vec{r}_u)$$

$$A_\mu = (F(\vec{r}), \eta_x(\vec{r}), \eta_y(\vec{r}), \xi_{xx}, \xi_{xy}, \xi_{yy})$$

$$F(\vec{r}) = F(r_u) + (r - r_u)_x \eta_x + \mathcal{O}(\delta r^2)$$

$$\eta_y(\vec{r}) \simeq (r - r_u)_y \xi_{xx}$$

$$\delta_D(F(\vec{r}) - F(r_u)) = \delta_D(x - x_u) |\eta_x|^{-1}$$

$$\delta_D(x - x_u) = |\eta_x| \delta_D(F(\vec{r}) - F(r_u))$$

$$\delta_D(y - y_u) = |\xi_{xx}| \delta_D(\eta_y)$$

$$\langle n_{up}(v) \rangle = \int dF d\eta_x d\eta_y d\vec{\xi} P(A_\mu) \delta_D(F - F(r_u)) |\eta_x| \delta_D(\eta_y) |\xi_{yy}|$$

$$= \langle \delta_D(F - v\sigma_x) |\eta_x| \delta_D(\eta_y) |\xi_{yy}| \rangle$$

Theoretical prediction

$$\langle n_{up}(r, \nu) n_{up}(r', \nu') \rangle \equiv \xi_{\nu\nu'}(\vec{r}, \vec{r}')$$

$$1 + \xi_{\nu\nu'}(\vec{r}, \vec{r}') = \frac{1}{n_{up}(r, \nu) n_{up}(r', \nu')} \int dA_{\mu_1} dA_{\mu_2} P(A_{\mu_1}, A_{\mu_2}) \Big|_{\text{Condition}}$$

For 2D : A_{μ} : $F(r), \gamma_x(r), \gamma_y(r), \xi_{xx}(r), \xi_{xy}(r), \xi_{yy}(r)$: 12-elements
 $F(r'), \gamma_x(r'), \gamma_y(r'), \xi_{xx}(r'), \xi_{xy}(r'), \xi_{yy}(r')$

To be Continued ...

Summary

- 1) Motivation regarding to Stochastic field
- 2) Perturbative expansion
- 3) Theoretical calculation of various features, e.g. extrema
- 4) Clustering and correlation function (Non-Gaussianity and Anisotropy)

Thank you