

(Gaussian) random fields

statistics and data analysis (chapter 12)

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outline

- 1 random fields
- 2 operations
- 3 matched filtering
- 4 deconvolution
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random fields

- consider a randomly fluctuating smooth field where the amplitude φ at position y depends on that at position x
- description with a probability density

$$p(\varphi(y), \varphi(x)) = p(\varphi(y)|\varphi(x)) \quad (1)$$

- examples
 - noise in an electric circuit
 - waves on the ocean surface
 - matter distribution in the universe

Gaussian random fields

- Gaussian probability density for the field amplitudes

$$p(\varphi(x), \varphi(y)) = \frac{1}{\sqrt{(2\pi)^2 \det C}} \exp \left(-\frac{1}{2} \begin{pmatrix} \varphi(x) \\ \varphi(y) \end{pmatrix}^t C^{-1} \begin{pmatrix} \varphi(x) \\ \varphi(y) \end{pmatrix} \right) \quad (2)$$

- with covariance

$$C = \begin{pmatrix} \langle \varphi(x)^2 \rangle & \langle \varphi(x)\varphi(y) \rangle \\ \langle \varphi(x)\varphi(y) \rangle & \langle \varphi(y)^2 \rangle \end{pmatrix} \quad (3)$$

- where $\langle \dots \rangle$ are ensemble averages with fixed positions x and y
- correlation function

$$\xi(x, y) = \langle \varphi(x)\varphi(y) \rangle \quad (4)$$

- obviously, $\langle \varphi(x)\varphi(y) \rangle \rightarrow \langle \varphi(x)^2 \rangle$ as $x \rightarrow y$
- think of $\langle \varphi(x)\varphi(y) \rangle$ as the memory of the field on its value at x

homogeneity

- Cauchy-Schwarz bound:

$$|\xi(x, y)| \leq \sqrt{\langle \varphi(x)^2 \rangle \langle \varphi(y)^2 \rangle} \quad (5)$$

making sure that $\det C \geq 0$

- separation of the Gaussian distribution occurs if $\langle \varphi(x) \varphi(y) \rangle = 0$
- **homogeneity of the random field**: statistical properties are identical everywhere, i.e. the correlation function does not depend on x , just on r :

$$\langle \varphi(x) \varphi(x + r) \rangle = \xi(r) \quad (6)$$

- for homogeneous fields, the Cauchy-Schwarz bound becomes:

$$|\xi(r)| \leq \langle \varphi(x)^2 \rangle = \sigma^2 \quad (7)$$

with a universal $\sigma^2 = \langle \varphi(x)^2 \rangle = \langle \varphi(y)^2 \rangle$

homogeneity

- homogeneous fields: $\sigma^2 = \langle \varphi(x)^2 \rangle = \langle \varphi(y)^2 \rangle$ and $\xi(r) = \langle \varphi(x)\varphi(x+r) \rangle$
- probability density

$$p(\varphi(x), \varphi(x+r)) = \frac{1}{\sqrt{(2\pi)^2 \det C}} \exp \left(-\frac{1}{2} \begin{pmatrix} \varphi(x) \\ \varphi(x+r) \end{pmatrix}^t C^{-1} \begin{pmatrix} \varphi(x) \\ \varphi(x+r) \end{pmatrix} \right) \quad (8)$$

- with covariance

$$C = \begin{pmatrix} \sigma^2 & \xi(r) \\ \xi(r) & \sigma^2 \end{pmatrix} \quad (9)$$

correlation functions and spectra

- spectrum of a random field: **only** for homogeneous fields
- Fourier-transform

$$\varphi(k) = \int dx \varphi(x) \exp(-ikx) \quad \leftrightarrow \quad \varphi(x) = \int dk \varphi(k) \exp(+ikx) \quad (10)$$

- is there a correlation between different Fourier-modes?

$$\langle \varphi(k) \varphi(k')^* \rangle = \int dx \int dx' \langle \varphi(x) \varphi(x') \rangle \exp(-ikx + ik'x') \quad (11)$$

- assume homogeneity: $x' = x + r$, $dx' = dr$ at fixed x :

$$= \int dx \int dr \langle \varphi(x) \varphi(x + r) \rangle \exp(-ikx + ik'x + ik'r) \quad (12)$$

correlation functions and spectra

- correlation function $\xi(r) = \langle \varphi(x) \varphi(x+r) \rangle$:

$$= \int dr \xi(r) \exp(ik'r) \int dx \exp(-i(k-k')x) \quad (13)$$

if the correlation function does not depend on position x

- dx -integration yields the Dirac- δ function

$$= \int dr \xi(r) \exp(ikr) \times 2\pi\delta_D(k-k') \quad (14)$$

- define **spectrum**:

$$C(k) = \int dr \xi(r) \exp(ikr) \quad (15)$$

as the Fourier-transform of the correlation function

- no correlation between Fourier-modes of a homogeneous random field:

$$\langle \varphi(k) \varphi(k') \rangle = 2\pi C(k) \delta_D(k-k') \quad (16)$$

random fields in more dimensions: isotropy

- derivation of the spectrum is identical in n dimensions:

$$C(k_i) = \int d^n r \xi(r_i) \exp(ik_j r_j) \quad (17)$$

- yields an identical orthogonality relation

$$\langle \varphi(k_i) \varphi(k'_i) \rangle = (2\pi)^n C(k_i) \delta_D(k_i - k'_i) \quad (18)$$

- if the field is isotropic, the spectra for different k_i are identical, so C depends only on the modulus $\sqrt{k_i k_i}$

units of spectra and correlation functions

- assume that φ has the unit A , which is some combination of length, time, mass and temperature
- correlation function

$$\xi(r) = \langle \varphi(x) \varphi(x+r) \rangle \quad (19)$$

as units of A^2

- then, $\varphi(k)$ has units of AL^n in n dimensions
- the Dirac- δ function has units of L^n , because $\int d^n x \delta_D(x) = 1$
- collect all results:

$$\underbrace{\langle \varphi(k) }_{AL^n} \underbrace{\varphi(k') \rangle}_{AL^n} \propto C(k) \underbrace{\delta_D(k-k')}_{L^n} \quad (20)$$

such that $C(k)$ needs to have units of $A^2 L^n$

operations on random fields: smoothing

- smoothing: by convolution with a convolution kernel p :

$$\varphi(\bar{x}) = \int dy \varphi(y) p(x - y) = \int dy \varphi(x - y) p(y) = \varphi * p \quad (21)$$

- slide p over the field φ and average around x weighted by p
- $p(x)$ is normalised, $\int dx p(x) = 1$
- the property

$$\int dy \varphi(y) \delta_D(x - y) = \varphi(x) \quad (22)$$

is defined through convolution, in particular with $\int dy \delta_D(y) = 1$

- properties of convolutions
 - $\varphi * p = p * \varphi$
 - $\varphi * (p * q) = (\varphi * p) * q$
 - $\varphi * (\alpha p + \beta q) = \alpha \varphi * p + \beta \varphi * q$

convolutions in Fourier-space

- convolutions in real space are products in Fourier-space:

$$\varphi * p = \int dy \varphi(x-y)p(y) \quad (23)$$

$$= \int dy \int dk \varphi(k) \exp(ik(x-y)) \int dk' p(k') \exp(ik'y) \quad (24)$$

$$= \int dy \int dk \varphi(k)p(k') \int dk' \exp(ikx) \exp(i(k-k')y) \quad (25)$$

$$= \int dk \int dk' \varphi(k)p(k') \exp(ikx) \delta_D(k-k') \quad (26)$$

$$= \int dk \varphi(k)p(k') \exp(ikx) \quad (27)$$

- Fourier-transform is symmetric: convolutions in Fourier-space are products in real space

correlation

- correlation with **lag** y :

$$\varphi \times \varphi = \int dx \varphi(x) \varphi(x + y) \quad (28)$$

- estimate for an **ergodic** process:

$$\varphi \times \varphi \simeq \lim_{y \rightarrow \infty} \frac{1}{y} \int_0^y dx \varphi(x) \varphi(x + y) \quad (29)$$

- correlations in Fourier-space

$$\varphi \times \varphi = \int dx \varphi(x) \varphi(x + y) \quad (30)$$

$$= \int dx \int dk \varphi(k) \exp(ikx) \int dk' \varphi(k') \exp(ik'(x + y)) \quad (31)$$

$$= \int dk \int dk' \varphi(k) \varphi(k')^* \exp(i(k - k')x) \exp(-ik'y) \quad (32)$$

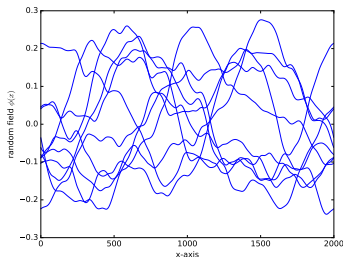
$$= \int dk \varphi(k) \varphi(k)^* \exp(iky) \quad (33)$$

generation of a (homogeneous) random field

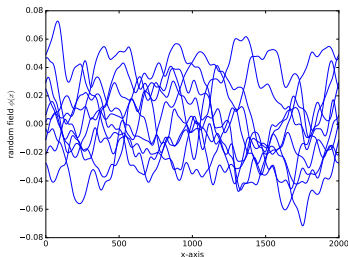
- use the fact that Fourier-modes of homogeneous random fields are independent
- and that the variance in Fourier-space is the spectrum $C(k)$
- algorithm:
 - draw Gaussian random numbers for $\varphi(k)$ on a grid in Fourier-space
 - from a distribution with $\langle \varphi(k) \rangle = 0$ and $\langle \varphi(k)^2 \rangle = C(k)$
 - impose hermiticity: $\varphi(k)^* = \varphi(-k)$ for a real-valued field
 - Fourier-transform into real space

$$\varphi(x) = \int \frac{dk}{2\pi} \varphi(k) \exp(+ikx) \quad (34)$$

examples of Gaussian random fields



$$C(k) \propto k^{-2}$$

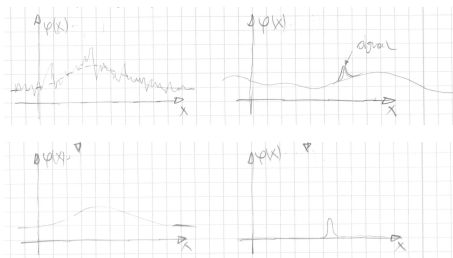


$$C(k) \propto k^{-1}$$

- 10 realisations of Gaussian random fields (different phases)

matched filtering: idea

- matched filtering: find weak signal **with known shape** in noisy data:
 - high-frequency noise on top of a slowly varying signal: low-pass
 - small-scale signal on top of a slowly varying background: high-pass



- should be possible if signal and noise look differently in Fourier-space, two competing effects: lowering of the noise φ vs. dispersing the signal a

construction of a matched filter

- filter p should operate by convolution on a field $\varphi(x)$ where the signal is hidden

$$\varphi'(x) = \int dy \varphi(y)p(x-y) \quad \leftrightarrow \quad \varphi'(k) = p(k)\varphi(k) \quad (35)$$

- require
 - the convolved field should on average conserve the amplitude of the signal:

$$\langle \varphi' \rangle = A \int dk a(k)p(k) \quad (36)$$

with the signal strength A and the signal profile $a(x)$

- noise fluctuations σ^2 are minimised

$$\langle (\varphi' - \langle \varphi' \rangle)^2 \rangle = \sigma^2 = \int dk p^2(k)C(k) \quad (37)$$

derivation by variation

- $\sigma^2[p]$ is a functional which maps the function p onto a number
- it's possible to optimise $\sigma^2[p]$ for being as small as possible, because then, the signal stands out
- one needs an additional assumption: clearly, the smallest σ^2 is obtained by setting $p = 0$, but then the signal is lost as well
- require unbiasedness

$$\langle \varphi' \rangle = A \int dk a(k)p(k) = \mu \quad (38)$$

when performing the variation for minimising the noise

- introduce unbiasedness with a Lagrange-multiplier:

$$\sigma^2[p] \rightarrow \sigma^2[p] + \lambda G[p] \quad \text{with} \quad G[p] = A \int dk a(k)p(k) - \mu \quad (39)$$

derivation by variation

- variation:

$$\frac{d\sigma^2}{dp} + \lambda \frac{dG}{dp} = 0 = \int dk (2pC(k) + \lambda Aa) \rightarrow p = -\frac{\lambda}{2} \frac{a(k)}{C(k)} \quad (40)$$

if one assumes a signal profile $a(k)$ and a noise spectrum $C(k)$

- λ is determined by the boundary conditions
- if the true profile or the noise spectrum are different, the signal is not enhanced

deconvolution

- convolution is an averaging process, so it is not possible to recover the original field φ from the convolved field $\varphi' = \varphi * p$
- it is **not possible** to divide out the filter in the Fourier-expression $\varphi' = \varphi p \rightarrow \varphi = \varphi' / p$ because the Fourier-transform of the filter is zero somewhere
- deconvolution can only be done approximatively

van Cittert deconvolution

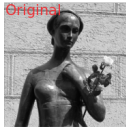
- idea: control noise by iterative partial deconvolution, and stop at the right moment
- $\varphi = \varphi' p^{-1}$ inverts $\varphi' = \varphi p$
- introduce $\bar{p} = 1 - p$,
- use the geometric series:

$$\varphi = \frac{\varphi'}{p} = \frac{\varphi'}{1 - \bar{p}} \simeq \varphi' (1 + \bar{p} + \bar{p}^2 + \dots) = \varphi' (1 + \bar{p}(1 + \bar{p}(\dots))) \quad (41)$$

and rewrite it as a "telescopic" sums

- then, define an iterative procedure:
 - $\varphi_0 = \varphi'$ starting point is the noisy signal
 - $\varphi_{n+1} = \varphi' + (1 - p)\varphi_n$

van Cittert deconvolution



Van-Cittert-Iterationen:



van Cittert deconvolution (source: wikipedia)

- picks up artefacts if n is too large

summary

- random fields are a generalisation to random variables, they're indexed by position
- correlation of field amplitudes given by correlation function
- homogeneous random fields have uncorrelated Fourier-modes
- convolutions and correlations can be carried out in Fourier-space
- filtering lets you search for a signal of known shape
- deconvolution is possible in an approximate way