

Lecture 1: Aspects of probability theory.

Gaussian Random Fields. (ref: Wandelt 2013)

• Definition: $f(x|\mu, C) = \frac{1}{\sqrt{|2\pi C|}} \exp\left(-\frac{1}{2}(x-\mu)^* C^{-1}(x-\mu)\right)$.

• Integration by differentiation:

$$\langle x \rangle = \mu \quad \text{from solving } \partial_x (\ln f(x|\mu, C)) = 0.$$

$$\langle (x-\mu)^*(x-\mu) \rangle = C \quad \text{from } \partial_x^2 (\ln f(x|\mu, C)) = -C^{-1}.$$

• Generating a GRF:

- draw white noise ξ .

- find the square root of C : \sqrt{C} (any such matrix works).

$$x = \sqrt{C} \xi + \mu.$$

Notebook: **GRF and JNL**

• Higher-order moments of GRFs:

- any odd moment is 0: $\langle x_1 x_2 x_3 \rangle = 0$ $\langle x_1 x_2 x_3 x_4 x_5 \rangle = 0$.

- even moments by Wick's theorem:

$$\langle x_1 x_2 x_3 x_4 \rangle = \langle x_1 x_2 \rangle \langle x_3 x_4 \rangle + \langle x_1 x_3 \rangle \langle x_2 x_4 \rangle + \langle x_1 x_4 \rangle \langle x_2 x_3 \rangle$$
$$= C_{12} C_{34} + C_{13} C_{24} + C_{14} C_{23}.$$

• Marginals:

$$\lambda = \begin{pmatrix} \lambda_x \\ \lambda_y \end{pmatrix} \quad \mu = \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix} \quad C = \begin{pmatrix} C_{xx} & C_{xy} \\ C_{yx} & C_{yy} \end{pmatrix}$$

GRF. (μ, C) .

$$\text{Then: } \langle \lambda_x \rangle = \mu_x.$$

$$\langle (\lambda_x - \mu_x)^* (\lambda_x - \mu_x) \rangle = C_{xx}$$

$$\langle \lambda_y \rangle = \mu_y.$$

$$\langle (\lambda_y - \mu_y)^* (\lambda_y - \mu_y) \rangle = C_{yy}.$$

The marginal means and covariances are just the corresponding parts of the joint mean and covariance.

• Conditionals:

$$\mu_{x|y} \equiv \langle \lambda_x | \lambda_y \rangle = \mu_x + C_{xy} C_{yy}^{-1} (\lambda_y - \mu_y)$$

$$C_{x|y} \equiv \langle (\lambda_x - \mu_x)^* (\lambda_x - \mu_x) | \lambda_y \rangle = C_{xx} - C_{xy} C_{yy}^{-1} C_{yx}$$

$$\mu_{y|x} \equiv \langle \lambda_y | \lambda_x \rangle = \mu_y + C_{yx} C_{xx}^{-1} (\lambda_x - \mu_x)$$

$$C_{y|x} \equiv \langle (\lambda_y - \mu_y)^* (\lambda_y - \mu_y) | \lambda_x \rangle = C_{yy} - C_{yx} C_{xx}^{-1} C_{xy}$$

demonstration: see e.g. Appendix A in Lecture 2015.
(arXiv: 1512.04385)

• Wiener Filtering: Denoising. data model: $d = s + m$. d, s, m are GRFs.

joint GRF: $g = \begin{pmatrix} d \\ s \end{pmatrix}$

assumptions: $\mu_d = \mu_s = \mu_m = 0$.

$$C_{sm} = C_{ms}^* = 0$$

$$\Rightarrow \begin{cases} C_{sd} = C_{ss} + C_{sm} = C_{ss} \\ C_{dd} = C_{ss} + C_{mm} \end{cases}$$

$$\begin{pmatrix} C_{ss} \equiv S \\ C_{mm} \equiv N \end{pmatrix}$$

WF equations: $\mu_{s|d} = C_{ss} (C_{ss} + C_{mm})^{-1} d = S (S + N)^{-1} d$
 $C_{s|d} = C_{ss} - C_{ss} (C_{ss} + C_{mm})^{-1} C_{ss} = S - S(S + N)^{-1} S$

other forms: $\mu_{s|d} = (S^{-1} + N^{-1})^{-1} N^{-1} d = S (\mathbb{1} + N^{-1} S)^{-1} N^{-1} d$

(check it)

$$C_{s|d} = (N^{-1} + S^{-1})^{-1} = S^{\frac{1}{2}} (\mathbb{1} + S^{\frac{1}{2}} N^{-1} S^{\frac{1}{2}})^{-1} S^{\frac{1}{2}}$$

Notebook: **Denoising** & **Denoising (CTB)**

• Wiener Filtering: Deblending. data model: $d = \begin{pmatrix} x_1 \\ x_2 \\ 0 \end{pmatrix} \text{ to } \begin{pmatrix} 0 \\ x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} m_1 \\ m_2 \\ m_3 \end{pmatrix}$

$$C_{x_1 d} = \begin{pmatrix} C_{x_1 x_1} & C_{x_1 x_2} & 0 \\ C_{x_1 x_1} + C_{m_1 m_1} & C_{x_1 x_1} & 0 \\ C_{x_1 x_1} & C_{x_1 x_1} + C_{x_2 x_2} + C_{m_2 m_2} & C_{x_2 x_2} \\ 0 & C_{x_2 x_2} & C_{x_2 x_2} + C_{m_3 m_3} \end{pmatrix}$$

$$C_{x_2 d} = \begin{pmatrix} 0 & C_{x_2 x_2} & C_{x_2 x_2} \\ 0 & C_{x_2 x_2} & C_{x_2 x_2} \\ 0 & C_{x_2 x_2} & C_{x_2 x_2} + C_{m_3 m_3} \end{pmatrix}$$

Notebook:

$$\mu_{x_1|d} = C_{x_1 d} C_{dd}^{-1} d$$

$$\mu_{x_2|d} = C_{x_2 d} C_{dd}^{-1} d$$

$$C_{x_1|d} = C_{x_1 x_1} - C_{x_1 d} C_{dd}^{-1} C_{d x_1}$$

$$C_{x_2|d} = C_{x_2 x_2} - C_{x_2 d} C_{dd}^{-1} C_{d x_2}$$

Deblending