

## Revision sheet

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### Part 1. Point referenced data / Geostatistics

**Exercise 1.** Consider the Gaussian c.f.  $c(h) = \sigma^2 \exp(-\beta \|h\|_2^2)$  for  $\sigma^2, \beta > 0$  and  $h \in \mathbb{R}^d$ . Compute the spectral density from Bochner's theorem

**Solution.** It is

$$\begin{aligned}
 f(\omega) &= \left(\frac{1}{2\pi}\right)^d \int_{\mathbb{R}^d} \exp(-i\omega^\top h) \sigma^2 \exp(-\beta \|h\|_2^2) dh \\
 &= \sigma^2 \left(\frac{1}{2\pi}\right)^d \prod_{j=1}^d \int_{\mathbb{R}} \exp(-i\omega_j h_j - \beta h_j^2) dh \\
 &= \sigma^2 \left(\frac{1}{2\pi}\right)^d \prod_{j=1}^d \left( \int_{\mathbb{R}} \exp(-\beta (h_j - (-i\omega_j/(2\beta)))^2) dh_j \exp(-\omega_j^2/(4\beta)) \right) \\
 &= \sigma^2 \left(\frac{1}{4\pi\beta}\right)^{d/2} \exp(-\|\omega\|_2^2/(4\beta))
 \end{aligned}$$

**Exercise 2.** Let  $(Z_s)_{s \in \mathcal{S}}$  be a specified statistical model. Assume that process  $(Z_s)_{s \in \mathcal{S}}$  has known mean  $\mu(s) = E(Z(s))$  and known covariance function  $c(\cdot, \cdot)$ . Assume there is available a dataset  $\{(s_i, Z_i := Z(s_i))\}_{i=1}^n$ . Assume that the matrix  $C$  such as  $[C]_{i,j} = c(s_i, s_j)$  has an inverse. Consider the “Kriging” estimator  $\mu_{\text{SK}}$ . Consider the “Kriging” estimator  $Z_{\text{SK}}(s_0)$  of  $Z(s_0)$  at an unseen spatial location  $s_0$  as the BLUE (Best Linear Unbiased Estimator)

$$Z_{\text{SK}}(s_0) = w_{n+1} + \sum_{i=1}^n w_i Z(s_i) = w_{n+1} + w^\top Z,$$

for some unknown  $\{w_i\}$  that we need to learn, and  $Z = (Z_1, \dots, Z_n)^\top$ . Let  $w = (w_1, \dots, w_n)^\top$ .

- (1) Find sufficient conditions on  $w = (w_1, \dots, w_n)^\top$  so that the Kriging estimator  $Z_{\text{SK}}(s_0)$  to be unbiased.
- (2) Derive the MSE of  $Z_{\text{SK}}(s_0)$  as

$$E(Z_{\text{SK}}(s_0) - Z(s_0))^2 = w^\top C w + c(s_0, s_0) - 2w^\top C_0$$

where  $C_0$  is a vector such as  $[C_0]_i = c(s_0, s_i)$ .

(3) Derive the Kriging estimator of  $Z(s_0)$  as

$$Z_{\text{SK}}(s_0) = \mu(s_0) + C_0^\top C^{-1} [Z - \mu(s_{1:n})]$$

where  $\mu(s_{1:n})$  is a vector such as  $[\mu(s_{1:n})]_i = \mu(s_i)$ .

(4) Compute the Kriging standard error  $\sigma_{\text{SK}} = \sqrt{\text{E}(Z_{\text{SK}}(s_0) - Z(s_0))^2}$ .

**Solution.** The method is called Simple Kriging, and hence we denote it as SK.

(1) It is

$$Z_{\text{SK}}(s_0) = w_{n+1} + \sum_{i=1}^n w_i Z(s_i) = w_{n+1} + w^\top Z,$$

where  $\{w_i\}$  is a set of unknown weights to be learned.

We assume that assume zero systematic error (unbiasness), hence

$$\text{E}(Z_{\text{SK}}(s_0) - Z(s_0)) = \text{E}\left(w_{n+1} + \sum_{i=1}^n w_i Z(s_i) - Z(s_0)\right) = w_{n+1} + \sum_{i=1}^n w_i \mu(s_i) - \mu(s_0)$$

which is satisfied given the assumption

$$w_{n+1} = \mu(s_0) - \sum_{i=1}^n w_i \mu(s_i) \iff w_{n+1} = \mu(s_0) - w^\top \mu(s_{1:n})$$

where  $w = (w_1, \dots, w_n)^\top$ .

(2) It is

$$\begin{aligned} \text{E}(Z_{\text{SK}}(s_0) - Z(s_0))^2 &= \text{Var}(Z_{\text{SK}}(s_0) - Z(s_0)) = \text{Var}(w_{n+1} + w^\top Z - Z(s_0)) \\ &= \text{Var}(w_{n+1} + w^\top Z) + \text{Var}(Z(s_0)) - 2\text{Cov}(w_{n+1} + w^\top Z, Z(s_0)) \\ &= w^\top C w + c(s_0, s_0) - 2w^\top \text{Cov}(Z, Z(s_0)) \\ &= w^\top C w + c(s_0, s_0) - 2w^\top C_0 \end{aligned}$$

where  $C_0 = \text{Cov}(Z, Z(s_0))$ , i.e.  $[C_0]_j = c(s_j, s_0)$ .

(3) To learn the unknown weights  $\{w_i\}$  we need to solve

$$w^{\text{SK}} = \arg \min_w \text{E}(Z_{\text{SK}}(s_0) - Z(s_0))^2, \text{ subject to } w_{n+1} = \mu(s_0) - w^\top \mu(s_{1:n})$$

As  $\text{E}(\mu_{\text{SK}} - Z(s_0))^2$  does not depend on  $w_{n+1}$  we minimize

$$\begin{aligned} 0 &= \nabla_w \text{E}(Z_{\text{SK}}(s_0) - Z(s_0))^2 = \nabla_w \text{Var}(Z_{\text{SK}}(s_0) - Z(s_0)) \\ &= 2Cw - 2C_0 \end{aligned}$$

So I get

$$w_{\text{SK}} = C^{-1} C_0$$

So

$$\begin{aligned}
Z_{\text{SK}}(s_0) &= w_{n+1} + C^{-1}C_0Z \\
&= \mu(s_0) - (C^{-1}C_0)^\top \mu(s_{1:n}) + (C^{-1}C_0)^\top Z \\
&= \mu(s_0) + C_0^\top C^{-1} [Z - \mu(s_{1:n})]
\end{aligned}$$

(4) It is

$$\begin{aligned}
\sigma_{\text{SK}} &= \sqrt{\text{E} (Z_{\text{SK}}(s_0) - Z(s_0))^2} \\
&= \sqrt{w_{\text{SK}}^\top C w_{\text{SK}} + c(s_0, s_0) - 2w_{\text{SK}}^\top C_0} \\
&= \sqrt{c(s_0, s_0) - C_0^\top C^{-1} C_0}
\end{aligned}$$


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## Part 2. Aerial unit data / spatial data on lattices

**Exercise 3.** Show that the conditionals  $x|y \sim \text{N}(a + by, \sigma^2 + \tau^2 y^2)$  and  $y|x \sim \text{N}(c + dx, \tilde{\sigma}^2 + \tilde{\tau}^2 x^2)$  are compatible if  $\tau^2 = \tilde{\tau}^2 = 0$ ,  $d/\tilde{\sigma}^2 = b/\sigma^2$ , and  $|db| < 1$ . In particular see what happens if  $x|y \sim \text{N}(y, \sigma^2)$  and  $y|x \sim \text{N}(x, \sigma^2)$  namely if  $\tau^2 = \tilde{\tau}^2 = 0$ ,  $d/\tilde{\sigma}^2 = b/\sigma^2$ ,  $\tilde{\sigma}^2 = \sigma^2$  and  $d = b = 1$ .

**Solution.** It is

$$\begin{aligned}
\frac{g(x|y)}{q(y|x)} &= \frac{\text{N}(x|a + by, \sigma^2 + \tau^2 y^2)}{\text{N}(y|c + dx, \tilde{\sigma}^2 + \tilde{\tau}^2 x^2)} \\
&= \frac{\sqrt{\tilde{\sigma}^2 + \tilde{\tau}^2 x^2}}{\sqrt{\sigma^2 + \tau^2 y^2}} \exp \left( -\frac{1}{2} \left( \frac{(x - a - by)^2}{\sigma^2 + \tau^2 y^2} - \frac{(y - c - dx)^2}{\tilde{\sigma}^2 + \tilde{\tau}^2 x^2} \right) \right) \quad (\text{set } \tau^2 = \tilde{\tau}^2 = 0) \\
&= \frac{\sqrt{\tilde{\sigma}^2}}{\sqrt{\sigma^2}} \exp \left( -\frac{1}{2} \left( \frac{(x - a - by)^2}{\sigma^2} - \frac{(y - c - dx)^2}{\tilde{\sigma}^2} \right) \right) \\
&= \frac{\sqrt{\tilde{\sigma}^2}}{\sqrt{\sigma^2}} \exp \left( -\frac{1}{2} \left( \frac{x^2}{\sigma^2} + \frac{a^2}{\sigma^2} + \frac{b^2 y^2}{\sigma^2} - \frac{2xa}{\sigma^2} - 2\frac{xb y}{\sigma^2} + \frac{2aby}{\tilde{\sigma}^2} \right. \right. \\
&\quad \left. \left. - \frac{y^2}{\tilde{\sigma}^2} - \frac{c^2}{\tilde{\sigma}^2} - \frac{d^2 x^2}{\tilde{\sigma}^2} + \frac{2yc}{\tilde{\sigma}^2} + 2\frac{ydx}{\tilde{\sigma}^2} - \frac{2cdx}{\tilde{\sigma}^2} \right) \right)
\end{aligned}$$

If  $d/\tilde{\sigma}^2 = b/\sigma^2$  (and  $\tau^2 = \tilde{\tau}^2 = 0$ )

$$\frac{g(x|y)}{q(y|x)} \propto \underbrace{\exp\left(-\frac{1}{2}\left(\left(\frac{1}{\sigma^2} - \frac{d^2}{\tilde{\sigma}^2}\right)x^2 - 2\left(\frac{a}{\sigma^2} + \frac{cd}{\tilde{\sigma}^2}\right)x\right)\right)}_{u(x)} \times \underbrace{\exp\left(+\frac{1}{2}\left(\left(\frac{1}{\tilde{\sigma}^2} - \frac{b^2}{\sigma^2}\right)y^2 - 2\left(\frac{c}{\tilde{\sigma}^2} + \frac{ab}{\sigma^2}\right)y\right)\right)}_{v(y)}$$

for  $N_g = N_q = N = \mathbb{R}$ . Also it is

$$\int_{\mathbb{R}} u(x) dx = \int_{\mathbb{R}} \exp\left(-\frac{1}{2}\left(\left(\frac{1}{\sigma^2} - \frac{d^2}{\tilde{\sigma}^2}\right)x^2 - 2\left(\frac{a}{\sigma^2} + \frac{cd}{\tilde{\sigma}^2}\right)x\right)\right) dx < \infty$$

when  $|db| < 1$ .

If  $\tau^2 = \tilde{\tau}^2 = 0$ ,  $d/\tilde{\sigma}^2 = b/\sigma^2$ ,  $\tilde{\sigma}^2 = \sigma^2$  and  $d = b = 1$ , then

$$\frac{g(x|y)}{q(y|x)} \propto \exp\left(-\frac{1}{2}\left(\left(\frac{1}{\sigma^2} - \frac{1}{\sigma^2}\right)x^2\right)\right) \exp\left(-\frac{1}{2}\left(\left(\frac{1}{\sigma^2} - \frac{1}{\sigma^2}\right)y^2\right)\right) \propto \text{const}$$

that is  $u(x)$  is constant and hence  $\int u(x) dx = \infty$  implying that they are not compatible.

**Exercise 4.** Consider that  $Z(s)$  represents presence or absence of a characteristic at location  $s \in \mathcal{S}$ . Mathematically, assume random field  $Z$  taking values on a set of indices  $\mathcal{S}$  in  $\mathcal{Z} = \{0, 1\}$  on  $\mathcal{S} = \{1, \dots, n\}$ ,  $n \in \mathbb{N} - \{0\}$ . Consider that for a given  $z_{-i}$  it is

$$\begin{cases} z_i | z_{-i} & \sim \text{Logit}(\theta_i(z_{-i})), \quad i \in \mathcal{S} \\ \theta_i(z_{-i}) & = \alpha_i + \sum_{j: j \sim i} \beta_{i,j} z_j \end{cases}$$

- (1) Show that the conditionals  $z_i | z_{-i}$  are compatible as a Besag's auto-model when  $\{\alpha_i\}$  and  $\{\beta_{i,j}\}$  satisfy certain conditions, and specify these conditions.

**Hint:** The PMF of Logistic distribution  $x | \theta \sim \text{Logit}(\theta)$  can be written as

$$\Pr(x | \theta) = \frac{\exp(x\theta)}{1 + \exp(\theta)} 1(x \in \{0, 1\})$$

- (2) Write down the marginal distribution of the associated random field.
- (3) What would be the sign of  $\{\beta_{i,j}\}$  if you wish to introduce competition between neighboring sites? What would be the sign of  $\{\beta_{i,j}\}$  if you wish to introduce similarity between neighboring sites? What does  $\alpha_i$  represent when  $\beta_{i,j} = 0$ ?

**Solution.**

(1) Then the characteristics are

$$\Pr_i(z_i|z_{-i}) = \frac{\exp(z_i \theta_i(z_{-i}))}{1 + \exp(\theta_i(z_{-i}))} 1(z_i \in \{0, 1\})$$

Now, we have parameterized  $\{\theta_i(\cdot)\}$  as

$$\theta_i(z_{-i}) = \alpha_i + \sum_{j:j \sim i} \beta_{i,j} z_j$$

for  $\{\alpha_i\}$  and  $\{\beta_{i,j}\}$  with  $\beta_{i,j} = \beta_{j,i}$ . Hence, we've got

$$\log \left( \Pr_i(z_i|z_{-i}) \right) = \underbrace{z_i}_{B_i(z_i)} \underbrace{\left( \alpha_i + \sum_{j \sim i} \beta_{i,j} \overbrace{z_j}^{B_i(z_j)} \right)}_{A_i(z_{-i})} + \underbrace{0}_{C_i(z_i)} + \underbrace{\left( -\log \left( 1 + \exp \left( \alpha_i + \sum_{j:j \sim i} \beta_{i,j} z_j \right) \right) \right)}_{D_i(z_{-i})}$$

Notice that all the conditionals  $z_i|z_{-i}$  follow an Exponential family with

$$A_i(z_{-i}) = \alpha_i + \sum_{j \sim i} \beta_{i,j} B_i(z_j)$$

$$B_i(z_i) = z_i$$

$$C_i(z_i) = 0$$

$$D_i(z_{-i}) = -\log \left( 1 + \exp \left( \alpha_i + \sum_{j:j \sim i} \beta_{i,j} z_j \right) \right)$$

I can get  $C_i(\zeta) = 0$  and  $B_i(\zeta) = 0$  by considering a reference point  $\zeta = 0$ . Hence the conditionals  $z_i|z_{-i}$  are compatible as a Besag's auto-model for any  $\{\alpha_i\}$  and  $\{\beta_{i,j}\}$  with  $\beta_{i,j} = \beta_{j,i}$  according to a Theorem discussed in the Lectures.

(2) The Besag auto-model has marginal distribution

$$\Pr_Z(z) \propto \exp \left( \overbrace{\sum_i \alpha_i z_i + \sum_i \sum_{j:j \sim i} \beta_{i,j} z_i z_j}^{U(z)=} \right)$$

$\underbrace{\underbrace{\sum_i \alpha_i z_i}_{B_i(z_i)}}_{V_i(z_i)} \quad \underbrace{\sum_i \sum_{j:j \sim i} \beta_{i,j} z_i z_j}_{\sum_{\{i,j\}:j \sim i}}$

according to a Theorem discussed in the Lectures.

- (3) I observe that: (1.) the model has spatially dependent coefficients  $\{\alpha_i\}$  and  $\{\beta_{i,j}\}$ .  
 (2.) when  $\beta_{i,j} = 0$ , for all  $j$  such as  $j \sim i$ , it is  $\Pr_i(z_i|z_{-i}) = \frac{\exp(z_i \alpha_i)}{1 + \exp(\alpha_i)}$  and (3.)  
 Characteristic's present at site  $i$  is encouraged in neighboring site  $j$  when  $\beta_{i,j} > 0$ , and discouraged when  $\beta_{i,j} < 0$ .