Spatio-temporal statistics (MATH4341) Michaelmas term, 2023

Homework 2: Geostatistics (Kriging and MLE inference)

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Exercise 1. ($\star$) Consider we the geostatistical model $(Z_s)_{s\in\mathcal{S}}$ with

$$Z(s)=\mu(s)+w(s)+\varepsilon(s)$$

where $w(s)$ is a weakly stationary process with mean zero and covariogram $c_w\left(h;\sigma^2,\phi\right)=\sigma^2\exp\left(-\frac{1}{\phi}\|h\|\right)$, $\mu(s;\beta)$ is a deterministic function

$$\mu(s;\beta)=\sum_{j=0}^{p}\psi_j(s)\,\beta_j=(\psi(s))^\top\beta$$

with unknown coefficients $\beta=(\beta_0,...,\beta_p)^\top$ and known basis functions $\psi(s)=(\psi_0(s),...,\psi_p(s))^\top$, $\varepsilon(s)$ is a nugget effect process whose covariogram has sill τ^2, and assume that $w(s)$ and $\varepsilon(s)$ are independent Gaussian Processes.

(1) Write down the formula of the covariogram $c\left(h;\left(\sigma^2,\phi,\tau\right)\right)$ of (Z_s).

(2) Consider a re-parametrization $\theta=\left(\sigma^2,\phi,\xi\right)$ where $\xi^2=\frac{\tau^2}{\sigma^2}$ is called signal to noise ratio. Assume there is available a dataset $\{(s_i,Z_i)\}_{i=1}^n$ where $,Z_i:=Z(s_i)$ is a realization of $(Z_s)_{s\in\mathcal{S}}$ at site s_i.

  (a) Let Ψ be a matrix with $[\Psi]_{i,j}=\psi_j(s_i)$. Let D be a matrix such as $[D]_{i,j}=\|s_i-s_j\|$. Consider that you can use convenient notation such as $\exp(D)$ meaning $[\exp(D)]_{i,j}=\exp(D_{i,j})$. Write down the covariance matrix $C(\theta)$ of $Z=(Z_1,...,Z_n)^\top$ as a function of D and θ.

  (b) Write down the log likelihood function $\log(L(Z;\theta))$ of $Z=(Z_1,...,Z_n)^\top$ given $\theta=\left(\sigma^2,\phi,\xi\right)$.

(3) Let $r(\cdot)$ (called correlogram) such as $c(\cdot)=\sigma^2r(\cdot)$. Assume that (ϕ,ξ) as known constants.

  (a) Compute the likelihood equations[1] w.r.t. $\left(\beta,\sigma^2\right)$, and for given (ϕ,ξ).

  (b) Compute the MLE $\hat{\beta}_{(\phi,\xi)}$ of β as a function of (ϕ,ξ)

  (c) Compute the MLE $\hat{\sigma}^2_{(\phi,\xi)}$ of σ^2 as a function of (ϕ,ξ).

  (d) Compute the unbiased estimator of $\tilde{\sigma}^2$ of σ^2.

    Hint: Consider the fitted values $e=(e_1,...,e_n)^\top$ as $e=[I-H]\,Z$ where $H=\left(\Psi^\top R^{-1}\Psi\right)^{-1}\Psi^\top R^{-1}$, and write $\hat{\sigma}^2_{(\phi,\xi)}$ w.r.t. e.

    Hint: It is given that $\mathrm{E}\left(Z^\top AZ\right)=\mathrm{E}(Z)^\top A\mathrm{E}(Z)^\top+\mathrm{tr}(A\mathrm{Var}(Z))$ when $Z\sim$ Normal

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[1] that is, the gradient of the log-likelihood

(e) What is the sampling distribution of $\hat{\beta}_{(\phi,\xi)}$? Specify the distribution family along with its parameters.

(4) Compute the so-called log "profiled likelihood" $\log\left(L\left(Z;(\phi,\xi)\right)\right)$ resulting as

$$L\left(Z;(\phi,\xi)\right)=L\left(Z;\beta=\hat{\beta}_{(\phi,\xi)},\sigma^2=\hat{\sigma}^2_{\left(\hat{\beta}_{(\phi,\xi)},\phi,\xi\right)},\phi,\xi\right)$$

by replacing the β with $\hat{\beta}_{(\phi,\xi)}$ and σ^2 with $\hat{\sigma}^2_{\left(\hat{\beta}_{(\phi,\xi)},\phi,\xi\right)}$ in the actual likelihood $L\left(Z;\beta,\theta=\left(\sigma^2,\phi,\xi\right)\right)$.

Describe how you would compute suitable values $\left(\hat{\phi},\hat{\xi}\right)$ for the MLE of (ϕ,ξ)

Solution. It is

(1) It is

$$\begin{aligned}c\left(h;\left(\sigma^2,\phi,\tau\right)\right)=&c_\delta\left(h;\sigma^2,\phi\right)+c_\varepsilon\left(h;\tau\right)\\=&\sigma^2\exp\left(-\frac{1}{\phi}\left\|h\right\|\right)+\tau 1_{\{0\}}\left(h\right)\end{aligned}$$

(2) It is

(a)

$$C\left(\sigma^2,\phi,\xi\right)=\sigma^2\exp\left(-\frac{1}{\phi}D\right)+\sigma^2\xi^2 I$$

(b)

$$\begin{aligned}2\log\left(L\left(Z;\theta\right)\right)=&2\log\left(\mathrm{N}\left(Z|\Psi\beta,C\left(\theta\right)\right)\right)\\=&-n\log\left(\sigma^2\right)-\log\left(\left|\exp\left(-\frac{1}{\phi}D\right)+\xi^2 I\right|\right)\\&-\frac{1}{\sigma^2}\left(Z-\Psi\beta\right)^\top\left(\exp\left(-\frac{1}{\phi}D\right)+\xi^2 I\right)^{-1}\left(Z-\Psi\beta\right)\end{aligned}$$

(3) It is

$$\begin{aligned}2\log\left(L\left(Z;\theta\right)\right)=&-n\log\left(\sigma^2\right)-\log\left(\left|\exp\left(-\frac{1}{\phi}D\right)+\xi^2 I\right|\right)\\=&\quad-\frac{1}{\sigma^2}\left(Z-\Psi\beta\right)^\top\left(\exp\left(-\frac{1}{\phi}D\right)+\xi^2 I\right)^{-1}\left(Z-\Psi\beta\right)\end{aligned}$$

Let $R_{(\phi,\xi)}$ matrix with $\left[R_{(\phi,\xi)}\right]_{i,j}=r\left(s_i-s_j|\phi,\xi\right)$

(a) So the likelihood equations are $0=\nabla_{(\beta,\sigma^2)}\log\left(L\left(Z;\theta\right)\right)$

$$\begin{cases}0=\Psi^\top\left(R_{(\phi,\xi)}\right)^{-1}Z-\Psi^\top\left(R_{(\phi,\xi)}\right)^{-1}\Psi\beta\\0=\frac{n}{2}\frac{1}{\sigma^2}+\frac{1}{2(\sigma^2)^2}\left(Z-\Psi\beta\right)^\top\left(R_{(\phi,\xi)}\right)^{-1}\left(Z-\Psi\beta\right)\end{cases}$$

(b) It is

$$\hat{\beta}_{(\phi,\xi)}=\left(\Psi^\top\left(R_{(\phi,\xi)}\right)^{-1}\Psi\right)^{-1}\Psi^\top\left(R_{(\phi,\xi)}\right)^{-1}Z$$

(c) It is

$$\hat{\sigma}_{(\beta,\phi,\xi)}=\frac{1}{n}\left(Z-\Psi\beta\right)^\top\left(R_{(\phi,\xi)}\right)^{-1}\left(Z-\Psi\beta\right)$$

and by subtituting I get

$$
\begin{aligned}
\hat{\sigma}_{(\phi,\xi)} =&\hat{\sigma}_{\left(\hat{\beta}_{(\phi,\xi)},\phi,\xi\right)} = \frac{1}{n}\left(Z-\Psi\hat{\beta}_{(\phi,\xi)}\right)^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\left(Z-\Psi\hat{\beta}_{(\phi,\xi)}\right)\\
=&\frac{1}{n}\left(Z-\Psi\hat{\beta}_{(\phi,\xi)}\right)^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\left(Z-\Psi\hat{\beta}_{(\phi,\xi)}\right)
\end{aligned}
$$

(d) It is

$$
e = Z-\Psi\hat{\beta}_{(\phi,\xi)} = (I-H)\,Z
$$

So

$$
\begin{aligned}
n\hat{\sigma}_{(\phi,\xi)} =&Z^{\top}(I-H)\left(R_{(\phi,\xi)}\right)^{-1}(I-H)\,Z\\
=&\left[(I-H)\,Z\right]^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\left[(I-H)\,Z\right]\\
=&e^{\top}R_{(\phi,\xi)}e
\end{aligned}
$$

where

$$
\mathrm{E}\left[e\right]=0
$$

then

$$
\begin{aligned}
\mathrm{E}\left(n\hat{\sigma}\left(\phi,\xi\right)\right) =&\mathrm{E}\left(Z^{\top}(I-H)\left(R_{(\phi,\xi)}\right)^{-1}(I-H)\,Z\right)\\
=&\cancelto{=0}{\left(\mathrm{E}\left[e\right]\right)^{\top}}\left(R_{(\phi,\xi)}\right)^{-\frac{1}{2}}\cancelto{=0}{\mathrm{E}\left[e\right]}+\mathrm{tr}\left(\left(R_{(\phi,\xi)}\right)^{-1}\mathrm{Var}\left(e\right)\right)\\
=&\mathrm{tr}\left(\left(R_{(\phi,\xi)}\right)^{-1}\mathrm{Var}\left((I-H)\,Z\right)\right)\\
=&\mathrm{tr}\left(\left(R_{(\phi,\xi)}\right)^{-1}(I-H)\,\sigma^{2}R_{(\phi,\xi)}\,(I-H)\right)=\sigma^{2}\mathrm{tr}\left(\left(R_{(\phi,\xi)}\right)^{-1}(I-H)\,R_{(\phi,\xi)}\,(I-H)\right)\\
=&\mathrm{tr}\left((I-H)\right)=\sigma^{2}\left(n-p\right)
\end{aligned}
$$

So it is

$$
\tilde{\sigma}\left(\beta,\phi,\xi\right)=\frac{1}{n-p}\left(Z-\Psi\beta\right)^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\left(Z-\Psi\beta\right)
$$

because

$$
\mathrm{E}\left(\tilde{\sigma}\left(\beta,\phi,\xi\right)\right)=\sigma^{2}
$$

(e) It is

$$
\hat{\beta}\left(\phi,\xi\right)=\left(\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\Psi\right)^{-1}\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}Z
$$

so it is Normal as a linear combination of normal random variables, with mean

$$
\mathrm{E}\left(\hat{\beta}\left(\phi,\xi\right)\right)=\left(\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\Psi\right)^{-1}\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\mathrm{E}\left(Z\right)=\beta
$$

and Variance

$$
\begin{aligned}
\mathrm{Var}\left(\hat{\beta}_{(\phi,\xi)}\right)=&\left(\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\Psi\right)^{-1}\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\cancelto{=\sigma^{2}R_{(\phi,\xi)}}{\mathrm{Var}\left(Z\right)}\\
&\left(R_{(\phi,\xi)}\right)^{-1}\Psi\left(\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\Psi\right)^{-1}=\left(\Psi^{\top}\left(R_{(\phi,\xi)}\right)^{-1}\Psi\right)^{-1}
\end{aligned}
$$

(4) It is

$$\log\left(L\left(Z;(\phi,\xi)\right)\right) = L\left(Z;\beta=\hat{\beta}_{(\phi,\xi)},\sigma^2=\hat{\sigma}^2_{\left(\hat{\beta}_{(\phi,\xi)},\phi,\xi\right)},\phi,\xi\right)$$
$$-\frac{n}{2}\log\left(\hat{\sigma}^2_{\left(\hat{\beta}_{(\phi,\xi)},\phi,\xi\right)}\right)-\frac{1}{2}\log\left(\left|R_{(\phi,\xi)}\right|\right)$$

where obviously

$$0=\nabla_{(\phi,\xi)}\log\left(L\left(Z;(\phi,\xi)\right)\right)\Big|_{(\phi,\xi)=(\hat{\phi},\hat{\xi})}$$

cannot be solved numerically. The Newton method or the gradient descent method can be used to maximize $\log\left(L\left(Z;(\phi,\xi)\right)\right)$.

Exercise 2. ($\star$) Let $(Z_s)_{s\in\mathcal{S}}$ be a specified statistical model. Assume that process $(Z_s)_{s\in\mathcal{S}}$ has known mean $\mu(s)=\mathrm{E}(Z(s))$ 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 μ_{SK} Consider the "Kriging" estimator $Z_{\mathrm{SK}}(s_0)$ of $Z(s_0)$ at an unseen spatial location s_0 as the BLUE (Best Linear Unbiased Estimator)

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

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

(1) Find sufficient conditions on $w=(w_1,...,w_n)^\top$ so that the Kriging estimator $Z_{\mathrm{SK}}(s_0)$ to be unbiased.

(2) Derive the MSE of $Z_{\mathrm{SK}}(s_0)$ as

$$\mathrm{E}\left(Z_{\mathrm{SK}}(s_0)-Z(s_0)\right)^2=w^\top Cw+c(s_0,s_0)-2w^\top C_0$$

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

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

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

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

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

(1) It is

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

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

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

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

which is satisfied given the assumption

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

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

(2) It is

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

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

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

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

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

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

So I get

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

So

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

(4) It is

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