

Discussion of
"Screening the Discrepancy Function of a Computer
Model"

by Pierre Barbillon, Anabel Forte and Rui Paulo

Marilena Barbieri
Università Roma Tre

O'Bayes 2022: Objective Bayes Methodology Conference
UC Santa Cruz - September 6-10, 2022

Computer model

Discrepancy (bias) function

$$y(\mathbf{x}_i) = f(\mathbf{x}_i, \boldsymbol{\theta}) + \delta(\mathbf{x}_i) + \epsilon_i \quad i = 1, \dots, n$$

Field data

$$\epsilon_i \sim N(0, \sigma_0^2)$$

$$\mathbf{x}_i = (x_{1i}, \dots, x_{pi})^T \quad \text{input variables}$$

$$\delta(\cdot) | \sigma^2, \rho \sim GaSP(0, \sigma^2 c(\cdot, \cdot | \rho))$$

Separable correlation kernel:

$$c(\mathbf{x}_i, \mathbf{x}_j | \rho) = \prod_{l=1}^p c(x_{li}, x_{lj} | \rho_l)$$

$$c(x_{li}, x_{lj} | \rho_l) = \rho_l^{2^a |x_{li} - x_{lj}|^a} \quad \text{where } 0 < a \leq 2 \quad \text{is a fixed constant}$$

$$\rho_l \in [0, 1]$$

If $\rho_l = 1$: x_l is "inert"

? Which of the input variables is active in the discrepancy function?

Sampling distribution of the field data

$$\mathbf{y} | \boldsymbol{\rho}, \sigma^2, \sigma_0^2, \boldsymbol{\theta}, f(\mathbf{x}) \sim N_n (f(\boldsymbol{\theta}), \sigma^2 R + \sigma_0^2 I_n)$$

$$R = [c(\mathbf{x}_i, \mathbf{x}_j | \boldsymbol{\rho})]_{i,j=1,\dots,n}$$

Screening as a variable selection problem: models are indexed using

$$\boldsymbol{\gamma} = (\gamma_1, \dots, \gamma_p)^T \in \{0, 1\}^p$$

Under model M_l : $\gamma_l = 0 \quad \leftrightarrow \quad \rho_l = 1$

Prior

$$\pi(\sigma^2, \sigma_0^2, \boldsymbol{\theta}, \boldsymbol{\rho}, \boldsymbol{\gamma}) = \pi(\sigma^2, \sigma_0^2, \boldsymbol{\theta}) \pi(\boldsymbol{\rho} | \boldsymbol{\gamma}) \pi(\boldsymbol{\gamma})$$

$$\pi(\boldsymbol{\rho} | \boldsymbol{\gamma}) = \prod_{l=1}^p [\gamma_l I_{(0,1)}(\rho_l) + (1 - \gamma_l) B(\rho_l | \alpha_l, 1)]$$

Proposal:

- ✓ run an MCMC under $\boldsymbol{\gamma} = \mathbf{1}$
- ✓ obtain $\pi(\boldsymbol{\gamma} | \mathbf{y})$ using the importance sampling approximation

$$B_{\boldsymbol{\gamma}} \approx \frac{1}{M} \sum_{r=1}^M \pi(\boldsymbol{\rho}^{(r)} | \boldsymbol{\gamma})$$

a sample from the posterior distribution of $\boldsymbol{\rho}$ under $\boldsymbol{\gamma} = \mathbf{1}$

Posterior Inclusion
Probabilities
Screening (PIPS)

$$\pi(x_l | \mathbf{y}) = \sum_{\boldsymbol{\gamma}: \gamma_l = 1} \pi(\boldsymbol{\gamma} | \mathbf{y})$$

- ? Use of the proposal in variable selection
- ? Which strategy do you suggest when p is large?

Proposal:

- ✓ run an MCMC under $\gamma = \mathbf{1}$
- ✓ obtain $\pi(\gamma|\mathbf{y})$ using the importance sampling approximation

$$B\gamma \approx \frac{1}{M} \sum_{r=1}^M \pi(\boldsymbol{\rho}^{(r)}|\gamma)$$

← a sample from the posterior distribution of $\boldsymbol{\rho}$ under $\gamma = \mathbf{1}$

Posterior Inclusion
Probabilities
Screening (PIPS)

$$\pi(x_l|\mathbf{y}) = \sum_{\gamma:\gamma_l=1} \pi(\gamma|\mathbf{y})$$

$$\delta(\cdot) | \sigma^2, \rho \sim GaSP(0, \sigma^2 c(\cdot, \cdot | \rho))$$

Separable correlation kernel: $c(\mathbf{x}_i, \mathbf{x}_j | \rho) = \prod_{l=1}^p c(x_{li}, x_{lj} | \rho_l)$

$$c(x_{li}, x_{lj} | \rho_l) = \rho_l^{2^a |x_{li} - x_{lj}|^a}$$

where $0 < a \leq 2$ is a fixed constant

? $a = 1.9$

Thank you!