

# Calibration of computer experiments

## Problem 1

### Description of the problem

The aim of this problem is to implement the models of Sections 1 and 3 in the lecture slides (calibration without model error and Gaussian process model for the model error, both with a linear approximation of the code). We address here a one-dimensional problem, in order to conveniently plot and interpret the results.

We work on  $D = [0, 1]$  and the physical system is, for  $x \in D$ ,

$$\phi(x) = -\sin(\pi x / (1.3)).$$

We consider the linear code function

$$f(x, \beta) = \beta_0 + \beta_1 x,$$

so that  $p = 2$ . We have, for the prior distribution on  $\beta$ ,

$$\beta_{prior} = \begin{pmatrix} -0.6 \\ 0 \end{pmatrix} \quad \text{and} \quad Q_{prior} = \begin{pmatrix} 0.36 & 0 \\ 0 & 0.36 \end{pmatrix}.$$

The choice of the nominal  $\beta_{nom}$  is here arbitrary since the code is linear with respect to  $\beta$ .

We consider  $n = 10$  equi-spaced observations, with noise variance  $\sigma_m^2 = 0.1^2$ .

### Part a)

(R code refers here to `Problem_1a.R` unless stated otherwise.)

In this Part a), we only address the model

$$\phi(x) = \sum_{i=1}^p \beta_{0,i} h_i(x)$$

of Section 1.

1. Complete `fct_H` in the R code.
2. Complete `y=` in the R code.
3. Plot the physical system function and the code function parameterized by  $\beta_{prior}$ .
4. Complete `hat_sigma_m=` in the R code.
5. Complete `fct_beta_post` in the R code `functions.R`.
6. Add to the plot the code function parameterized by  $\beta_{post}$ .
7. Complete `fct_Q_post` in the R code `functions.R`.
8. Complete `cond_var_cont=` in the R code.
9. Add the curve of the 95% confidence intervals for the value of  $\phi(x)$ , conditionally to  $\mathbf{y}$  for  $x \in [0, 1]$ . These confidence intervals are of the form

$$\mathbf{h}(x)^t \beta_{post} \pm 1.96 \sqrt{\mathbf{h}(x)^t Q_{post} \mathbf{h}(x)}.$$

10. Comment the final plot
11. Redo the plot with  $n = 50$  and re-comment.

## Part b)

(R code refers here to `Problem_1b.R` unless stated otherwise.)

In this Part b), we only address the model

$$\phi(x) = \sum_{i=1}^p \beta_{0,i} h_i(x) + Z(x)$$

of Section 3.

We work with the Gaussian covariance function (slide 30) with fixed parameters  $\sigma^2 = 1$  and  $\ell = 0.5$ .

1. Complete `fct_H` in the R code.
2. Complete `y=` in the R code.
3. Plot the physical system function and the code function parameterized by  $\beta_{prior}$ .
4. Complete `fct_cov_gauss` in the R code `functions.R`.
5. Calculate  $\beta_{post}$  and  $Q_{post}$  (slide 71). Compare the value of  $Q_{post}$  here and the value of  $Q_{post}$  in Part a). Redo this comparison with  $n = 50$ . Comment this in relation with the identifiability of  $\beta_0$  in the models in Sections 1 and 3.
6. Add to the plot the code function parameterized by  $\beta_{post}$ .
7. Complete `fct_hat_phi` and `fct_hat_sigma_2` in the R code `functions.R`.
8. For 100 equi-spaced values of  $x_0 \in D$ , compute  $\hat{\phi}(x_0)$  and  $\hat{\sigma}^2(x_0)$ , cf slide 73.
9. Add to the plot the curves of  $\hat{\phi}(x_0)$  and of the confidence intervals

$$\hat{\phi}(x_0) \pm 1.96\hat{\sigma}(x_0).$$

10. Comment the final plot.
11. Redo the plot with  $n = 50$  and re-comment.

## Other venues for implementation

With this one-dimensional model, one can consider the following, additionally to the above questions.

1. Changing the simulation parameters.
2. Estimating the covariance parameters by restricted maximum likelihood.
3. Working with a non-linear computer model, and observing what happens graphically.