

**SUPPLEMENTARY MATERIAL: PREDICTION BASED ON  
THE KENNEDY-O'HAGAN CALIBRATION MODEL:  
ASYMPTOTIC CONSISTENCY AND OTHER PROPERTIES**

*Chinese Academy of Sciences and Georgia Institute of Technology*

**Supplementary Material**

In this supplementary material, we present the proofs for Lemma 1, Lemma 2, Lemma 4 and Theorem 2 in the main article.

**S1 Technical Proofs**

*Proof of Lemma 1.* We first assume  $f \in F_\Phi$ . If  $f = s_{f,\mathbf{x}}$ , there is nothing to prove. If  $f \neq s_{f,\mathbf{x}}$ , without loss of generality, we write

$$f(x) = \sum_{i=1}^{n+m} \alpha_i \Phi(x, x_i),$$

for an extra set of distinct points  $\{x_{n+1}, \dots, x_{n+m}\} \subset \Omega$ . Now partition  $(A_{i,j}) = \Phi(x_i, x_j)$ ,  $1 \leq i, j \leq n+m$  into

$$A = \begin{pmatrix} (A_1)_{n \times n} & (A_2)_{n \times m} \\ (A_3)_{m \times n} & (A_4)_{m \times m} \end{pmatrix},$$

where  $A_3 = A_2^\top$  because  $\Phi$  is symmetric.

Let  $\mathbf{y} = (f(x_1), \dots, f(x_n))^\top$ ,  $\mathbf{a}_1 = (\alpha_1, \dots, \alpha_n)^\top$ ,  $\mathbf{a}_2 = (\alpha_{n+1}, \dots, \alpha_{n+m})^\top$ .

Clearly,  $\mathbf{y} = A_1 \mathbf{a}_1 + A_2 \mathbf{a}_2$ . By the definition of  $s_{f,\mathbf{x}}$ , we have

$$s_{f,\mathbf{x}}(x) = \sum_{i=1}^n u_i \Phi(x, x_i),$$

with  $\mathbf{u} = (u_1, \dots, u_n)^\top$  satisfying  $\mathbf{y} = A_1 \mathbf{u}$ . Then from (??) we obtain

$$\begin{aligned} & \langle s_{f,\mathbf{x}}, f - s_{f,\mathbf{x}} \rangle_{\mathcal{N}_\Phi(\Omega)} \\ &= \left\langle \sum_{i=1}^n u_i \Phi(x, x_i), \sum_{i=1}^n (\alpha_i - u_i) \Phi(x, x_i) + \sum_{i=n+1}^{n+m} \alpha_i \Phi(x, x_i) \right\rangle_{\mathcal{N}_\Phi(\Omega)} \\ &= \begin{pmatrix} \mathbf{u}^\top & 0 \end{pmatrix} \begin{pmatrix} A_1 & A_2 \\ A_3 & A_4 \end{pmatrix} \begin{pmatrix} \mathbf{a}_1 - \mathbf{u} \\ \mathbf{a}_2 \end{pmatrix} \\ &= \mathbf{u}^\top (A_1 \mathbf{a}_1 + A_2 \mathbf{a}_2 - A_1 \mathbf{u}) \\ &= \mathbf{u}^\top (\mathbf{y} - \mathbf{y}) = 0. \end{aligned} \tag{S1.1}$$

For a general  $f \in \mathcal{N}_\Phi(\Omega)$ , we can find a sequence  $f_n \in F_\Phi$  with  $f_n \rightarrow f$  in  $\mathcal{N}_\Phi(\Omega)$  as  $n \rightarrow \infty$ . The desired result then follows from a limiting form of (S1.1).  $\square$

*Proof of Lemma 2.* For any  $g \in L_2(\mathbf{R}^d) \cap C(\mathbf{R}^d)$ , its native norm admits the representation

$$\|g\|_{\mathcal{N}_\Phi(\mathbf{R}^d)}^2 = (2\pi)^{-d/2} \int_{\mathbf{R}^d} \frac{|\tilde{g}(\omega)|^2}{\tilde{\Phi}(\omega)} d\omega, \tag{S1.2}$$

where  $\tilde{g}$  and  $\tilde{\Phi}$  denote the Fourier transforms of  $g$  and  $\Phi$  respectively. See Theorem 10.12 of Wendland [2005]. The (fractional) Sobolev norms have a similar representation

$$\|g\|_{H^s(\mathbf{R}^d)}^2 = (2\pi)^{-d/2} \int_{\mathbf{R}^d} |\tilde{g}(\omega)|^2 (1 + \|\omega\|^2)^s d\omega. \quad (\text{S1.3})$$

See Adams and Fournier [2003] for details. Tuo and Wu [2016] show that

$$\tilde{C}_{v,\gamma}(\omega) = 2^{d/2} (4v\gamma^2)^v \frac{\Gamma(v + d/2)}{\Gamma(v)} (4v\gamma^2 + \|\omega\|^2)^{-(v+d/2)}.$$

Using the inequality

$$(1 + b) \min(1, a) \leq a + b \leq (1 + b) \max(1, a),$$

for  $a, b \geq 0$ , we obtain

$$\begin{aligned} \tilde{C}_{v,\gamma}(\omega) &\leq 2^{d/2} (4v\gamma^2)^v \frac{\Gamma(v + d/2)}{\Gamma(v)} \max\{1, (4v\gamma^2)^{-(v+d/2)}\} (1 + \|\omega\|^2)^{-(v+d/2)} \\ &\leq 2^{d/2} \frac{\Gamma(v + d/2)}{\Gamma(v)} \max\{(4v\gamma_2^2)^v, (4v\gamma_1^2)^{-d/2}\} (1 + \|\omega\|^2)^{-(v+d/2)} \\ &=: C_1 (1 + \|\omega\|^2)^{-(v+d/2)}, \end{aligned} \quad (\text{S1.4})$$

and

$$\begin{aligned} \tilde{C}_{v,\gamma}(\omega) &\geq 2^{d/2} (4v\gamma^2)^v \frac{\Gamma(v + d/2)}{\Gamma(v)} \min\{1, (4v\gamma^2)^{-(v+d/2)}\} (1 + \|\omega\|^2)^{-(v+d/2)} \\ &\geq 2^{d/2} \frac{\Gamma(v + d/2)}{\Gamma(v)} \min\{(4v\gamma_1^2)^v, (4v\gamma_2^2)^{-d/2}\} (1 + \|\omega\|^2)^{-(v+d/2)} \\ &=: C_2 (1 + \|\omega\|^2)^{-(v+d/2)}, \end{aligned} \quad (\text{S1.5})$$

hold for all  $\omega \in \mathbf{R}^d$ .

Now we apply the extension theorem of the native spaces (Theorem 10.46 of Wendland, 2005) to obtain a function  $f^E \in \mathcal{N}_{C_v, \gamma}(\mathbf{R}^d)$  such that  $f^E|_{\Omega} = f$  and  $\|f\|_{\mathcal{N}_{C_v, \gamma}(\Omega)} = \|f^E\|_{\mathcal{N}_{C_v, \gamma}(\mathbf{R}^d)}$  for each  $\gamma \in [\gamma_1, \gamma_2]$ . We use (S1.2)-(S1.4) to obtain

$$\begin{aligned}
\|f\|_{\mathcal{N}_{C_v, \gamma}(\Omega)}^2 &= \|f^E\|_{\mathcal{N}_{C_v, \gamma}(\mathbf{R}^d)}^2 = (2\pi)^{-d/2} \int_{\mathbf{R}^d} \frac{|\tilde{f}^E(\omega)|^2}{\tilde{C}_{v, \gamma}(\omega)} d\omega \\
&\geq C_1^{-1} (2\pi)^{-d/2} \int_{\mathbf{R}^d} |\tilde{f}^E(\omega)|^2 (1 + \|\omega\|^2)^{v+d/2} d\omega \\
&= C_1^{-1} \|f^E\|_{H^{v+d/2}(\mathbf{R}^d)}^2 \geq C_1^{-1} \|f\|_{H^{v+d/2}(\Omega)}^2, \quad (\text{S1.6})
\end{aligned}$$

where the last inequality follows from the fact that  $f^E|_{\Omega} = f$ . On the other hand, because  $\Omega$  is convex,  $f$  has an extension  $f_E \in H^{v+d/2}(\mathbf{R}^d)$  satisfying  $\|f_E\|_{H^k(\mathbf{R}^d)} \leq c \|f\|_{H^k(\Omega)}$  for some constant  $c$  independent of  $f$ . Then we use (S1.2), (S1.3) and (S1.5) to obtain

$$\begin{aligned}
\|f_E\|_{H^k(\Omega)}^2 &\geq c^{-2} \|f\|_{H^k(\Omega)}^2 \\
&= c^{-2} (2\pi)^{-d/2} \int_{\mathbf{R}^d} |\tilde{f}^E(\omega)|^2 (1 + \|\omega\|^2)^{v+d/2} d\omega \\
&\geq c^{-2} C_2 (2\pi)^{-d/2} \int_{\mathbf{R}^d} \frac{|\tilde{f}^E(\omega)|^2}{\tilde{C}_{v, \gamma}(\omega)} d\omega \\
&= c^{-2} C_2 \|f_E\|_{\mathcal{N}_{C_v, \gamma}(\mathbf{R}^d)}^2 \geq c^{-2} C_2 \|f\|_{\mathcal{N}_{C_v, \gamma}(\Omega)}^2,
\end{aligned}$$

where the last inequality follows from the restriction theorem of the native space, which states that the restriction  $f = f_E|_{\Omega}$  is contained in  $\mathcal{N}_{C_v, \gamma}(\Omega)$  with a norm that is less than or equal to the norm  $\|f_E\|_{\mathcal{N}_{C_v, \gamma}(\mathbf{R}^d)}$ . See Theorem 10.47 of Wendland [2005]. The desired result is proved by combining

(S1.6) and (S1.7). □

*Proof of Lemma 4.* For  $f \in \mathcal{N}_\Phi(\Omega)$ , define

$$M(f) = L(f(x_1), \dots, f(x_n)) + \|f\|_{\mathcal{N}_\Phi(\Omega)}^2.$$

Now consider  $s_{\hat{f}, X}$ , i.e., the interpolant of  $\hat{f}$  over  $X = \{x_1, \dots, x_n\}$  using the kernel function  $\Phi$ . Because  $\hat{f}(x_i) = s_{\hat{f}, X}(x_i)$  for  $i = 1, \dots, n$ , we have

$$L(f(x_1), \dots, f(x_n)) = L(s_{\hat{f}, X}(x_1), \dots, s_{\hat{f}, X}(x_n)). \quad (\text{S1.7})$$

In addition, it is easily seen from Lemma 1, (9) and (10) in the main article that

$$\|s_{\hat{f}, X}\|_{\mathcal{N}_\Phi(\Omega)}^2 \leq \|\hat{f}\|_{\mathcal{N}_\Phi(\Omega)}^2, \quad (\text{S1.8})$$

and the equality holds if and only if  $s_{\hat{f}, X} = \hat{f}$ . By combining (S1.7) and (S1.8) we obtain

$$M(s_{\hat{f}, X}) \leq M(\hat{f}). \quad (\text{S1.9})$$

Because  $\hat{f}$  minimizes  $M(f)$ , the reverse of (S1.9) also holds. Hence we deduce  $s_{\hat{f}, X} = \hat{f}$ , which proves the theorem according to the definition of the interpolant. □

*Proof of Theorem 2.* We first rewrite the minimization problem (16) in the

main article as the following iterated form

$$\begin{aligned} & \min_{\substack{\theta \in \Theta \\ f \in \mathcal{N}_{C_v, \gamma}(\Omega)}} \sum_{i=1}^n (y_i^p - y^s(x_i, \theta) - f(x_i))^2 + \frac{\sigma^2}{\tau^2} \|f\|_{\mathcal{N}_{C_v, \gamma}(\Omega)}^2 \\ &= \min_{\theta \in \Theta} \min_{f \in \mathcal{N}_{C_v, \gamma}(\Omega)} \sum_{i=1}^n (y_i^p - y^s(x_i, \theta) - f(x_i))^2 + \frac{\sigma^2}{\tau^2} \|f\|_{\mathcal{N}_{C_v, \gamma}(\Omega)}^2 \end{aligned} \quad (\text{S1.10})$$

Now we apply Lemma 4 to the inner minimization problem in (S1.10) and obtain the following representation for  $\hat{\Delta}$ :

$$\hat{\Delta} = \sum_{i=1}^n \alpha_i C_{v, \gamma}(x_i, \cdot),$$

with an undetermined vector of coefficients  $\alpha = (\alpha_1, \dots, \alpha_n)^T$ . Using the definition  $\Sigma_\gamma = (C_{v, \gamma}(x_i, x_j))_{ij}$ , clearly we have the matrix representation

$$\hat{\Delta}(\mathbf{x}) = \Sigma_\gamma \alpha. \quad (\text{S1.11})$$

Now using (7) in the main article we have

$$\|\hat{\Delta}\|_{\mathcal{N}_{C_v, \gamma}(\Omega)}^2 = \left\langle \sum_{i=1}^n \alpha_i C_{v, \gamma}(x_i, \cdot), \sum_{i=1}^n \alpha_i C_{v, \gamma}(x_i, \cdot) \right\rangle_{\mathcal{N}_{C_v, \gamma}(\Omega)} = \alpha^T \Sigma_\gamma \alpha.$$

The minimization problem (16) in the main article then reduces to

$$\underset{\substack{\theta \in \Theta \\ \alpha \in \mathbf{R}^n}}{\operatorname{argmin}} \|\mathbf{y}^p - y^s(\mathbf{x}, \theta) - \alpha \Sigma_\gamma\|^2 + \frac{\sigma^2}{\tau^2} \alpha^T \Sigma_\gamma \alpha.$$

Applying a change-of-variable argument using (S1.11) we obtain the following optimization formula

$$\underset{\substack{\theta \in \Theta \\ \Delta(\mathbf{x}) \in \mathbf{R}^n}}{\operatorname{argmin}} \|\mathbf{y}^p - y^s(\mathbf{x}, \theta) - \Delta(\mathbf{x})\|^2 + \frac{\sigma^2}{\tau^2} \Delta(\mathbf{x})^T \Sigma_\gamma^{-1} \Delta(\mathbf{x}).$$

Elementary calculations show its equivalence to the definition of  $(\hat{\theta}_{KO}, \hat{\delta}(\mathbf{x}))$ .

□

## Bibliography

Robert A Adams and John JF Fournier. *Sobolev Spaces*, volume 140. Access

Online via Elsevier, 2003.

R. Tuo and C. F. J. Wu. A theoretical framework for calibration in computer models: parametrization, estimation and convergence properties.

*SIAM/ASA Journal on Uncertainty Quantification*, 4(1):767–795, 2016.

H. Wendland. *Scattered Data Approximation*. Cambridge University Press, 2005.