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Maximum likelihood estimation and prediction error for a Matérn model on the circle

Sébastien J. Petit^{*1, 2}

¹ Université Paris-Saclay, CNRS, CentraleSupélec,
Laboratoire des signaux et systèmes, 91190, Gif-sur-Yvette, France

²Laboratoire National de Métrologie et d'Essais, 78197 Trappes Cedex, France

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Abstract

This work considers Gaussian process interpolation with a periodized version of the Matérn covariance function (Stein, 1999, Section 6.7) with Fourier coefficients $\phi(\alpha^2 + j^2)^{-\nu-1/2}$. Convergence rates are studied for the joint maximum likelihood estimation of ν and ϕ when the data is sampled according to the model. The mean integrated squared error is also analyzed with fixed and estimated parameters, showing that maximum likelihood estimation yields asymptotically the same error as if the ground truth was known. Finally, the case where the observed function is a “deterministic” element of a continuous Sobolev space is also considered, suggesting that bounding assumptions on some parameters can lead to different estimates.

1 Introduction

Gaussian process regression or kriging is a common technique for inferring an unknown function from data, which has applications in geostatistics (Stein, 1999), computer experiments (Santner et al., 2003), and machine learning (Rasmussen and Williams, 2006). Stein (1999) stresses the importance of choosing a covariance function that fits the problem, promotes the use of the Matérn (1986) family of covariance functions, and advocates using maximum likelihood to estimate its parameters.

A distinction is generally made between increasing and fixed-domain asymptotic frameworks for parameter estimation of Gaussian processes (see, e.g., Bachoc, 2021, for a review). While several increasing-domain asymptotic frameworks have been exhaustively studied (see, e.g., Mardia and Marshall, 1984; Bachoc, 2014), fixed-domain frameworks are studied only with simplifications and for a restrained number of parameters to our knowledge (Ying, 1991, 1993; van der Vaart, 1996; Zhang, 2004; Loh, 2006; Anderes, 2010).

^{*}sebastien.petit@lne.fr

Considering fixed-domain asymptotics, the regularity parameter of the Matérn covariance function seems to have been little studied, although [Stein \(1999\)](#) presents numerous results suggesting it as the most impactful from the point of view of prediction error. To study parameter estimation, [Stein \(1999, Section 6.7\)](#) proposes an asymptotic framework¹ with uniformly distributed observations on the torus and makes a conjecture about the asymptotic behavior of maximum likelihood based on the Fisher information matrix. This topic has only recently regained popularity. Indeed, [Chen et al. \(2021\)](#) used the previous framework to show that the estimation of the regularity parameter is consistent if the other parameters remain fixed. Moreover, [Karvonen \(2022\)](#) has recently shown an asymptotic lower bound in the general case of a “nice” bounded domain of \mathbb{R}^d , also covering the case of a deterministic function from a continuous Sobolev space. Other results were obtained in similar frameworks ([Szabó et al., 2015](#); [Knapik et al., 2016](#); [Karvonen et al., 2020](#)).

This article presents three main contributions. First, we focus on the one-dimensional case of the framework proposed by [Stein \(1999, Section 6.7\)](#) to give an asymptotic normality result for maximum likelihood parameter estimation. Then, we leverage these convergence rates to analyze the expected integrated error, taking constant factors into account and showing that estimating the parameters yields the same error asymptotically as if the ground truth was known. Finally, we investigate the deterministic case by deriving the large sample limit of the likelihood criterion in a particular case. This suggests that bounding assumptions on some parameters can lead to different estimates.

The article is organized as follows. First, Section 2.1 details the asymptotic framework and notations. Then, Section 3 gives the main results. Finally, Section 4 provides a few results on the deterministic case.

2 Gaussian process interpolation on the circle

2.1 Framework

Let $f : [0, 1] \rightarrow \mathbb{R}$ be a continuous periodic function observed on a regular grid:

$$\{j/n, 0 \leq j \leq n-1\}.$$

Consider the periodic version of the stationary Matérn covariance function $\{k_\theta, \theta \in (0, +\infty)^3\}$ proposed by [Stein \(1999, Section 6.7\)](#) and defined, for $\theta = (\nu, \phi, \alpha) \in (0, +\infty)^3$, by the uniformly absolutely convergent Fourier series with coefficients:

$$\underline{c}_j(\theta) = \frac{\phi}{(\alpha^2 + j^2)^{\nu+1/2}}, \quad j \in \mathbb{Z}. \quad (1)$$

The parameter α is not identifiable as different values yield equivalent probability measures. However, ν and ϕ are identifiable (see, e.g., [Stein, 1999](#), Chapter 4 and Section 6.7). [Stein \(1999\)](#) advocates the *regularity* parameter ν as the key quantity governing the asymptotics of the kriging error. The amplitude parameter ϕ does not impact the kriging predictor but is known to be critical for uncertainty quantification (see, e.g., [Stein, 1993b](#)) and to be consistently estimated by maximum likelihood if ν and α are known (see, e.g., [Zhang, 2004](#), who use a different parametrization).

The usual task in kriging is to infer the function f from the data

$$Z = (f(0), \dots, f(1 - 1/n))^T.$$

¹This framework is similar to that proposed by [Stein \(1993a\)](#) in a slightly different setting, where a different conjecture is made about the error on noisy training data.

2.2 Best linear prediction

The function f is usually predicted using the posterior mean function given by the kriging equations (Matheron, 1971). This predictor can be written simply in the framework presented above.

Proposition 1. *Let $n \geq 1$ and $f: [0, 1] \rightarrow \mathbb{R}$ a continuous periodic function. Suppose also that f is the pointwise absolute limit of its Fourier serie. Writing \hat{f}_n for the posterior mean function given Z and the parameter $\theta \in \Theta$, we have:*

$$\hat{f}_n(x) = \sum_{j \in \mathbb{Z}} \left(\frac{\sum_{j_1 \in j+n\mathbb{Z}} c_{j_1}(f)}{\sum_{j_1 \in j+n\mathbb{Z}} \mathcal{L}_{j_1}(\theta)} \right) \mathcal{L}_j(\theta) e^{2\pi i x j}, \quad x \in [0, 1], \quad (2)$$

where the $c_j(f)$ s are the Fourier coefficients of f .

The expression (2) shows how the posterior mean function approximates f : it transforms the Fourier coefficients of k_θ into those of f using the ratio of the discrete Fourier transforms. Finally, we also define the integrated squared error:

$$\text{ISE}_n(\mathbf{v}, \alpha; f) = \int_0^1 (f - \hat{f}_n)^2. \quad (3)$$

Note that it does not depend on ϕ .

2.3 Maximum likelihood estimation

Given the observations Z and $\Theta \subset (0, +\infty)^3$, the maximum likelihood estimate is defined by $\hat{\theta}_n = (\hat{\mathbf{v}}_n, \hat{\phi}_n, \hat{\alpha}_n)$ minimizing (a linear transform of) the negative log-likelihood:

$$\mathbb{L}_n(\theta) = n^{-1} (\ln(\det(K_\theta)) + Z^\top K_\theta^{-1} Z), \quad \theta = (\mathbf{v}, \phi, \alpha) \in \Theta, \quad (4)$$

with ties broken arbitrarily and K_θ the covariance matrix of Z under θ .

The parameters \mathbf{v} and α will be assumed to be bounded in this work, i.e., we take $\Theta = N \times (0, +\infty) \times A$ with N and A bounded away from zero and infinity. Most of our results will be stated with A being a singleton, with α enforced to a value (which will not necessarily be the ground truth). This type of assumption is more or less standard in the field, as it leads to simplifications (see, e.g., Ying, 1991; Loh, 2006; Chen et al., 2021). However, keeping ϕ unbounded is key to our results and for discussing the deterministic case in Section 4.

2.4 A symmetrized version of the Hurwitz zeta function

As Stein (1999, Section 6.7) points out, a great simplification emerges when we restrict ourselves to the framework presented in Section 2.1. This will allow us to derive a sharp analysis, taking into account constant factors in the evaluation of the prediction accuracy with estimated parameters. Similarly to Stein (1999), the function

$$\gamma: (\alpha; x) \in (1, +\infty) \times (0, 1) \mapsto \sum_{j \in \mathbb{Z}} \frac{1}{|j+x|^\alpha},$$

will play a major role in deriving the limiting constants. It is C^∞ with respect to both arguments and related to the Hurwitz zeta function ζ_H by:

$$\gamma(\alpha; x) = \zeta_H(\alpha; x) + \zeta_H(\alpha; 1-x), \quad x \in (0, 1). \quad (5)$$

Moreover, the function $\gamma(\alpha; \cdot)$ is symmetric with respect to $1/2$ for $\alpha > 1$.

Integrals involving $\gamma(\alpha; \cdot)$, for some $\alpha > 0$, will appear in the main body of the article. All of them are well-defined, and integrability statements are postponed to the proofs of Appendix A.

3 Main results

3.1 Standing assumptions

Consider the framework presented in Section 2.1 and suppose that the function is sampled according to the (real-valued) centered Gaussian process:

$$\xi : x \in [0, 1] \mapsto \frac{1}{\sqrt{2}} \sum_{j \in \mathbb{Z}} \sqrt{c_j(\theta_0)} (U_{1,|j|} + iU_{2,|j|}\text{sign}(j)) e^{2\pi i x j}, \quad (6)$$

with $\theta_0 = (v_0, \phi_0, \alpha_0) \in (0, +\infty)^3$ and $(U_{q,j})_{q \in \{1,2\}, j \geq 0}$ independent random variables such that $U_{2,0} = 0$, $U_{1,0} \sim \mathcal{N}(0, 2)$, and $U_{q,j} \sim \mathcal{N}(0, 1)$ for $q \in \{1, 2\}$ and $j \geq 1$. The convergence of the expansion (6) is meant pointwise both in $L^2(P)$ and almost surely. It is easy to check that $\xi \sim \text{GP}(0, k_{\theta_0})$.

Let $\hat{\theta}_n = (\hat{v}_n, \hat{\phi}_n, \hat{\alpha}_n)$ be a maximum likelihood estimate defined in Section 2.3 for some $\Theta = N \times (0, +\infty) \times A$ with $A \subset (0, +\infty)$ and $N = [a_v, b_v] \ni v_0$. The following sections give convergence rates in terms of parameter estimation and predictions.

3.2 Convergence rate of maximum likelihood estimation

The following result states the consistency for the identifiable parameters and an upper bound of the corresponding rates.

Theorem 2. *Let $0 < \beta < 1/4$ and $A = [a_\alpha, b_\alpha]$ be bounded away from zero and infinity. The bounds $\hat{v}_n - v_0 = o_P(n^{-\beta})$ and $\hat{\phi}_n - \phi_0 = o_P(\ln(n)n^{-\beta})$ hold in probability.*

Informally, Theorem 2 is proven by showing that a linear transformation of

$$\inf_{\phi > 0} \mathbb{L}_n(v, \phi, \alpha)$$

converges to

$$\ln(\gamma(2v+1; \cdot)) + \ln\left(\int_0^1 \frac{\gamma(2v_0+1; \cdot)}{\gamma(2v+1; \cdot)}\right), \quad (7)$$

for $v > v_0 - 1/2$. Jensen inequality then shows that (7) is maximized by taking $v = v_0$.

Furthermore, similarly to Stein (1999, Section 6.7), let us define

$$\psi_v : x \in (0, 1) \mapsto \frac{\sum_{j \in \mathbb{Z}} |x+j|^{-2v-1} \ln|x+j|}{\sum_{j \in \mathbb{Z}} |x+j|^{-2v-1}}, \quad \text{for } v > 0,$$

which is square integrable on $(0, 1)$ and $e(v) = \mathbb{E}(\psi_v(U))$ and $V(v) = \text{Var}(\psi_v(U))$, with $U \sim \mathcal{U}(0, 1)$. The following result proves the conjecture made by Stein (1999, Section 6.7) when \hat{v}_n is bounded and α_0 is known.

Theorem 3. *Suppose that $A = \{\alpha_0\}$. Then*

$$\sqrt{2n} \left(\frac{\hat{\phi}_n - \phi_0}{2\phi_0} - \frac{(\ln(n) + e(v_0))(\hat{v}_n - v_0)}{\sqrt{V(v_0)}(\hat{v}_n - v_0)} \right) \rightsquigarrow \mathcal{N}(0, I_2). \quad (8)$$

3.3 Convergence rate of the integrated prediction error

This section states our results about the expectation of (3) with estimated parameters. To avoid technical difficulties, we suppose that $v_0 > 1/2$ in this section. We begin with the case of fixed parameters.

For $v, v_0 > 0$, define

$$\vartheta_{v,v_0} : x \in (0, 1) \mapsto \frac{\gamma(4v+2;x)\gamma(2v_0+1;x)}{\gamma^2(2v+1;x)} + \gamma(2v_0+1;x) - 2\frac{\gamma(2v+2v_0+2;x)}{\gamma(2v+1;x)}.$$

The function ϑ_{v,v_0} is C^1 on $(0, 1)$, symmetric with respect to $1/2$, and a Taylor expansion around $x = 0$ shows that it is integrable if $v > (v_0 - 1)/2$.

The following result states the asymptotics of the prediction error with fixed parameters.

Theorem 4. *Let $\theta = (v, \phi, \alpha) \in N \times \mathbb{R} \times A$. Then,*

$$\mathbb{E}(\text{ISE}_n(v, \alpha; \xi)) \lesssim \frac{1}{n^{4v+2}}, \text{ for } v < (v_0 - 1)/2 \quad (9)$$

$$\mathbb{E}(\text{ISE}_n(v, \alpha; \xi)) \lesssim \frac{\ln(n)}{n^{2v_0}}, \text{ for } v = (v_0 - 1)/2 \quad (10)$$

and

$$\mathbb{E}(\text{ISE}_n(v, \alpha; \xi)) \sim \frac{\phi_0 \int_0^1 \vartheta_{v,v_0}}{n^{2v_0}}, \text{ otherwise.} \quad (11)$$

The symbol \lesssim denotes an inequality up to a universal constant.

This result shows that half of the smoothness is sufficient for optimal convergence rates. However, the constant $\int_0^1 \vartheta_{v,v_0}$ is minimized by taking $v = v_0$. This is in line with the result of Stein (1999, Theorem 3) obtained in a different framework.

Then, our last result gives the asymptotic behavior of the prediction error with estimated v and ϕ and fixed—but not necessarily known— α .

Theorem 5. *Let $A = \{\alpha\}$ with $0 < \alpha < +\infty$. Then,*

$$\mathbb{E}(\text{ISE}_n(\hat{v}_n, \alpha; \xi)) \sim \frac{\phi_0 \int_0^1 \vartheta_{v_0,v_0}}{n^{2v_0}}. \quad (12)$$

This last result shows that estimating the parameters is optimal both in terms of the rate and the constant.

4 The deterministic case

This section studies the case of an unknown fixed deterministic function from a continuous Sobolev space. Let $\beta > 0$ and define the Sobolev space

$$H_{[0,1]}^{\beta+1/2} = \left\{ g \in L_{[0,1]}^2, \|g\|_{H_{[0,1]}^{\beta+1/2}}^2 = \sum_{j \in \mathbb{Z}} (1+j^2)^{\beta+1/2} |c_j(f)|^2 < +\infty \right\} \quad (13)$$

of (continuous) periodic functions.

Furthermore, let $f \in H_{[0,1]}^{\beta+1/2}$ for some $\beta > 0$ and define the smoothness

$$v_0(f) = \inf \left\{ \beta > 0, f \notin H_{[0,1]}^{\beta+1/2} \right\}$$

of f as Wang and Jing (2022) and Karvonen (2022).

Suppose that $\hat{\theta}_n = (\hat{v}_n, \hat{\phi}_n, \hat{\alpha}_n)$ is estimated by maximizing the likelihood as in Section 2.3 for $\Theta = N \times F \times A$ with N and A bounded away from zero and infinity. This section discusses the behavior of \hat{v}_n under three assumptions on F : 1) a singleton; 2) a range bounded away from zero and infinity; and 3) the whole $(0, +\infty)$. For the last case, the definition

$$\mathbb{M}_n^f: (v, \alpha) \in N \times A \mapsto \inf_{\phi > 0} \mathbb{L}_n(v, \phi, \alpha) + (2v_0(f) + 1) \ln(n) - 1,$$

will be used.

On “nice” bounded regions of \mathbb{R}^d , Karvonen (2022) shows that $\liminf \hat{v}_n \geq v_0(f)$ if α and ϕ are fixed². The following result shows that it holds on the circle no matter the assumption on F .

Proposition 6. *If N and A are bounded away from zero and infinity, then*

$$\liminf \hat{v}_n \geq v_0(f)$$

holds for the three previous assumptions on F .

Regarding the precise behavior of \hat{v}_n above $v_0(f)$, Karvonen (2022) conjectures that \hat{v}_n converges to $v_0(f) + 1/2$ if ϕ and α are fixed but deems that a joint estimation may give a different behavior. The rest of this section is devoted to supporting this idea.

Write \approx for a two-way inequality up to universal constants and use the more stringent assumption that

$$|c_j(f)| \approx |j|^{-v_0(f)-1}$$

for simplicity. The following result is a minor adaptation of the reasoning used by Chen et al. (2021) and Karvonen (2022), showing that the conjecture is verified more generally if ϕ is bounded. The proof is omitted for brevity.

Proposition 7. *Suppose that $|c_j(f)| \approx |j|^{-v_0(f)-1}$ and that N , A , and F are bounded away from zero and infinity. Then, the convergence $\hat{v}_n \rightarrow v_0(f) + 1/2$ holds.*

However, our last results suggest that it does not hold when $F = (0, +\infty)$.

Proposition 8. *Suppose that $c_j(f) = |j|^{-v_0(f)-1}$, for $j \neq 0$. Then, for $v > v_0(f)$ and $\alpha > 0$, we have*

$$\mathbb{M}_n^f(v, \alpha) \rightarrow \mathbb{M}_\infty^f(v) = \int_0^1 \ln(\gamma(2v+1; \cdot)) + \ln \left(\int_0^1 \frac{\gamma^2(v_0(f)+1; \cdot)}{\gamma(2v+1; \cdot)} \right).$$

It is possible to obtain a uniform version of the previous convergence. However, it is omitted for brevity and because we could not identify the minimizer(s) of the limit analytically. Figure 1 shows a numerical approximation of \mathbb{M}_∞^f .

²Note that Karvonen (2022) does not supposed that v is bounded.

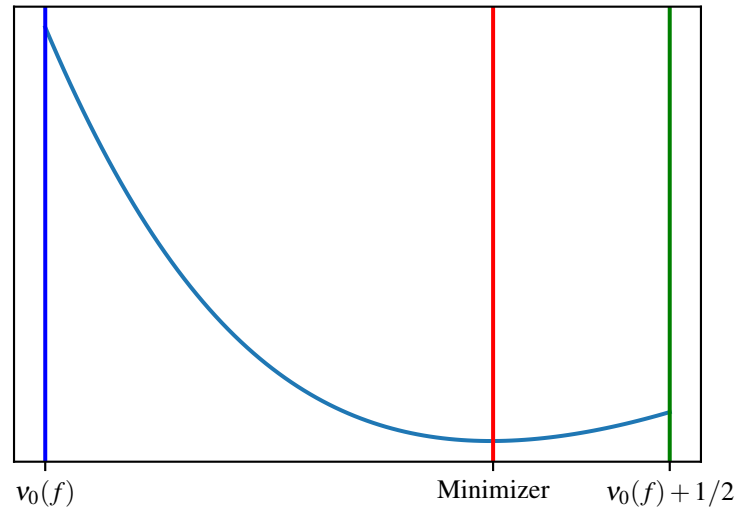


Figure 1: The function M_∞^f , for $v_0(f) = 1$. A numerical approximation of the minimizer is about 1.359. Note that M_∞^f is approximated numerically using finite sums for γ and discretizations for the integrals.

A Proofs

A.1 Additional notations

The symbol \lesssim denotes an inequality up to a universal constant. For compactness, the symbol \approx is used when the two-way inequality \lesssim holds.

Write $K_\theta = \phi R_{v,\alpha}$ and $\underline{c}_j(\theta) = \phi c_j(v, \alpha)$, for $\theta = (v, \phi, \alpha) \in (0, +\infty)^3$ and $j \in \mathbb{Z}$. All results suppose that $\Theta = N \times (0, +\infty) \times A$ with $N = [a_v, b_v]$, $A = [a_\alpha, b_\alpha]$, $0 < a_v \leq b_v < +\infty$, $0 < a_\alpha \leq b_\alpha < +\infty$, and $F = (0, +\infty)$ unless explicitly stated otherwise. Without loss of generality, suppose that $a_v < v_0 - 1/2$ and define $N_\varepsilon = [v_0 - 1/2 + \varepsilon, b_v] \subset N$ for $\varepsilon > 0$.

Furthermore, for $\theta_0 = (v_0, \phi_0, \alpha_0)$, define \mathbb{M}_n to be the stochastic process:

$$\mathbb{M}_n: (v, \alpha) \in N \times A \mapsto \inf_{\phi > 0} \mathbb{L}_n(v, \phi, \alpha) + 2v_0 \ln(n) - 1.$$

Its expression is given almost surely by the following Lemma.

Lemma 9. (see, e.g., [Santner et al., 2003](#), Section 3.3.2) Let $v, \alpha > 0$. If $Z \neq 0$, then

$$\inf_{\phi > 0} \mathbb{L}_n(v, \phi, \alpha) = 1 + n^{-1} \ln(\det(R_{v,\alpha})) + \ln \left(\frac{Z^\top R_{v,\alpha}^{-1} Z}{n} \right), \quad (14)$$

where the supremum is reached by $\hat{\phi}_n = Z^\top R_{v,\alpha}^{-1} Z / n$.

Note that \mathbb{M}_n has therefore almost surely continuous sample paths. The proofs mostly consist in studying \mathbb{M}_n , which is often called the profiled likelihood. For a compact $A \subset (0, +\infty)$, define now $\mathbb{U}_n: v \in N \mapsto \inf_{\alpha \in A} \mathbb{M}_n(v, \alpha)$. The object \mathbb{U}_n is still a collection of measurable maps and is also almost surely continuous since A is compact.

Also, define

$$g_v = \ln(\gamma(2v + 1; \cdot)),$$

for $v > 0$ and

$$h_{v,v_0} = \frac{\gamma(2v_0 + 1; \cdot)}{\gamma(2v + 1; \cdot)},$$

for $v > v_0 - 1/2$. These functions are C^∞ and integrable.

Finally, suppose $n \geq 3$ and use the notation $l = \lfloor (n-1)/2 \rfloor$ throughout the following.

A.2 Circulant matrices and useful facts

Let us remind how the framework of Section 2.1 yields simplifications that can be traced back at least to [Craven and Wahba \(1979\)](#).

First let W be the $n \times n$ matrix with entries $W_{j,m} = \sqrt{n}^{-1} e^{2\pi i j m / n}$, for $0 \leq j, m \leq n-1$. For every $\theta = (v, \phi, \alpha) \in (0, +\infty)^3$, the matrix $R_{v,\alpha}$ is circulant and thus $R_{v,\alpha} = W \Delta_{v,\alpha} W^*$ (see, e.g., [Brockwell and Davis, 1987](#), p. 130) with

$$\Delta_{v,\alpha} = \text{diag}(\lambda_{0,n}, \dots, \lambda_{n-1,n})$$

and

$$\lambda_{m,n} = \sum_{j=0}^{n-1} e^{-2\pi i j m / n} k_\theta(j/n) = n \sum_{j \in \mathbb{Z}} c_{m+nj}(\theta), \quad 0 \leq m \leq n-1. \quad (15)$$

These coefficients verify

$$\lambda_{m,n} = \lambda_{n-m,n}, \text{ for } 0 \leq m \leq n-1. \quad (16)$$

Furthermore, the matrices $R_{v,\alpha}$ are symmetric so one also has $R_{v,\alpha} = P\Delta P^\top$ for a unitary matrix P , obtained, e.g., by taking the real and imaginary parts of W . For $\theta_0 = (v_0, \phi_0, \alpha_0)$, write

$$P^\top Z = \sqrt{\phi_0} (\lambda_{0,n}^0 U_{0,n}, \dots, \lambda_{n-1,n}^0 U_{n-1,n}),$$

with $\lambda_{0,n}^0, \dots, \lambda_{n-1,n}^0$ the eigenvalues of R_{v_0, α_0} and $U_{0,n}, \dots, U_{n-1,n}$ drawn independently from a standard Gaussian. We have

$$Z^\top R_{v,\alpha}^{-1} Z = \phi_0 \sum_{m=0}^{n-1} \frac{U_{m,n}^2 \lambda_{m,n}^0}{\lambda_{m,n}}. \quad (17)$$

A.3 Proofs of Section 2.2

Proof of Proposition 1. The kriging equations yield $\hat{f}_n(x) = k_{\theta,x}^\top K_\theta^{-1} Z$, with $k_{\theta,x} = (k_\theta(m/n - x))_{0 \leq m \leq n-1}$, for $x \in [0, 1]$. The simplifications described in Section A.2 give:

$$W^* Z = \sqrt{n} \left(\sum_{j \in m+n\mathbb{Z}} c_j(f) \right)_{0 \leq m \leq n-1},$$

and

$$W^* k_{\theta,x} = \sqrt{n} \left(\sum_{j \in m+n\mathbb{Z}} c_j(\theta) e^{-2\pi i x j} \right)_{0 \leq m \leq n-1}.$$

The result follows from elementary manipulations. \square

A.4 Proof of Theorem 2

Lemma 10. *The quantities $\lambda_{0,n}/n$ and $\lambda_{m,n} m^{2v+1}/n$ are bounded away from zero and infinity uniformly in $v \in N$, $\alpha \in A$, n and $1 \leq m \leq \lfloor n/2 \rfloor$.*

Proof. Let $0 \leq m \leq \lfloor n/2 \rfloor$, we have using (15)

$$c_m(v, \alpha) \leq \lambda_{m,n}/n \leq 2c_m(v, \alpha) + 2 \sum_{j=1}^{+\infty} c_{m+nj}(v, \alpha).$$

Moreover

$$\sum_{j=1}^{+\infty} c_{m+nj}(v, \alpha) / c_m(v, \alpha) \leq \sum_{j=1}^{+\infty} (b_\alpha^2 + 1/4)^{v+1/2} / j^{2v+1} \leq C_1^{b_\alpha, a_v, b_v} \quad (18)$$

where $C_1^{b_\alpha, a_v, b_v} = \max(1, (b_\alpha^2 + 1/4)^{b_v+1/2}) \zeta(2a_v + 1)$. The result follows from elementary operations. \square

Lemma 11. *Let $v \in N$, $\alpha \in A$, and $1 \leq m \leq l$, we have*

$$c_{m+nj}(v, \alpha) = \frac{(1 + u_{n,m,j}(v, \alpha))}{|jn + m|^{2v+1}}, \quad (19)$$

with $-1 < v_m \leq u_{n,m,j}(v, \alpha) \leq 0$ and $v_m = \mathcal{O}(m^{-2})$.

Proof. Using (15), we have

$$\begin{aligned} c_{m+nj}(\mathbf{v}, \alpha) &= \frac{1}{(\alpha^2 + (jn+m)^2)^{v+1/2}} \\ &= \frac{(1 + u_{n,m,j}(\mathbf{v}, \alpha))}{|jn+m|^{2v+1}}, \end{aligned}$$

with $u_{n,m,j}(\mathbf{v}, \alpha) = (1 + (\alpha/(jn+m))^2)^{-v-1/2} - 1$. Elementary operations show that

$$0 \geq u_{n,m,j}(\theta_1) \geq \left(\left(\frac{b_\alpha}{m} \right)^2 + 1 \right)^{-b_v-1/2} - 1,$$

which gives the desired result thanks to the Taylor inequality. \square

Lemma 12. *Uniformly in $\mathbf{v} \in N$ and $\alpha \in A$, we have*

$$\ln(\det(R_{\mathbf{v},\alpha})) = -2vn \ln(n) + n \int_0^1 g_{\mathbf{v}}(x) dx + \mathcal{O}(\ln(n)).$$

Proof. Using (15) and Lemma 11, we have

$$\begin{aligned} \lambda_{m,n}/n &= \sum_{j \in \mathbb{Z}} c_{m+nj}(\mathbf{v}, \alpha) \\ &= \sum_{j \in \mathbb{Z}} \frac{(1 + u_{n,m,j}(\mathbf{v}, \alpha))}{|jn+m|^{2v+1}}, \end{aligned}$$

and therefore

$$\sum_{m=1}^l \ln(\lambda_{m,n}/n) = -(2v+1)l \ln(n) + a_n + \sum_{m=1}^l g_{\mathbf{v}}(m/n),$$

with

$$|a_n| \leq \left| \sum_{m=1}^l \ln(1 + v_m) \right|$$

which is thus $\mathcal{O}(1)$ uniformly in $\mathbf{v} \in N$ and $\alpha \in A$.

One has $g_{\mathbf{v}}(x) = g_{\mathbf{v}}(1-x)$ for $x \in (0,1)$ and it is easy to see that $g_{\mathbf{v}}$ is non-increasing on $(0, 1/2]$, so

$$\int_{1/n}^{(l+1)/n} g_{\mathbf{v}}(x) dx \leq \frac{1}{n} \sum_{m=1}^l g_{\mathbf{v}}(m/n) \leq \int_0^{l/n} g_{\mathbf{v}}(x) dx.$$

First we have $\left| \int_{l/n}^{1/2} g_{\mathbf{v}} \right| \leq |g_{\mathbf{v}}(1/4)|/(2n) = \mathcal{O}(n^{-1})$ uniformly in $\mathbf{v} \in N$ thanks to a compacity argument and similarly for $\left| \int_{(l+1)/n}^{1/2} g_{\mathbf{v}} \right|$.

Moreover observe that

$$\gamma_{2v+1}(x) - 1/x^{2v+1} = \sum_{j \in \mathbb{Z}, j \neq 0} \frac{1}{|j+x|^{2v+1}}$$

is uniformly bounded in $v \in N$ and thus that the equivalence

$$\mathcal{Y}_{2v+1}(x) \sim_{x \rightarrow 0} 1/x^{2v+1} \quad (20)$$

is uniform and so is

$$g_v(x) \sim_{x \rightarrow 0} -(2v+1)\ln(x).$$

Therefore, we have

$$\int_0^{1/n} g_v(x) dx = \mathcal{O}(\ln(n)/n),$$

uniformly in $v \in N$ and so

$$\sum_{m=1}^l g_v(m/n) = n \int_0^{1/2} g_v(x) dx + \mathcal{O}(\ln(n)).$$

Moreover, Lemma 10 shows that $\ln(\lambda_{0,n}/n) = \mathcal{O}(1)$ and $\ln(\lambda_{n/2,n}/n) = \mathcal{O}(\ln(n))$ uniformly for n even. One can then conclude using (16). \square

Lemma 13. *The function h_{v,v_0} is non-decreasing (resp. non-increasing) on $(0, 1/2]$ when $v \geq v_0$ (resp. $v \leq v_0$).*

Proof. Suppose that $v \geq v_0$. Use (5) along with the fact that the Hurwitz Zeta function verifies (Postnikov, 1988)

$$\frac{\partial \zeta_H}{\partial x}(\alpha; x) = -\alpha \zeta_H(\alpha+1; x), \quad x > 0, \alpha > 1 \quad (21)$$

and has the representation

$$\zeta_H(\alpha; x) = \frac{1}{\Gamma(\alpha)} \int_0^{+\infty} \frac{t^{\alpha-1} e^{-tx}}{1-e^{-t}} dt, \quad x > 0, \alpha > 1,$$

where Γ is the classical Gamma function. So we have

$$\mathcal{Y}_{2v+1}(x) = \frac{1}{\Gamma(2v+1)} \int_0^{+\infty} \frac{t^{2v} (e^{-tx} + e^{-t(1-x)})}{1-e^{-t}} dt, \quad x \in (0, 1),$$

and

$$\frac{d\mathcal{Y}_{2v+1}}{dx}(x) = \frac{1}{\Gamma(2v+1)} \int_0^{+\infty} \frac{t^{2v+1} (e^{-t(1-x)} - e^{-tx})}{1-e^{-t}} dt, \quad x \in (0, 1).$$

Now let $x \in [1/2, 1)$, the derivative of h_{v,v_0} at x has the sign of

$$\begin{aligned} & \mathcal{Y}_{2v+1}(x) \frac{d\mathcal{Y}_{2v_0+1}}{dx}(x) - \mathcal{Y}_{2v_0+1}(x) \frac{d\mathcal{Y}_{2v+1}}{dx}(x) \\ &= \frac{1}{\Gamma(2v+1)\Gamma(2v_0+1)} \int_0^{+\infty} \int_0^{+\infty} \frac{t^{2v} s^{2v_0} (\eta(s, t; x) - \eta(t, s; x))}{\kappa(s, t)} dt ds \end{aligned}$$

with $\eta(s, t; x) = s(e^{-tx} + e^{-t(1-x)})(e^{-s(1-x)} - e^{-sx})$ and $\kappa(s, t) = (1-e^{-t})(1-e^{-s}) = \kappa(t, s)$ thanks to the Fubini-Lebesgue theorem. Then, one can split the integral to have:

$$\frac{1}{\Gamma(2v+1)\Gamma(2v_0+1)} \left(\int_0^{+\infty} \int_t^{+\infty} \frac{t^{2v} s^{2v_0} (\eta(s, t; x) - \eta(t, s; x))}{\kappa(s, t)} dt ds \right.$$

$$\begin{aligned}
& + \int_0^{+\infty} \int_t^{+\infty} \frac{s^{2v} t^{2v_0} (\eta(t, s; x) - \eta(s, t; x))}{\kappa(t, s)} dt ds \Big) \\
& = \frac{1}{\Gamma(2v+1)\Gamma(2v_0+1)} \int_0^{+\infty} \int_t^{+\infty} \frac{(t^{2v} s^{2v_0} - s^{2v} t^{2v_0}) (\eta(s, t; x) - \eta(t, s; x))}{\kappa(s, t)} dt ds \leq 0
\end{aligned}$$

since $t^{2v} s^{2v_0} \leq s^{2v} t^{2v_0}$ when $s \geq t$, $\kappa(s, t) \geq 0$ and $\eta(s, t; x) \geq \eta(t, s; x)$ when $s \geq t$ and $x \geq 1/2$.

So we proved that $h_{v;v_0}$ is non-increasing on $[1/2, 1)$ and the first claim is due to the symmetry with respect to $1/2$. Observe that $h_{v;v_0} = 1/h_{v_0;v}$ for the second claim. \square

Lemma 14. *Let $\varepsilon > 0$, we have*

$$\frac{1}{n} \sum_{m=1}^{n-1} h_{v;v_0}(m/n) = \int_0^1 h_{v;v_0}(x) dx + \mathcal{O}\left(\frac{1}{n^{\min(1, 2\varepsilon)}}\right),$$

uniformly in $v \in N_\varepsilon$.

Proof. Using Lemma 13 and the symmetry w.r.t. $1/2$, we have again the classical

$$\int_{1/n}^{(l+1)/n} h_{v;v_0}(x) dx \leq \frac{1}{n} \sum_{m=1}^l h_{v;v_0}(m/n) \leq \int_0^{l/n} h_{v;v_0}(x) dx, \quad (22)$$

when $v \geq v_0$ and the reversed inequality when $v \leq v_0$.

The behaviour near $1/2$ is elucidated as for Lemma 12 with a compacity argument to bound the values of $h_{v;v_0}$ uniformly at $1/4$ and $1/2$, thus giving a uniform $\mathcal{O}(n^{-1})$.

Moreover, it is straightforward to show that

$$h_{v;v_0}(x) \sim_{x \rightarrow 0} x^{2(v-v_0)}, \quad (23)$$

uniformly in $v \in N$ and then

$$\int_0^{1/n} h_{v;v_0}(x) dx = \mathcal{O}(n^{-2\varepsilon}), \quad (24)$$

uniformly in $v \in N_\varepsilon$. Therefore, we have

$$\sum_{m=1}^l h_{v;v_0}(m/n) = n \int_0^{1/2} h_{v;v_0}(x) dx + \mathcal{O}(1) + \mathcal{O}(n^{1-2\varepsilon}),$$

uniformly and using the symmetry of $h_{v;v_0}$ gives the desired result. \square

Lemma 15. *Let $1 \leq m \leq l$, we have*

$$\frac{\lambda_{m,n}^0}{n^{2(v-v_0)} \lambda_{m,n}} = (1 + \mathcal{O}(m^{-2})) h_{v;v_0}(m/n)$$

uniformly in $v \in N$ and $\alpha \in A$.

Proof. Lemma 11 gives

$$\frac{\lambda_{m,n}^0}{n^{2(v-v_0)} \lambda_{m,n}} = \frac{\sum_{j \in \mathbb{Z}} \frac{(1+u_{n,m,j}(v_0, \alpha_0))}{|j+m/n|^{2v_0+1}}}{\sum_{j \in \mathbb{Z}} \frac{(1+u_{n,m,j}(v, \alpha))}{|j+m/n|^{2v+1}}},$$

with

$$\sum_{j \in \mathbb{Z}} \frac{(1+u_{n,m,j}(v, \alpha))}{|j+m/n|^{2v+1}} = \gamma_{2v+1}(m/n) (1 + \mathcal{O}(m^{-2})),$$

uniformly. The desired result follows then from elementary manipulations. \square

Lemma 16. *Let $0 < \varepsilon < 1/2$, we have*

$$\sup_{(\mathbf{v}, \alpha) \in N_\varepsilon \times A} \frac{1}{n} \left| \sum_{m=1}^{n-1} \left(\frac{\lambda_{m,n}^0}{n^{2(\mathbf{v}-\mathbf{v}_0)} \lambda_{m,n}} - h_{\mathbf{v}; \mathbf{v}_0} \left(\frac{m}{n} \right) \right) \right| = \mathcal{O} \left(\frac{1}{n^{\min(3/4, 5\varepsilon/4)}} \right).$$

Proof. Let $1 \leq m \leq l$ and $\beta \in (0, 1)$. Using Lemma 15 and the correct sign for the big- \mathcal{O} term we have

$$\begin{aligned} \frac{1}{n} \left| \sum_{m=1}^l \left(\frac{\lambda_{m,n}^0}{n^{2(\mathbf{v}-\mathbf{v}_0)} \lambda_{m,n}} - h_{\mathbf{v}; \mathbf{v}_0} \left(\frac{m}{n} \right) \right) \right| &\leq \frac{1}{n} \sum_{m=1}^l \mathcal{O}(m^{-2}) h_{\mathbf{v}; \mathbf{v}_0} \left(\frac{m}{n} \right) \\ &= \frac{1}{n} \sum_{m=1}^{\lfloor n^\beta \rfloor} \mathcal{O}(m^{-2}) h_{\mathbf{v}; \mathbf{v}_0}(m/n) + \frac{1}{n} \sum_{m=\lfloor n^\beta \rfloor + 1}^l \mathcal{O}(m^{-2}) h_{\mathbf{v}; \mathbf{v}_0}(m/n), \end{aligned}$$

with

$$\frac{1}{n} \sum_{m=\lfloor n^\beta \rfloor + 1}^l \mathcal{O}(m^{-2}) h_{\mathbf{v}; \mathbf{v}_0}(m/n) = \mathcal{O} \left(\frac{1}{n^{2\beta}} \right) \frac{1}{n} \sum_{m=1}^l h_{\mathbf{v}; \mathbf{v}_0}(m/n) = \mathcal{O} \left(\frac{1}{n^{2\beta}} \right)$$

uniformly in $\mathbf{v} \in N_\varepsilon$ and $\alpha \in A$ thanks to (22) and by observing that the mapping $\mathbf{v} \in N_\varepsilon \mapsto \int_0^{1/2} h_{\mathbf{v}; \mathbf{v}_0}$ is continuous. Moreover we have

$$\sum_{m=1}^{\lfloor n^\beta \rfloor} \mathcal{O}(m^{-2}) h_{\mathbf{v}; \mathbf{v}_0}(m/n) \leq \mathcal{O}(1) n \int_0^{\frac{\lfloor n^\beta \rfloor + 1}{n}} h_{\mathbf{v}; \mathbf{v}_0}(x) dx = \mathcal{O} \left(\frac{1}{n^{2\varepsilon(1-\beta)}} \right)$$

uniformly thanks to (22) and (24). Using (16), the symmetry of $h_{\mathbf{v}; \mathbf{v}_0}$ and taking $\beta = 3/8$ then gives the desired result. \square

Lemma 17. *The family $\mathcal{F} = \{h_{\mathbf{v}; \mathbf{v}_0}, \mathbf{v} \in N\}$ is a VC-subgraph class of functions (Van Der Vaart and Wellner, 1996, Section 2.6.2).*

Proof. We have $h_{\mathbf{v}; \mathbf{v}_0} = \gamma_{2\mathbf{v}_0+1} / \gamma_{2\mathbf{v}+1}$, with

$$\gamma_{2\mathbf{v}+1}(x) = \sum_{j=0}^{+\infty} \frac{1}{(j+1+x)^{2\mathbf{v}+1}} + \sum_{j=0}^{+\infty} \frac{1}{(j+2-x)^{2\mathbf{v}+1}} + \frac{1}{x^{2\mathbf{v}+1}} + \frac{1}{(1-x)^{2\mathbf{v}+1}}, \quad 0 < x < 1.$$

The four families of functions involved in the last expression of $\gamma_{2\mathbf{v}+1}$ are monotonous with respect to $\mathbf{v} \in N$ so they are VC-subgraph classes of functions. Indeed, let $(x_1, y_1), (x_2, y_2) \in (0, 1) \times \mathbb{R}$, there cannot be $f, g \in \mathcal{F}$ such that $f(x_1) < y_1, f(x_2) \geq y_2, g(x_1) \geq y_1$, and $g(x_2) < y_2$, since we have either $g \leq f$ or $f \leq g$.

The class \mathcal{F} is therefore a VC-subgraph class of functions thanks to Lemma 2.6.18 from Van Der Vaart and Wellner (1996) by observing that the statement (viii) remains valid for a monotonous function defined only on a subset of \mathbb{R} containing the ranges of the elements of \mathcal{F} . \square

Lemma 18. *We have*

$$\frac{1}{n} \sum_{m=0}^{n-1} (h_{\mathbf{v}_1; \mathbf{v}_0}(m/n) - h_{\mathbf{v}_2; \mathbf{v}_0}(m/n))^2 \rightarrow \int_0^1 (h_{\mathbf{v}_1; \mathbf{v}_0} - h_{\mathbf{v}_2; \mathbf{v}_0})^2,$$

uniformly in $\mathbf{v}_1, \mathbf{v}_2 \in [\mathbf{v}_0 - 1/4, \mathbf{v}_0]$.

Proof. Let $\varepsilon > 0$, we have

$$\int_0^\alpha (h_{v_1;v_0} - h_{v_2;v_0})^2 \leq 4 \int_0^\alpha F_\varepsilon^2 \leq \varepsilon/5$$

and

$$\frac{1}{n} \sum_{m=1}^{\lfloor \alpha n \rfloor} (h_{v_1;v_0}(m/n) - h_{v_2;v_0}(m/n))^2 \leq \frac{4}{n} \sum_{m=1}^{\lfloor \alpha n \rfloor} F_\varepsilon^2(m/n) \leq \varepsilon/5$$

and similarly for $\frac{1}{n} \sum_{m=\lfloor (1-\alpha)n \rfloor}^{n-1} (h_{v_1;v_0}(m/n) - h_{v_2;v_0}(m/n))^2$ for some $\alpha > 0$ and n that is large enough. Now a compacity argument shows that the derivative of $(h_{v_1;v_0} - h_{v_2;v_0})^2$ is uniformly bounded on $[\alpha, 1 - \alpha]$ so an adaptation of the traditional technique for error bounds on Riemann sums give

$$\left| \frac{1}{n} \sum_{m=\lfloor \alpha n \rfloor+1}^{\lfloor (1-\alpha)n \rfloor-1} (h_{v_1;v_0}(m/n) - h_{v_2;v_0}(m/n))^2 - \int_\alpha^{1-\alpha} (h_{v_1;v_0} - h_{v_2;v_0})^2 \right| \leq \varepsilon/5,$$

uniformly in $v_1, v_2 \in [v_0 - 1/4, b_v]$ for n large enough. □

For $n \geq 3$ and $0 \leq m \leq n-1$, define $B_{m,n} = U_{m,n}^2 - 1$.

Lemma 19. *Let $3/8 < \varepsilon < 1/2$, we have*

$$\frac{1}{\sqrt{n}} \sum_{m=1}^{n-1} B_{m,n} h_{\cdot;v_0} \left(\frac{m}{n} \right) \rightsquigarrow \text{GP} \left(0, (v_1, v_2) \mapsto \int_0^1 h_{v_1;v_0} h_{v_2;v_0} \right),$$

in $L^\infty(N_\varepsilon)$.

Proof. The inequality (23) gives the $L_{(0,1)}^4$ integrable envelope

$$\sup_{v \in N_\varepsilon} h_{v;v_0}(x) \leq C \min(x, 1-x)^{-1+2\varepsilon} = F_\varepsilon(x), \quad 0 < x < 1,$$

for some $C > 0$. Moreover, Lemma 17 shows that \mathcal{F} satisfies the uniformly integrable entropy condition (see, e.g., Ziegler, 1997, Lemma 2.4).

(Note that Ziegler (1997) and Van Der Vaart and Wellner (1996) use apparently slightly different definitions of the VC dimension, which can be shown to be equivalent (see, e.g., Van Der Vaart and Wellner, 1996, Exercice 2.6.11).)

The standard approach for monotonous Riemann sums applies by splitting on $(0, 1/2]$ and $[1/2, 1)$ and we have $\sum_{m=1}^{n-1} F_\varepsilon^4(m/n) = \mathcal{O}(n)$ and therefore

$$\sum_{m=1}^{n-1} \mathbb{P} \left(\frac{F_\varepsilon(m/n) |B_{m,n}|}{\sqrt{n}} > \theta_n \right) \leq \frac{\mathbb{E}(B_{0,1}^4)}{n^2 \theta_n^4} \sum_{m=1}^{n-1} F_\varepsilon^4(m/n) = \mathcal{O} \left(\frac{1}{n \theta_n^4} \right),$$

which converges to zero with $\theta_n = n^{-1/5}$.

Moreover let $d = \|\cdot - \cdot\|_{L_{(0,1)}^2}$, one has $\|F\|_{L_{(0,1)}^2} < +\infty$ so (\mathcal{F}, d) is totally bounded since it is covered by the uniformly integrable entropy condition. Let $\beta, \rho > 0$, we have

$$a_n(\beta, \rho) = \sup_{d(f, g) \leq \beta} \mathbb{E} \left(\left(\sum_{m=1}^{n-1} (f(m/n) - g(m/n)) \frac{B_{m,n}}{\sqrt{n}} \mathbb{1}_{F_\varepsilon(m/n) |B_{m,n}| \leq \sqrt{n} \theta_n} \right)^2 \right)$$

$$\begin{aligned}
&\leq \sup_{d(f, g) \leq \beta} \mathbb{E} \left(\left(\sum_{m=1}^{n-1} (f(m/n) - g(m/n)) \frac{B_{m,n}}{\sqrt{n}} \right)^2 \right) \\
&= \frac{\text{Var}(B_{0,1})}{n} \sup_{d(f, g) \leq \beta} \sum_{m=1}^{n-1} (f(m/n) - g(m/n))^2 \rightarrow \text{Var}(B_{0,1}) \sup_{d(f, g) \leq \beta} d^2(f, g).
\end{aligned}$$

thanks to Lemma 18. Finally

$$\sup_{n \geq 1} \sum_{m=0}^{n-1} \mathbb{E} \left(F_\varepsilon^2(m/n) \frac{B_{m,n}^2}{n} \mathbb{1}_{F_\varepsilon(m/n) B_{m,n} \leq \sqrt{n} \theta_n} \right) \leq \sup_{n \geq 1} \frac{\text{Var}(B_{0,1})}{n} \sum_{m=0}^{n-1} F_\varepsilon^2(m/n),$$

is finite.

Now the finite dimensional laws convergence is stated using a classical Lyapunov condition observing that the $B_{m,n}$ s admit moments of every order, that $F_\varepsilon^{2+\delta}$ is integrable for δ that is small enough and that

$$\frac{1}{n} \sum_{m=0}^{n-1} h_{v_1; v_0}(m/n) h_{v_1; v_0}(m/n) \rightarrow \int_0^1 h_{v_1; v_0} h_{v_2; v_0},$$

using Lemma 18 and the standard monotonous approach for $\frac{1}{n} \sum_{m=0}^{n-1} h_{v_1; v_0}^2(m/n)$.

We can then apply the Theorem 6.1 of Ziegler (1997) to prove the claim. \square

Lemma 20. *Let $2/5 < \varepsilon < 1/2$. The sequence*

$$(v, \alpha) \in N_\varepsilon \times A \mapsto \sqrt{n} \left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1+2(v-v_0)} \int_0^1 h_{v; v_0}} - 1 \right)$$

of processes converges weakly to

$$\text{GP} \left(0, (v_1, v_2) \mapsto \frac{\int_0^1 h_{v_1; v_0} h_{v_2; v_0}}{\int_0^1 h_{v_1; v_0} \int_0^1 h_{v_2; v_0}} \right),$$

in $L^\infty(N_\varepsilon \times A)$.

Proof.

$$\begin{aligned}
&\sqrt{n} \left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1+2(v-v_0)}} - \int_0^1 h_{v; v_0}(x) dx \right) \\
&= \sqrt{n} U_{0,n}^2 \left(\frac{\lambda_{0,n}^0}{n^{1+2(v-v_0)} \lambda_{0,n}} \right) + \frac{1}{\sqrt{n}} \sum_{m=1}^{n-1} U_{m,n}^2 \left(\frac{\lambda_{m,n}^0}{n^{2(v-v_0)} \lambda_{m,n}} - h_{v; v_0}(m/n) \right) \\
&\quad + \frac{1}{\sqrt{n}} \sum_{m=1}^{n-1} B_{m,n} h_{v; v_0}(m/n) + \sqrt{n} \left(\frac{1}{n} \sum_{m=1}^{n-1} h_{v; v_0}(m/n) - \int_0^1 h_{v; v_0}(x) dx \right),
\end{aligned}$$

with $B_{m,n} = U_{m,n}^2 - 1$. Then a classical Borel-Cantelli argument (see, e.g., Ying, 1991, Lemma 4) shows that $\sup_{0 \leq m \leq n-1} |U_{m,n}^2| = o_P(n^\delta)$ for every $\delta > 0$, so

$$\sup_{v \in N_\varepsilon, \alpha \in A} \left| \sqrt{n} U_{0,n}^2 \left(\frac{\lambda_{0,n}^0}{n^{1+2(v-v_0)} \lambda_{0,n}} \right) \right| = o_P(1),$$

and

$$\sup_{\mathbf{v} \in N_\varepsilon, \alpha \in A} \left| \frac{1}{\sqrt{n}} \sum_{m=1}^{n-1} U_{m,n}^2 \left(\frac{\lambda_{m,n}^0}{n^{2(\mathbf{v}-\mathbf{v}_0)} \lambda_{m,n}} - h_{\mathbf{v};\mathbf{v}_0}(m/n) \right) \right| = o_P(1).$$

thanks to Lemma 16. Finally Lemma 14, Lemma 19, Slutsky's lemma, and the continuous mapping theorem give the claim observing that the mapping $\mathbf{v} \in N_\varepsilon \mapsto \int_0^1 h_{\mathbf{v};\mathbf{v}_0}$ is bounded away from zero. \square

Lemma 21. *Let $\mathbf{v} \in (\mathbf{v}_0 - 1/2, \mathbf{b}_\mathbf{v}]$, we have*

$$g_n(\mathbf{v}) = \frac{1}{n} \sum_{m=1}^{n-1} B_{m,n} h_{\mathbf{v};\mathbf{v}_0} \left(\frac{m}{n} \right) = o_P(1).$$

Proof. Let $\delta = \mathbf{v} - \mathbf{v}_0 + 1/2 > 0$. Then, the equivalence (23) gives

$$\mathbb{E}(g_n^2(\mathbf{v})) = \frac{\text{Var}(B_{0,n})}{n^2} \sum_{m=1}^{n-1} h_{\mathbf{v};\mathbf{v}_0}^2 \left(\frac{m}{n} \right) \lesssim \frac{1}{n^2} \sum_{m=1}^l \left(\frac{m}{n} \right)^{4\delta-2} = \frac{1}{n^{4\delta}} \sum_{m=1}^l m^{4\delta-2},$$

which converges to zero no matter how δ compares with $1/4$. \square

Lemma 22. *Let $0 < \varepsilon < 1/2$, we have*

$$\sup_{\mathbf{v} \in N_\varepsilon, \alpha \in A} \left| \frac{Z^\top R_{\mathbf{v},\alpha}^{-1} Z}{n^{1+2(\mathbf{v}-\mathbf{v}_0)}} - \int_0^1 h_{\mathbf{v};\mathbf{v}_0} \right| = o_P(1).$$

Proof. First we have

$$\sup_{\mathbf{v} \in N_\varepsilon} \left| \frac{1}{n} \sum_{m=1}^{n-1} B_{m,n} h_{\mathbf{v};\mathbf{v}_0} \left(\frac{m}{n} \right) \right| = o_P(1),$$

thanks to Lemma 21, Lemma 23, and (Van Der Vaart and Wellner, 1996, Theorem 1.5.4 and Theorem 1.5.7). Then, proceed as for Lemma 20. \square

Lemma 23. *Let $0 < \varepsilon < 1/2$ and define*

$$g_n: \mathbf{v} \in N_\varepsilon \mapsto \frac{1}{n} \sum_{m=1}^{n-1} B_{m,n} h_{\mathbf{v};\mathbf{v}_0} \left(\frac{m}{n} \right).$$

The sequence (g_n) is asymptotically uniformly equicontinuous in probability for $(x, y) \mapsto |x - y|$ (Van Der Vaart and Wellner, 1996, Chapter 1.5).

Proof. Let $1 \leq m \leq \lfloor n/2 \rfloor$ and define

$$\eta_{m,n}: \mathbf{v} \in N_\varepsilon \mapsto \gamma_{2\mathbf{v}+1}(m/n) = \sum_{j \in \mathbb{Z}} \frac{1}{|j + m/n|^{2\mathbf{v}+1}}.$$

These functions are C^1 and some calculations show that $(n/m)^{2\mathbf{v}+1} \lesssim \eta_{m,n}(\mathbf{v}) \lesssim (n/m)^{2\mathbf{v}+1}$ and that $(n/m)^{2\mathbf{v}+1} \ln(n/m) \lesssim \frac{d\eta_{m,n}}{d\mathbf{v}}(\mathbf{v}) \lesssim (n/m)^{2\mathbf{v}+1} \ln(n/m)$, for $\mathbf{v} \in N_\varepsilon$, $1 \leq m \leq \lfloor n/2 \rfloor$, and n .

Write $\kappa_{m,n}: \mathbf{v} \in N_\varepsilon \mapsto h_{\mathbf{v};\mathbf{v}_0}(m/n)$. Then, for all $\delta > 0$ and $\mathbf{v} \in N_\varepsilon$, we have

$$\left| \frac{d\kappa_{m,n}}{d\mathbf{v}}(\mathbf{v}) \right| \lesssim \left(\frac{n}{m} \right)^{1-2\varepsilon+2\delta}.$$

Now let $v_1, v_2 \in N_\varepsilon$. If one choose $p > 1$ and $\delta > 0$ such that $p(1 - 2\varepsilon + 2\delta) < 1$, then we have by Hölder's inequality with $1/q + 1/p = 1$

$$\begin{aligned} & |g_n(v_1) - g_n(v_2)| \\ & \leq \left(\frac{1}{n} \sum_{m=1}^{n-1} B_{m,n}^q \right)^{1/q} \cdot \left(\frac{1}{n} \sum_{m=1}^{n-1} \sup_{v \in N_\varepsilon} \left| \frac{d\kappa_{m,n}}{dv}(v) \right|^p \right)^{1/p} \cdot |v_1 - v_2|, \end{aligned}$$

which gives the result since the $B_{m,n}$ s admit moments of every order. \square

Lemma 24. *Let $2/5 < \varepsilon < 1/2$. Then, the sequence*

$$(v, \alpha) \in N_\varepsilon \times A \mapsto \sqrt{n} \left(M_n(v, \alpha) - \int_0^1 g_v - \ln \left(\int_0^1 h_{v;v_0} \right) \right)$$

of processes converges weakly to

$$\text{GP} \left(0, (v_1, v_2) \mapsto \frac{\int_0^1 h_{v_1;v_0} h_{v_2;v_0}}{\int_0^1 h_{v_1;v_0} \int_0^1 h_{v_2;v_0}} \right)$$

in $L^\infty(N_\varepsilon \times A)$.

Proof. Let \mathbb{E} be the set of continuous real-valued functions on the compact $N_\varepsilon \times A$ and $\mathbb{D}_\psi \subset \mathbb{E}$ be the subset of strictly positive functions, both endowed with the supremum norm. The mapping $\psi : g \in \mathbb{D}_\psi \subset \mathbb{E} \mapsto \ln \circ g \in \mathbb{E}$ is Fréchet-differentiable at the unit function and $\psi'(1) : h \in \mathbb{E} \rightarrow h$. Then, Theorem 3.9.4 from [Van Der Vaart and Wellner \(1996\)](#) and Lemma 20 show that

$$\sup_{(v, \alpha) \in N_\varepsilon \times A} \left| \sqrt{n} \ln \left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1+2(v-v_0)} \int_0^1 h_{v;v_0}} \right) - \sqrt{n} \left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1+2(v-v_0)} \int_0^1 h_{v;v_0}} - 1 \right) \right|$$

is $o_P(1)$. Lemma 12 and Slutsky's Lemma allows then to conclude. \square

Lemma 25. *The convergence $\hat{v}_0 \rightarrow v_0$ holds in probability.*

Proof. First for $v \in N$ and $\alpha \in A$, we have

$$\begin{aligned} M_n(v, \alpha) &= \ln(\det(R_{v, \alpha}))/n + \ln \left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1-2v_0}} \right) \\ &= \int_0^1 g_v(x) dx + \mathcal{O}(\ln(n)/n) + \ln \left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1+2(v-v_0)}} \right) \\ &= \mathcal{O}(1) + \ln \left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1+2(v-v_0)}} \right) \end{aligned}$$

uniformly thanks to Lemma 12 and by observing that the mapping $v \in [a_v, b_v] \mapsto \int_0^1 g_v$ is continuous. Now let $v \in [a_v, v_0 - 1/2 + \varepsilon]$ and $\alpha \in A$, Lemma 10 yields

$$\frac{Z^\top R_{v, \alpha}^{-1} Z}{n^{1+2(v-v_0)}} \gtrsim \frac{1}{n} \sum_{m=1}^l U_{m,n}^2 \left(\frac{m}{n} \right)^{2(v-v_0)} \gtrsim \frac{1}{n} \sum_{m=1}^l U_{m,n}^2 \left(\frac{m}{n} \right)^{-1+2\varepsilon}$$

$$= \frac{1}{n^{2\varepsilon}} \sum_{m=1}^l U_{m,n}^2 m^{-1+2\varepsilon} \rightarrow \frac{1}{2^{1+2\varepsilon}\varepsilon}$$

in probability using a similar argument as the one from Lemma 21. Considering \mathbb{U}_n from Section A.1, Lemma 24 gives $\mathbb{U}_n(\mathbf{v}_0) \rightarrow \int_0^1 g_{\mathbf{v}_0}$ in probability, so we have

$$\begin{aligned} & \inf_{\mathbf{v} \in [a_{\mathbf{v}}, \mathbf{v}_0 - 1/2 + \varepsilon]} \mathbb{U}_n(\mathbf{v}) - \mathbb{U}_n(\mathbf{v}_0) \\ & \geq C + \inf_{\mathbf{v} \in [a_{\mathbf{v}}, \mathbf{v}_0 - 1/2 + \varepsilon], \alpha \in A} \ln \left(\frac{Z^\top R_{\mathbf{v}, \alpha}^{-1} Z}{n^{1+2(\mathbf{v}-\mathbf{v}_0)}} \right) - \mathbb{U}_n(\mathbf{v}_0) \rightarrow C - \ln(2^{1+2\varepsilon}\varepsilon) - \int_0^1 g_{\mathbf{v}_0}, \end{aligned}$$

with the later convergence holding in probability, for a universal constant C . Letting $\varepsilon \rightarrow 0$ shows that the above limit can be made arbitrarily high.

Finally let $0 < \varepsilon < 1/2$, we have

$$\begin{aligned} & \sup_{\mathbf{v} \in N_\varepsilon} \left| \mathbb{U}_n(\mathbf{v}) - \int_0^1 g_{\mathbf{v}}(x) dx - \ln \left(\int_0^1 h_{\mathbf{v}; \mathbf{v}_0} \right) \right| \\ & \leq \sup_{\mathbf{v} \in N_\varepsilon, \alpha \in A} \left| \mathbb{M}_n(\mathbf{v}, \alpha) - \int_0^1 g_{\mathbf{v}}(x) dx - \ln \left(\int_0^1 h_{\mathbf{v}; \mathbf{v}_0} \right) \right| = o_P(1), \end{aligned}$$

thanks to Lemma 12, Lemma 22 and the continuous mapping theorem applied from the space of functions that are bounded away from zero and infinity to the space of bounded functions. Moreover the function

$$\mathbb{U} : \mathbf{v} \in N_\varepsilon \mapsto \int_0^1 g_{\mathbf{v}}(x) dx + \ln \left(\int_0^1 h_{\mathbf{v}; \mathbf{v}_0} \right)$$

is continuous, and strictly maximized by taking $\mathbf{v} = \mathbf{v}_0$ thanks to Jensen inequality and the fact that $h_{\mathbf{v}; \mathbf{v}_0}$ is constant only if $\mathbf{v} = \mathbf{v}_0$. \square

Lemma 26. *Let $0 < \beta < 1/4$. The bound $\hat{\mathbf{v}}_n - \mathbf{v}_0 = o_P(n^{-\beta})$ holds in probability.*

Proof. Let $2/5 < \varepsilon < 1/2$, $0 < \beta < 1/2$ and let us reuse the function \mathbb{U} from the proof of Lemma 25. We have

$$\mathbb{M}_n(\mathbf{v}, \alpha) - \mathbb{U}(\mathbf{v}) = \mathcal{O} \left(\frac{\ln(n)}{n} \right) + \ln \left(\frac{Z^\top R_{\mathbf{v}, \alpha}^{-1} Z}{n^{1+2(\mathbf{v}-\mathbf{v}_0)}} \right) - \ln \left(\int_0^1 h_{\mathbf{v}; \mathbf{v}_0} \right), (\mathbf{v}, \alpha) \in N_\varepsilon \times A.$$

So this yields

$$n^\beta \sup_{\mathbf{v} \in N_\varepsilon} |\mathbb{U}_n(\mathbf{v}) - \mathbb{U}(\mathbf{v})| \leq n^\beta \sup_{\mathbf{v} \in N_\varepsilon, \alpha \in A} |\mathbb{M}_n(\mathbf{v}, \alpha) - \mathbb{U}(\mathbf{v})|,$$

which converges in probability to zero thanks to Lemma 24 and Slutsky's Lemma. Moreover, \mathbb{U} is C^3 and some calculations show that

$$\mathbb{U}''(\mathbf{v}_0) = \int_0^1 \left(\frac{\tilde{\gamma}_{2\mathbf{v}_0+1}}{\gamma_{2\mathbf{v}_0+1}} \right)^2 - \left(\int_0^1 \frac{\tilde{\gamma}_{2\mathbf{v}_0+1}}{\gamma_{2\mathbf{v}_0+1}} \right)^2 > 0,$$

with $\tilde{\gamma}$ the derivative of $(\mathbf{v}, x) \mapsto \gamma_{2\mathbf{v}+1}(x)$ with respect to \mathbf{v} . Then, Lemma 25 and the fact that the maximum of \mathbb{U} on the compact N_ε is unique give the rate $n^{-\beta/2}$ thanks to a standard Taylor expansion around \mathbf{v}_0 . \square

Proof of Theorem 2. Let $0 < \beta < 1/4$, Lemma 9 gives

$$\ln(\hat{\phi}_n) = \ln(\phi_0) + \ln\left(\frac{Z^\top K_{\hat{v}_n, \hat{\alpha}_n}^{-1} Z}{n^{1+2(\hat{v}_n - v_0)}}\right) + 2(\hat{v}_n - v_0) \ln(n).$$

So

$$\begin{aligned} \frac{n^\beta}{\ln(n)} \left(\ln(\hat{\phi}_n) - \ln(\phi_0) \right) &= \frac{n^\beta}{\ln(n)} \ln\left(\frac{Z^\top K_{\hat{v}_n, \hat{\alpha}_n}^{-1} Z}{n^{1+2(\hat{v}_n - v_0)}}\right) + 2n^\beta (\hat{v}_n - v_0) \\ &= \frac{n^\beta}{\ln(n)} \ln\left(\int_0^1 h_{\hat{v}_n; v_0}\right) + \frac{n^\beta}{\ln(n)} \left(\ln\left(\frac{Z^\top K_{\hat{v}_n, \hat{\alpha}_n}^{-1} Z}{n^{1+2(\hat{v}_n - v_0)}}\right) - \ln\left(\int_0^1 h_{\hat{v}_n; v_0}\right) \right) + 2n^\beta (\hat{v}_n - v_0). \end{aligned}$$

The latter converges to zero in probability thanks to Lemma 24, Slutsky's Lemma, Lemma 26, and to the univariate Delta method, observing that the mapping $v \mapsto \ln\left(\int_0^1 h_{v; v_0}\right)$ is C^1 in a neighborhood of v_0 . \square

A.5 Proof of Theorem 3

We start by providing a few cumbersome expressions. Remember that the quantities $\lambda_{m,n}$ depends on v and α but have their argument dropped to avoid cumbersome notations. The function \mathbb{L}_n is C^3 for any realization, and

$$\begin{aligned} \mathbb{L}_n(v, \phi, \alpha) &= \ln(\phi) + \frac{1}{n} \sum_{m=0}^{n-1} \ln(\lambda_{m,n}) + \frac{\phi_0}{n\phi} \sum_{m=0}^{n-1} \frac{\lambda_{m,n}^0 U_{m,n}^2}{\lambda_{m,n}} \\ \frac{\partial \mathbb{L}_n}{\partial v}(v, \phi, \alpha) &= \frac{1}{n} \sum_{m=0}^{n-1} \frac{\frac{\partial \lambda_{m,n}}{\partial v}}{\lambda_{m,n}} - \frac{\phi_0}{n\phi} \sum_{m=0}^{n-1} \frac{\lambda_{m,n}^0 \frac{\partial \lambda_{m,n}}{\partial v} U_{m,n}^2}{\lambda_{m,n}^2} \\ \frac{\partial^2 \mathbb{L}_n}{\partial v^2}(v, \phi, \alpha) &= \frac{1}{n} \sum_{m=0}^{n-1} \frac{\frac{\partial^2 \lambda_{m,n}}{\partial v^2} \lambda_{m,n} - \left(\frac{\partial \lambda_{m,n}}{\partial v}\right)^2}{\lambda_{m,n}^2} \\ &\quad - \frac{\phi_0}{n\phi} \sum_{m=0}^{n-1} \frac{\lambda_{m,n}^0 \left(\frac{\partial^2 \lambda_{m,n}}{\partial v^2} \lambda_{m,n} - 2 \left(\frac{\partial \lambda_{m,n}}{\partial v} \right)^2 \right) U_{m,n}^2}{\lambda_{m,n}^3} \\ \frac{\partial^3 \mathbb{L}_n}{\partial v^3}(v, \phi, \alpha) &= \frac{1}{n} \sum_{m=0}^{n-1} \lambda_{m,n}^{-3} \left(\frac{\partial^3 \lambda_{m,n}}{\partial v^3} \lambda_{m,n} + \frac{\partial^2 \lambda_{m,n}}{\partial v^2} \frac{\partial \lambda_{m,n}}{\partial v} \right. \\ &\quad \left. - 2 \frac{\partial^2 \lambda_{m,n}}{\partial v^2} \frac{\partial \lambda_{m,n}}{\partial v} \right) \lambda_{m,n} - 2 \frac{\partial \lambda_{m,n}}{\partial v} \left(\frac{\partial^2 \lambda_{m,n}}{\partial v^2} \lambda_{m,n} - \left(\frac{\partial \lambda_{m,n}}{\partial v} \right)^2 \right) \\ &\quad - \frac{\phi_0}{n\phi} \sum_{m=0}^{n-1} \lambda_{m,n}^{-4} \lambda_{m,n}^0 \left(\lambda_{m,n} \left(\frac{\partial^3 \lambda_{m,n}}{\partial v^3} \lambda_{m,n} + \frac{\partial^2 \lambda_{m,n}}{\partial v^2} \frac{\partial \lambda_{m,n}}{\partial v} - 4 \frac{\partial^2 \lambda_{m,n}}{\partial v^2} \frac{\partial \lambda_{m,n}}{\partial v} \right) \right. \\ &\quad \left. - 3 \frac{\partial \lambda_{m,n}}{\partial v} \left(\frac{\partial^2 \lambda_{m,n}}{\partial v^2} \lambda_{m,n} - 2 \left(\frac{\partial \lambda_{m,n}}{\partial v} \right)^2 \right) \right) U_{m,n}^2 \end{aligned}$$

Lemma 10 and the following will help to analyze roughly the previous expressions. Exceptionally, the arguments of the $\lambda_{m,n}$ s are not dropped.

Lemma 27. Let $\delta > 0$, $0 \leq m \leq \lfloor n/2 \rfloor$, $v \in N$, $\alpha \in A$ and $k \in \{1, 2, 3\}$. The functions $\lambda_{m,n}$ are C^3 and:

$$\frac{1}{n} \left| \frac{\partial^k \lambda_{m,n}}{\partial v^k}(v, \alpha) \right| \lesssim \frac{1}{m^{2v+1-\delta}}, \quad \text{if } 1 \leq m \leq \lfloor n/2 \rfloor$$

and

$$1 \lesssim \frac{1}{n} \left| \frac{\partial^k \lambda_{0,n}}{\partial v^k}(v, \alpha) \right| \lesssim 1.$$

Proof. We have

$$\left| \frac{\partial^k \lambda_{m,n}}{\partial v^k}(v, \alpha) \right| = \sum_{j \in \mathbb{Z}} \frac{|\ln^k(\alpha^2 + (m + jn)^2)|}{(\alpha^2 + (m + jn)^2)^{v+1/2}} \lesssim \sum_{j \in \mathbb{Z}} \frac{1}{(\alpha^2 + (m + jn)^2)^{v+1/2-\delta/2}}.$$

Lemma 10 gives the result. \square

Proof of Theorem 3. Remember that $A = \{\alpha_0\}$ and consider \mathbb{L}_n as a function of (v, ϕ) only. We start by elucidating the behavior of the score function.

Let $e_2(v) = E(\psi_v^2(U))$ for $v > 0$. Stein (1999, proof of Theorem 1, Section 6.7) shows that

$$\text{Cov} \left(\frac{\sqrt{n}}{2} \nabla \mathbb{L}_n(v_0, \phi_0) \right) = \underbrace{\begin{pmatrix} 2\ln^2(n) + 4\ln(n)e(v_0) + 2e_2(v_0) & -\frac{\ln(n)}{\phi_0} - \frac{e(v_0)}{\phi_0} \\ -\frac{\ln(n)}{\phi_0} - \frac{e(v_0)}{\phi_0} & \frac{1}{2\phi_0^2} \end{pmatrix}}_{C_n} + \mathcal{O}(n^{-\varepsilon}),$$

for some $\varepsilon > 0$.

Define

$$A_n = \frac{2\phi_0}{\sqrt{V(v_0)}} \begin{pmatrix} \frac{1}{2\phi_0} & 0 \\ \ln(n) + e(v_0) & \sqrt{V(v_0)} \end{pmatrix}.$$

One has $A_n^\top C_n A_n = 2I_2$ and so

$$\text{Cov} \left(\frac{\sqrt{n}}{2} A_n^\top \nabla \mathbb{L}_n(v_0, \phi_0) \right) = A_n^\top \text{Cov} \left(\frac{\sqrt{n}}{2} \nabla \mathbb{L}_n(v_0, \phi_0) \right) A_n \rightarrow 2I_2.$$

Let us show the Lyapunov condition. To do so, write

$$\mathbb{L}_{m,n}(v, \phi) = \ln(\phi) + \ln(\lambda_{m,n}) + \frac{\phi_0}{\phi} \frac{\lambda_{m,n}^0 U_{m,n}^2}{\lambda_{m,n}},$$

so $\mathbb{L}_n(v, \phi) = n^{-1} \sum_{m=0}^{n-1} \mathbb{L}_{m,n}(v, \phi)$. Let $\delta > 0$, we have

$$\sum_{m=0}^{n-1} E \left(\left| \frac{\partial \mathbb{L}_{m,n}}{\partial \phi}(v_0, \phi_0) \right|^{2+\delta} \right) = \frac{1}{\phi_0^{2+\delta} n^{2+\delta}} \sum_{m=0}^{n-1} E \left(|1 - U_{m,n}^2|^{2+\delta} \right) = \frac{E \left(|1 - U_{0,1}^2|^{2+\delta} \right)}{\phi_0^{2+\delta} n^{1+\delta}},$$

and

$$\sum_{m=0}^{n-1} E \left(\left| \frac{\partial \mathbb{L}_{m,n}}{\partial v}(v_0, \phi_0) \right|^{2+\delta} \right) = \frac{E \left(|1 - U_{0,1}^2|^{2+\delta} \right)}{n^{2+\delta}} \sum_{m=0}^{n-1} \left(\frac{\partial \lambda_{m,n}^0}{\lambda_{m,n}^0} \right)^{2+\delta} \lesssim \frac{1}{n^{1+3\delta/4}},$$

using Lemma 10, Lemma 27, and the derivatives expressions. Therefore,

$$\sum_{m=0}^{n-1} \mathbb{E} \left(\left\| \sqrt{n} A_n^\top \nabla \mathbb{L}_{m,n}(\mathbf{v}_0, \phi_0) \right\|^{2+\delta} \right) \lesssim n^{1+\delta/2} \ln(n)^{2+\delta} \sum_{m=0}^{n-1} \mathbb{E} \left(\left\| \nabla \mathbb{L}_{m,n}(\mathbf{v}_0, \phi_0) \right\|^{2+\delta} \right) \rightarrow 0.$$

The Lyapunov condition is fulfilled, and it is straightforward to verify that the score function is centered, yielding

$$\frac{\sqrt{n}}{2\sqrt{2}} A_n^\top \nabla \mathbb{L}_n(\mathbf{v}_0, \phi_0) \rightsquigarrow \mathcal{N}(0, I_2).$$

Consider now the Hessian matrix. One has

$$\mathbb{E}(\nabla^2 \mathbb{L}_n(\mathbf{v}_0, \phi_0)) = \frac{n}{2} \text{Cov}(\nabla \mathbb{L}_n(\mathbf{v}_0, \phi_0)),$$

so

$$\frac{1}{2} \mathbb{E}(\nabla^2 \mathbb{L}_n(\mathbf{v}_0, \phi_0)) - C_n = \mathcal{O}(n^{-\varepsilon}).$$

Furthermore, using Lemma 10, Lemma 27, and the previous expressions, it is straightforward to check that

$$\text{Var} \left(\frac{\partial^2 \mathbb{L}_n}{(\partial \mathbf{v})^p (\partial \phi)^{2-p}}(\mathbf{v}_0, \phi_0) \right) = \mathcal{O}(n^{-2\varepsilon}),$$

for $\varepsilon > 0$ small enough, so $\nabla^2 \mathbb{L}_n(\mathbf{v}_0, \phi_0)/2 - C_n = \mathcal{O}_P(n^{-\varepsilon})$ for some $\varepsilon > 0$ and therefore $A_n^\top \nabla^2 \mathbb{L}_n(\mathbf{v}_0, \phi_0) A_n \rightarrow 4I_2$, in probability.

Let us now roughly bound the third derivatives. For $\varepsilon > 0$, $m \geq 1$, $k \in \{0, 1, 2, 3\}$, and $|\mathbf{v} - \mathbf{v}_0| \leq \varepsilon$, one has

$$\left| \frac{\partial^k \lambda_{m,n}}{\partial \mathbf{v}^k}(\mathbf{v}_0 + \varepsilon, 1) \right| \leq \left| \frac{\partial^k \lambda_{m,n}}{\partial \mathbf{v}^k}(\mathbf{v}, 1) \right| \leq \left| \frac{\partial^k \lambda_{m,n}}{\partial \mathbf{v}^k}(\mathbf{v}_0 - \varepsilon, 1) \right|.$$

Therefore, using again the previous expressions, Lemma 10, and Lemma 27, it is straightforward to show that

$$\mathbb{E} \left(\sup_{p \in \{0, 1, 2, 3\}, |\mathbf{v} - \mathbf{v}_0| \leq \varepsilon, |\phi - \phi_0| \leq \varepsilon} \left| \frac{\partial^3 \mathbb{L}_n}{(\partial \mathbf{v})^p (\partial \phi)^{3-p}}(\mathbf{v}, \phi) \right| \right) = \mathcal{O}(n^{17\varepsilon}). \quad (25)$$

Now we have

$$0 = \Delta \mathbb{L}_n(\mathbf{v}_0, \phi_0) + \Delta^2 \mathbb{L}_n(\mathbf{v}_0, \phi_0) \begin{pmatrix} \hat{\mathbf{v}}_n - \mathbf{v}_0 \\ \hat{\phi}_n - \phi_0 \end{pmatrix} + \mathcal{O}_P \left(n^{17\varepsilon} \left\| \begin{pmatrix} \hat{\mathbf{v}}_n - \mathbf{v}_0 \\ \hat{\phi}_n - \phi_0 \end{pmatrix} \right\|^2 \right),$$

thanks to (25) and using Theorem 2 leads to

$$0 = A_n^\top \Delta \mathbb{L}_n(\mathbf{v}_0, \phi_0) + (A_n^\top \Delta^2 \mathbb{L}_n(\mathbf{v}_0, \phi_0) A_n + o_P(1)) A_n^{-1} \begin{pmatrix} \hat{\mathbf{v}}_n - \mathbf{v}_0 \\ \hat{\phi}_n - \phi_0 \end{pmatrix},$$

and

$$\sqrt{2n} A_n^{-1} \begin{pmatrix} \hat{\mathbf{v}}_n - \mathbf{v}_0 \\ \hat{\phi}_n - \phi_0 \end{pmatrix} = - (A_n^\top \Delta^2 \mathbb{L}_n(\mathbf{v}_0, \phi_0) A_n + o_P(1))^{-1} A_n^\top \Delta \mathbb{L}_n(\mathbf{v}_0, \phi_0) \rightsquigarrow \mathcal{N}(0, I_2),$$

thanks to Slutsky's Lemma. This gives the result. \square

A.6 Proofs of Theorem 4 and Theorem 5

The posterior mean and the error of the GP does not depend on ϕ , so all derivations will be written with $\phi = 1$. We also suppose that $\phi_0 = 1$ without loss of generality. Furthermore, we will write $\omega = (\nu, \alpha)$ and use the coefficients $c_j(\omega) = c_j(\nu, \alpha)$ defined in Section A.1 to avoid cumbersome expressions in this section.

The sample paths are square-integrable almost surely so the convergence of the Fourier expansion (6) holds with probability one also in $L^2_{[0,1]}$. The proofs will rely on using Parseval's identity. Note that we assume $\nu_0 > 1/2$ to avoid dealing with conditionally convergent series. Indeed, in this case the expansion (6) converges almost surely absolutely pointwise, so the hypothesis of Proposition 1 are fulfilled.

Let $\alpha > 0$, $\nu > 0$ and $j \in \mathbb{Z}$, we have

$$\begin{aligned} 2 \left| c_j(\xi - \widehat{\xi}_n) \right|^2 &= \left(\frac{c_j(\omega) \sum_{j_1 \in \mathbb{Z} \setminus \{0\}} \sqrt{c_{j+j_1n}(\omega_0)} U_{1,|j+j_1n|}}{\sum_{j_1 \in \mathbb{Z}} c_{j+nj_1}(\omega)} \right. \\ &\quad \left. - \frac{\sqrt{c_j(\omega_0)} U_{1,|j|} \sum_{j_1 \in \mathbb{Z} \setminus \{0\}} c_{j+nj_1}(\omega)}{\sum_{j_1 \in \mathbb{Z}} c_{j+nj_1}(\omega)} \right)^2 \\ &+ \left(\frac{c_j(\omega) \sum_{j_1 \in \mathbb{Z} \setminus \{0\}} \sqrt{c_{j+nj_1}(\omega_0)} U_{2,|j+nj_1|} \text{sign}(j+nj_1)}{\sum_{j_1 \in \mathbb{Z}} c_{j+nj_1}(\omega)} \right. \\ &\quad \left. - \frac{\sqrt{c_j(\omega_0)} U_{2,|j|} \text{sign}(j) \sum_{j_1 \in \mathbb{Z} \setminus \{0\}} c_{j+nj_1}(\omega)}{\sum_{j_1 \in \mathbb{Z}} c_{j+nj_1}(\omega)} \right)^2. \end{aligned} \quad (26)$$

The two terms in (26) are independent and they are also identically distributed if $m \notin \{0, n/2\}$.

Proof of Theorem 4. Consider $m \notin \{0, n/2\}$ and the indexes of the form $m+nj$, with $j \in \mathbb{Z}$. The two terms in (26) are independent and identically distributed, so there exists a χ^2_2 distributed variable $A_{m,j,n}$ such that

$$\left| c_{m+jn}(\xi - \widehat{\xi}_n) \right|^2 = a_{m,j,n}(\nu) A_{m,j,n}/2,$$

with

$$\begin{aligned} a_{m,j,n}(\nu) &= c_{m+jn}^2(\omega) \frac{\sum_{j_1 \in \mathbb{Z}} c_{m+nj_1}(\omega_0) - c_{m+jn}(\omega_0)}{\left(\sum_{j_1 \in \mathbb{Z}} c_{m+nj_1}(\omega) \right)^2} \\ &\quad + c_{m+jn}(\omega_0) \left(1 - \frac{c_{m+jn}(\omega)}{\sum_{j_1 \in \mathbb{Z}} c_{m+nj_1}(\omega)} \right)^2, \end{aligned} \quad (27)$$

and the dependence of $a_{m,j,n}$ on (the fixed) α be removed for readability. Using Lemma 10 gives, for $1 \leq m \leq l$ and $j \neq 0$:

$$a_{m,j,n}(\nu) \lesssim (jn)^{-4\nu-2} m^{4\nu+2-2\nu_0-1} + (jn)^{-2\nu_0-1}, \quad (28)$$

and

$$a_{m,0,n}(\nu) \lesssim n^{-2\nu_0-1} + m^{4\nu-2\nu_0+1} n^{-4\nu-2}, \quad (29)$$

uniformly in j and m . So, this yields

$$\sum_{j \in \mathbb{Z}} a_{m,j,n}(\nu) \lesssim n^{-2\nu_0-1} + n^{-4\nu-2} m^{4\nu-2\nu_0+1}. \quad (30)$$

The first two statements then follow from Lemma 28, Lemma 29, the identity

$$\sum_{j \in \mathbb{Z}} \left| c_{m+jn}(\xi - \widehat{\xi}_n) \right|^2 = \sum_{j \in \mathbb{Z}} \left| c_{n-m+jn}(\xi - \widehat{\xi}_n) \right|^2, \quad (31)$$

for every $0 \leq m \leq n-1$, and the Fubini-Tonelli theorem.

For the last statement, let $1 \leq m \leq l$. We have

$$\begin{aligned} \mathbb{E} \left(\left| c_{m+jn}(\xi - \widehat{\xi}_n) \right|^2 \right) &= c_{m+jn}^2(\omega) \frac{\sum_{j_1 \in \mathbb{Z}} c_{m+nj_1}(\omega)}{\left(\sum_{j_1 \in \mathbb{Z}} c_{m+nj_1}(\omega) \right)^2} \\ &\quad + c_{m+jn}(\omega) \left(1 - 2 \frac{c_{m+jn}(\omega)}{\sum_{j_1 \in \mathbb{Z}} c_{m+nj_1}(\omega)} \right), \end{aligned}$$

for every $j \in \mathbb{Z}$ and therefore

$$\begin{aligned} &\sum_{j \in \mathbb{Z}} \mathbb{E} \left(\left| c_{m+jn}(\xi - \widehat{\xi}_n) \right|^2 \right) \\ &= (1 + \mathcal{O}(m^{-2})) \sum_{j \in \mathbb{Z}} |m+jn|^{-4v-2} \frac{\sum_{j_1 \in \mathbb{Z}} |m+nj_1|^{-2v_0-1}}{\left(\sum_{j_1 \in \mathbb{Z}} |m+nj_1|^{-2v-1} \right)^2} \\ &\quad + |m+jn|^{-2v_0-1} \left(1 - 2 \frac{|m+jn|^{-2v-1}}{\sum_{j_1 \in \mathbb{Z}} |m+nj_1|^{-2v-1}} \right) \\ &= \frac{(1 + \mathcal{O}(m^{-2}))}{n^{2v_0+1}} \vartheta_{v,v_0}(m/n), \end{aligned}$$

using Lemma 11 and after a few algebraic manipulations. If $v \geq (v_0 - 1/2)/2$, then the function ϑ_{v,v_0} has a finite limit in zero. If $(v_0 - 1)/2 < v < (v_0 - 1/2)/2$, then a Taylor expansion of its derivative shows that it is decreasing in a neighborhood of zero. This shows:

$$\frac{1}{n} \sum_{m=1}^l \vartheta_{v,v_0}(m/n) \rightarrow \int_0^{1/2} \vartheta_{v,v_0}, \quad (32)$$

and Parseval's identity and the Fubini-Tonelli theorem gives

$$n^{2v_0} \mathbb{E}(\text{ISE}_n(v, \alpha; \xi)) = o(1) + \frac{2}{n} \sum_{m=1}^l (1 + \mathcal{O}(m^{-2})) \vartheta_{v,v_0}(m/n) \rightarrow \int_0^1 \vartheta_{v,v_0},$$

killing the $\mathcal{O}(m^{-2})$ term by splitting by how m compares with \sqrt{n} as in the proof of Lemma 16. \square

Lemma 28. *Let $n \geq 2$ be even, one has*

$$\mathbb{E} \left(\sup_{v \in N, \alpha \in A} \sum_{j \in \mathbb{Z}} \left| c_{n/2+jn}(\xi - \widehat{\xi}_n) \right|^2 \right) \lesssim n^{-2v_0-1}.$$

Proof. First, observe that $\sum_{j \in \mathbb{Z}} \left| c_{n/2+jn}(\xi - \widehat{\xi}_n) \right|^2 = 2 \sum_{j \geq 0} \left| c_{n/2+jn}(\xi - \widehat{\xi}_n) \right|^2$.

Let $\mathbf{v} \in N$, $\alpha \in A$, and $j \geq 0$. One has

$$\begin{aligned}
& 2 \left| c_{n/2+jn}(\xi - \widehat{\xi}_n) \right|^2 \left(\sum_{j_1 \in \mathbb{Z}} c_{n/2+nj_1}(\omega) \right)^2 \\
&= \left(\left(c_{n/2+jn}(\omega) \sqrt{c_{n/2+jn}(\omega_0)} - \sqrt{c_{n/2+jn}(\omega_0)} \sum_{j_1 \in \mathbb{Z} \setminus \{j\}} c_{n/2+nj_1}(\omega) \right) U_{1,|n/2+jn|} \right. \\
&\quad \left. + 2c_{n/2+jn}(\omega) \sum_{j_1=0, j_1 \neq |j|}^{+\infty} \sqrt{c_{n/2+j_1n}(\omega_0)} U_{1,|n/2+j_1n|} \right)^2 \\
&\quad + \left(\sqrt{c_{n/2+jn}(\omega_0)} \sum_{j_1 \in \mathbb{Z}} c_{n/2+nj_1}(\omega) U_{2,|n/2+jn|} \right)^2
\end{aligned}$$

So

$$2 \left| c_{n/2+jn}(\xi - \widehat{\xi}_n) \right|^2 = d_{j,n}^2 D_{j,n}^2 + b_{j,n}^2 B_{j,n}^2$$

with $D_{j,n}$ and $B_{j,n}$ standard Gaussians and

$$\begin{aligned}
d_{j,n}^2 &\leq c_{n/2+jn}(\omega_0) + 4c_{n/2+jn}^2(\omega) \frac{\sum_{j_1=0}^{+\infty} c_{n/2+j_1n}(\omega_0)}{\left(\sum_{j_1 \in \mathbb{Z}} c_{n/2+nj_1}(\omega) \right)^2} \\
&\lesssim ((j+1/2)n)^{-2v_0-1} + (j+1/2)^{-4v-2} n^{-2v_0-1}
\end{aligned}$$

uniformly in \mathbf{v} and α using Lemma 10 and the inequality $c_{n/2+jn}(\omega) \leq ((j+1/2)n)^{-2v-1}$. Similarly, one has $b_{j,n}^2 \lesssim ((j+1/2)n)^{-2v_0-1}$. The statement then follows using the Fubini-Tonelli theorem. \square

Lemma 29. *Let $n \geq 2$ and $p \geq 1$. Then, there exists standard Gaussians $\{A_{j,n}, j \in \mathbb{Z}\}$ and $\varepsilon > 0$ such that*

$$\sum_{j \in n\mathbb{Z}} \left| c_{jn}(\xi - \widehat{\xi}_n) \right|^{2p} \lesssim A_{0,n}^{2p} (n^{-2v_0-1} + n^{-4v-2})^p + \sum_{j \in \mathbb{Z} \setminus \{0\}} A_{j,n}^{2p} j^{-1-\varepsilon} (n^{-2v_0-1} + n^{-4v-2})^p,$$

uniformly in $\mathbf{v} \in N$ and $\alpha \in A$.

Proof. Let $\mathbf{v} \in N$ and $\alpha \in A$. For $j \in \mathbb{Z} \setminus \{0\}$, one has

$$\begin{aligned}
& 2 \left| c_{jn}(\xi - \widehat{\xi}_n) \right|^2 \left(\sum_{j_1 \in \mathbb{Z}} c_{nj_1}(\omega) \right)^2 \\
&= \left(\left(c_{jn}(\omega) \sqrt{c_{jn}(\omega_0)} - \sqrt{c_{jn}(\omega_0)} \sum_{j_1 \in \mathbb{Z} \setminus \{j\}} c_{nj_1}(\omega) \right) U_{1,|jn|} \right. \\
&\quad \left. + c_{jn}(\omega) \sqrt{c_0(\omega_0)} U_{1,0} + 2c_{jn}(\omega) \sum_{j_1=1, j_1 \neq j}^{+\infty} \sqrt{c_{j_1n}(\omega_0)} U_{1,|j_1n|} \right)^2 \\
&\quad + \left(\sqrt{c_{jn}(\omega_0)} \sum_{j_1 \in \mathbb{Z}} c_{nj_1}(\omega) U_{2,|jn|} \right)^2
\end{aligned}$$

Moreover,

$$2 \left| c_0(\xi - \widehat{\xi}_n) \right|^2 \left(\sum_{j_1 \in \mathbb{Z}} c_{nj_1}(\omega) \right)^2 = \left(\sqrt{c_0(\omega_0)} \sum_{j_1 \in \mathbb{Z} \setminus \{0\}} c_{nj_1}(\omega) U_{1,|0|} \right. \\ \left. + 2c_0(\omega) \sum_{j_1=1}^{+\infty} \sqrt{c_{j_1 n}(\omega_0)} U_{1,|j_1 n|} \right)^2$$

Then, proceed as in Lemma 28 to conclude, observing that $c_{nj_1}(\omega) \lesssim (|j_1|n)^{-2\nu-1}$ for $j_1 \neq 0$. \square

Lemma 30. *Let $\varepsilon > 0$. With the notations of Theorem 5, we have:*

$$\mathbb{P}(\widehat{v}_n \leq v_0 - 1/2 - \varepsilon) \lesssim e^{-C\sqrt{n}},$$

for some $C > 0$.

Proof. First, one has

$$\mathbb{P}(\widehat{v}_n \leq v_0 - 1/2 - \varepsilon) \leq \mathbb{P} \left(\inf_{a_v \leq v \leq v_0 - 1/2 - \varepsilon} \mathbb{M}_n(v, \alpha) \leq \inf_{v_0 - 1/2 - \varepsilon \leq v \leq b_v} \mathbb{M}_n(v, \alpha) \right) \\ \leq \mathbb{P} \left(\inf_{a_v \leq v \leq v_0 - 1/2 - \varepsilon} \mathbb{M}_n(v, \alpha) - \mathbb{M}_n(v_0, \alpha) \leq 0 \right).$$

Then, let $a_v \leq v \leq v_0 - 1/2 - \varepsilon$, we have, using Lemma 12, Lemma 10, and Jensen

inequality:

$$\begin{aligned}
\mathbb{M}_n(\mathbf{v}, \alpha) &= \mathcal{O}\left(\frac{\ln(n)}{n}\right) + \ln\left(\frac{Z^\top R_{\mathbf{v}, \alpha}^{-1} Z}{n}\right) + \int_0^1 g_{\mathbf{v}} + 2(\mathbf{v}_0 - \mathbf{v}) \ln(n) \\
&= \mathcal{O}(1) + \ln\left(\frac{Z^\top R_{\mathbf{v}, \alpha}^{-1} Z}{n}\right) + 2(\mathbf{v}_0 - \mathbf{v}) \ln(n) \\
&\geq \mathcal{O}(1) + \ln\left(\frac{\sum_{m=1}^l U_{m,n}^2 m^{2(\mathbf{v}-\mathbf{v}_0)}}{n^{1+2(\mathbf{v}-\mathbf{v}_0)}}\right) \\
&= \mathcal{O}(1) + \ln\left(\frac{1}{n} \sum_{m=1}^l U_{m,n}^2 \left(\frac{m}{n}\right)^{2(\mathbf{v}-\mathbf{v}_0)}\right) \\
&\geq \mathcal{O}(1) + \ln\left(\frac{1}{n} \sum_{m=1}^l U_{m,n}^2 \left(\frac{m}{n}\right)^{-1-2\varepsilon}\right) \\
&\geq \mathcal{O}(1) + 2\varepsilon \ln(n) + \ln\left(\sum_{m=1}^l U_{m,n}^2 m^{-1-2\varepsilon}\right) \\
&\geq \mathcal{O}(1) + 2\varepsilon \ln(n) + \ln\left(\sum_{m=1}^{\lfloor \sqrt{n} \rfloor} U_{m,n}^2 m^{-1-2\varepsilon}\right) \\
&\geq \mathcal{O}(1) + 2\varepsilon \ln(n) + \ln\left(\sum_{m=1}^{\lfloor \sqrt{n} \rfloor} U_{m,n}^2 \lfloor \sqrt{n} \rfloor^{-1-2\varepsilon}\right) \\
&\geq \mathcal{O}(1) + \varepsilon \ln(n) + \ln\left(\frac{1}{\lfloor \sqrt{n} \rfloor} \sum_{m=1}^{\lfloor \sqrt{n} \rfloor} U_{m,n}^2\right) \\
&\geq \mathcal{O}(1) + \varepsilon \ln(n) + \frac{1}{\lfloor \sqrt{n} \rfloor} \sum_{m=1}^{\lfloor \sqrt{n} \rfloor} \ln(U_{m,n}^2)
\end{aligned}$$

with a uniform big- \mathcal{O} . Let $\delta > 0$ and $t > 0$, we have

$$\begin{aligned}
\mathbb{P}\left(-\frac{1}{\lfloor \sqrt{n} \rfloor} \sum_{m=1}^{\lfloor \sqrt{n} \rfloor} \ln(U_{m,n}^2) \geq \delta\right) &= \mathbb{P}\left(e^{-\frac{t}{\lfloor \sqrt{n} \rfloor} \sum_{m=1}^{\lfloor \sqrt{n} \rfloor} \ln(U_{m,n}^2)} \geq e^{t\delta}\right) \\
&= \mathbb{P}\left(\left(\prod_{m=1}^{\lfloor \sqrt{n} \rfloor} U_{m,n}^{-2}\right)^{\frac{t}{\lfloor \sqrt{n} \rfloor}} \geq e^{t\delta}\right) \\
&= \mathbb{P}\left(\prod_{m=1}^{\lfloor \sqrt{n} \rfloor} |U_{m,n}|^{-2t} \geq e^{t\delta \lfloor \sqrt{n} \rfloor}\right) \\
&\leq e^{-\delta \lfloor \sqrt{n} \rfloor / 4} \mathbb{E}\left(|U_{1,1}|^{-1/2}\right)^{\lfloor \sqrt{n} \rfloor},
\end{aligned}$$

with $t = 1/4$ and $C = \mathbb{E}\left(U_{1,1}^{-1/2}\right) < +\infty$. Therefore:

$$C^{\lfloor \sqrt{n} \rfloor} e^{-\delta \lfloor \sqrt{n} \rfloor / 4} = e^{(\ln(C) - \delta/4) \lfloor \sqrt{n} \rfloor},$$

which converges exponentially to zero if δ is high enough.

Furthermore, Lemma 10 gives

$$\mathbb{M}_n(v_0, \alpha) = \mathcal{O}(1) + \ln \left(\frac{Z^\top R_{v_0, \alpha}^{-1} Z}{n} \right) = \mathcal{O}(1) + \ln \left(n^{-1} \sum_{m=0}^{n-1} U_{m,n}^2 \right),$$

and we have

$$\mathbb{P} \left(\ln \left(n^{-1} \sum_{m=0}^{n-1} U_{m,n}^2 \right) \geq \delta \right) = \mathbb{P} \left(n^{-1} \sum_{m=0}^{n-1} U_{m,n}^2 \geq e^\delta \right) \leq e^{-Cn},$$

for some $C > 0$ if $\delta > 0$ is high enough, using also a Chernoff bound argument. Now, putting all the pieces together yields:

$$\begin{aligned} & \inf_{a_v \leq v \leq v_0 - 1/2 - \varepsilon} \mathbb{M}_n(v, \alpha) - \mathbb{M}_n(v_0, \alpha) \\ & \geq \mathcal{O}(1) + \varepsilon \ln(l) + \frac{1}{\lfloor \sqrt{n} \rfloor} \sum_{m=1}^{\lfloor \sqrt{n} \rfloor} \ln(U_{m,n}^2) - \ln \left(n^{-1} \sum_{m=0}^{n-1} U_{m,n}^2 \right) \end{aligned}$$

giving the result thanks to the pigeonhole principle. \square

Proof of Theorem 5. Let $\varepsilon > 0$ and use the notations (27). The functions $a_{m,j,n}$ are C^1 and, for $v \in [v_0 - 1/2 - \varepsilon, b_v]$, the derivatives of the $a_{m,j,n}$ s lead to tedious expressions, which in turns lead, with Lemma 10 and Lemma 27, to

$$\begin{aligned} |a'_{m,0,n}(v)| & \lesssim m^\delta n^{-2v_0-1} + m^{4v-2v_0+1} n^{-4v-2+\delta} \\ & \lesssim m^\delta n^{-2v_0-1} + m^{-2v_0+1} n^{-2+\delta} (m/n)^{2v_0-2+4\varepsilon} \\ & = m^\delta n^{-2v_0-1} + m^{-1+4\varepsilon} n^{-2v_0+\delta-4\varepsilon} \end{aligned}$$

and, for $j \neq 0$, to

$$\begin{aligned} |a'_{m,j,n}(v)| & \lesssim (|j|n)^{-4v-2+\delta} m^{-2v_0-1} + (|j|n)^{-2v_0-2v-2+\delta} m^{2v+1} \\ & \lesssim |j|^{-3/2} n^{-2v_0-4\varepsilon+\delta} m^{-2v_0-1} + |j|^{-3/2} n^{-2v_0-2+\delta} m^1 (m/n)^{v_0-1+2\varepsilon} \\ & = |j|^{-3/2} n^{-2v_0-4\varepsilon+\delta} m^{-2v_0-1} + |j|^{-3/2} n^{-3v_0-1+\delta-2\varepsilon} m^{v_0+2\varepsilon} \end{aligned}$$

for $\delta > 0$ small enough and uniformly in $1 \leq m \leq l$, $j \neq 0$ and $v \in [v_0 - 1/2 - \varepsilon, b_v]$. Then,

$$\begin{aligned} & \sum_{m=1}^l \sum_{j \in \mathbb{Z}} \mathbb{E} \left(A_{m,j,n} |a_{m,j,n}(\hat{v}_n) - a_{m,j,n}(v_0)| \mathbb{1}_{\hat{v}_n \geq v_0 - 1/2 - \varepsilon} \right) \\ & \leq \sum_{m=1}^l \sum_{j \in \mathbb{Z}} \mathbb{E} \left(A_{m,j,n} |\hat{v}_n - v_0| \sup_{v_0 - 1/2 - \varepsilon \leq v \leq b_v} |a'_{m,j,n}(v)| \right) \\ & = \sqrt{\mathbb{E}(A_{1,0,1}^2)} \sqrt{\mathbb{E}((\hat{v}_n - v_0)^2)} \sum_{m=1}^l \sum_{j \in \mathbb{Z}} \sup_{v_0 - 1/2 - \varepsilon \leq v \leq b_v} |a'_{m,j,n}(v)| = o(n^{-2v_0}), \end{aligned}$$

using the above inequalities and Theorem 2. Therefore, Lemma 28, Lemma 29, the identity (31), and the Fubini-Tonelli theorem shows that

$$\mathbb{E} \left(|\text{ISE}_n(\hat{v}_n, \alpha; \xi) - \text{ISE}_n(v_0, \alpha; \xi)| \mathbb{1}_{\hat{v}_n \geq v_0 - 1/2 - \varepsilon} \right) = o(n^{-2v_0}).$$

Furthermore, using again the Fubini-Tonelli theorem yields

$$\begin{aligned}
& \mathbb{E} \left(\sum_{m=1}^l \sum_{j \in \mathbb{Z}} \left| c_{m+jn}(\xi - \widehat{\xi}_n) \right|^2 \mathbb{1}_{\widehat{v}_n \leq v_0 - 1/2 - \varepsilon} \right) \\
&= \sum_{m=1}^l \sum_{j \in \mathbb{Z}} \mathbb{E} \left(a_{m,j,n}(\widehat{v}_n) A_{m,j,n} \mathbb{1}_{\widehat{v}_n \leq v_0 - 1/2 - \varepsilon} \right) \\
&\leq \sum_{m=1}^l \sum_{j \in \mathbb{Z}} \sup_{a_v \leq v \leq v_0 - 1/2 - \varepsilon} a_{m,j,n}(v) \mathbb{E} \left(A_{m,j,n} \mathbb{1}_{\widehat{v}_n \leq v_0 - 1/2 - \varepsilon} \right) \\
&\leq \sqrt{\mathbb{E} \left(A_{1,0,1}^2 \right)} \sqrt{\mathbb{E} \left(\mathbb{1}_{\widehat{v}_n \leq v_0 - 1/2 - \varepsilon} \right)} \sum_{m=1}^l \sum_{j \in \mathbb{Z}} \sup_{a_v \leq v \leq v_0 - 1/2 - \varepsilon} a_{m,j,n}(v) \\
&\leq \sqrt{\mathbb{E} \left(A_{1,0,1}^2 \right)} \sqrt{\mathbb{E} \left(\mathbb{1}_{\widehat{v}_n \leq v_0 - 1/2 - \varepsilon} \right)} n^{-4a_v - 2 + 4\varepsilon} \\
&= o \left(n^{-2v_0} \right),
\end{aligned}$$

using inequalities (28) and (29), and Lemma 30. Then, the case $m = n/2$ is treated by Lemma 28 and the case $m = 0$ can be managed similarly using Lemma 29.

Finally, one can treat

$$\mathbb{E} \left(\text{ISE}_n(v_0, \alpha; \xi) \mathbb{1}_{\widehat{v}_n \leq v_0 - 1/2 - \varepsilon} \right)$$

the same way and the desired result follows. \square

A.7 Proofs of Section 4

Proof of Proposition 6. The proof is based on the observation that

$$Z^T R_{v,\alpha}^{-1} Z = \sum_{m=0}^{n-1} \frac{|\sum_{j \in m+n\mathbb{Z}} c_j(f)|^2}{\sum_{j \in m+n\mathbb{Z}} c_j(v, \alpha)}.$$

We give a full proof only for the third assumption. The proof for the second assumption is similar and the first is a particular case of the second.

Let $\varepsilon > 0$, $a_v \leq v \leq v_0(f) - \varepsilon$, $\alpha \in A$, and $p \in \mathbb{Z}$ such that $c_p(f) \neq 0$. Then, Lemma 12 gives

$$\begin{aligned}
\mathbb{M}_n^f(v, \alpha) &= 2(v_0(f) - v) \ln(n) + \mathcal{O}(1) + \ln \left(\sum_{m=0}^{n-1} \frac{|\sum_{j \in m+n\mathbb{Z}} c_j(f)|^2}{\sum_{j \in m+n\mathbb{Z}} c_j(v, \alpha)} \right) \\
&\geq 2\varepsilon \ln(n) + \mathcal{O}(1) + \ln \left(\frac{|\sum_{j \in p+n\mathbb{Z}} c_j(f)|^2}{\sum_{j \in p+n\mathbb{Z}} c_j(v, \alpha)} \right) \\
&= 2\varepsilon \ln(n) + \mathcal{O}(1)
\end{aligned}$$

uniformly by Lemma 10 and since $|\sum_{j \in p+n\mathbb{Z}} c_j(f)| \rightarrow c_p(f)$.

Moreover, for any $\alpha \in A$, we have:

$$\begin{aligned}\mathbb{M}_n^f(v_0(f) - \varepsilon/2, \alpha) &= \varepsilon \ln(n) + \mathcal{O}(1) + \ln(Z^\top R_{v, \alpha}^{-1} Z) \\ &\leq \varepsilon \ln(n) + \mathcal{O}(1),\end{aligned}$$

since $f \in H_{[0,1]}^{\beta+1/2}$ for $\beta = v_0(f) - \varepsilon/2$. Indeed, this last Sobolev space is norm-equivalent to the reproducing kernel Hilbert space attached to the covariance function for $v = v_0(f) - \varepsilon/2$ and the quadratic term $Z^\top R_{v, \alpha}^{-1} Z$ is the squared norm of a projection of f (see, e.g., [Wendland, 2004](#), Theorem 13.1). This completes the proof. \square

Proof of Proposition 8. Let $v > v_0(f)$ and $\alpha > 0$. Then, Lemma 11 and Lemma 12 yield:

$$\begin{aligned}\mathbb{M}_n^f(v, \alpha) &= (2v_0(f) + 1) \ln(n) + n^{-1} \ln(\det(R_{v, \alpha})) + \ln\left(\frac{Z^\top R_{v, \alpha}^{-1} Z}{n}\right) \\ &= (2v_0(f) + 1) \ln(n) + \int_0^1 g_v + \mathcal{O}\left(\frac{\ln(n)}{n}\right) + \ln\left(n^{-2v-1} \sum_{m=0}^{n-1} \frac{|\sum_{j \in m+n\mathbb{Z}} c_j(f)|^2}{\sum_{j \in m+n\mathbb{Z}} c_j(v, \alpha)}\right) \\ &= (2v_0(f) + 1) \ln(n) + \int_0^1 g_v + \mathcal{O}\left(\frac{\ln(n)}{n}\right) \\ &\quad + \ln\left(\mathcal{O}(n^{-2v-1}) + \mathcal{O}(n^{-2v_0(f)-2}) + 2 \sum_{m=1}^l \frac{(1 + \mathcal{O}(m^{-2})) |\sum_{j \in m+n\mathbb{Z}} c_j(f)|^2}{\gamma(2v+1; m/n)}\right) \\ &= \int_0^1 g_v + \mathcal{O}\left(\frac{\ln(n)}{n}\right) \\ &\quad + \ln\left(\mathcal{O}(n^{2(v_0(f)-v)}) + \mathcal{O}(n^{-1}) + \frac{2}{n} \sum_{m=1}^l \frac{(1 + \mathcal{O}(m^{-2})) |n^{v_0(f)+1} \sum_{j \in m+n\mathbb{Z}} c_j(f)|^2}{\gamma(2v+1; m/n)}\right) \\ &= \int_0^1 g_v + \mathcal{O}\left(\frac{\ln(n)}{n}\right) \\ &\quad + \ln\left(\mathcal{O}(n^{2(v_0(f)-v)}) + \mathcal{O}(n^{-1}) + \mathcal{O}(n^{v_0(f)-v}) + \frac{2}{n} \sum_{m=1}^l \frac{\gamma^2(v_0(f)+1; m/n)}{\gamma(2v+1; m/n)}\right),\end{aligned}$$

by proceeding as in the proof of Lemma 16. To conclude, observe that $\gamma^2(v_0(f)+1; \cdot)/\gamma(2v+1; \cdot)$ is non-increasing in a neighborhood of zero if $v < v_0(f) + 1/2$ and has a finite limit otherwise. \square

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