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Nonparametric estimation of the stationary density and the transition density of a Markov chain

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Abstract

In this paper, we study first the problem of nonparametric estimation of the stationary density f of a discrete-time Markov chain (X_i) . We consider a collection of projection estimators on finite dimensional linear spaces. We select an estimator among the collection by minimizing a penalized contrast. The same technique enables to estimate the density g of (X_i, X_{i+1}) and so to provide an adaptive estimator of the transition density $\pi = g/f$. We give bounds in L^2 norm for these estimators and we show that they are adaptive in the minimax sense over a large class of Besov spaces. Some examples and simulations are also provided.

Key words: Adaptive estimation, Markov Chain, Stationary density, Transition density, Model selection, Penalized contrast, Projection estimators

1 Introduction

Nonparametric estimation is now a very rich branch of statistical theory. The case of i.i.d. observations is the most detailed but many authors are also interested in the case of Markov processes. Early results are stated by Roussas (1969), who studies nonparametric estimators of the stationary density and the transition density of a Markov chain. He considers kernel estimators and assumes that the chain satisfies the strong Doeblin's condition (D_0) (see Doob (1953) p.221). He shows consistency and asymptotic normality of his estimator. Several authors tried to consider weaker assumptions than the Doeblin's condition. Rosenblatt (1970) introduces an other condition, denoted by (G_2), and he gives results on the bias and the variance of the kernel estimator of the invariant density in this weaker framework. Yakowitz (1989) improves also the

result of asymptotic normality by considering a Harris-condition. The study of kernel estimators is completed by Masry and Györfi (1987) who find sharp rates for this kind of estimators of the stationary density and by Basu and Sahoo (1998) who prove a Berry-Esseen inequality under the condition (G_2) of Rosenblatt. Other authors are interested in the estimation of the invariant distribution and the transition density in the non-stationary case: Doukhan and Ghindès (1983) bound the integrated risks for any initial distribution. In Hernández-Lerma et al. (1988), recursive estimators for a non-stationary Markov chain are described. Liebscher (1992) gives results for the invariant density in this non-stationary framework using a condition denoted by (D_1) derived from the Doeblin's condition but weaker than (D_0) . All the above papers deal with kernel estimators. Among those who are not interested in such estimators, let us mention Bosq (1973) who studies an estimator of the stationary density by projection on a Fourier basis, Prakasa Rao (1978) who outlines a new estimator for the stationary density by using delta-sequences and Gillert and Wartenberg (1984) who present estimators based on Hermite bases or trigonometric bases.

The recent work of Cléménçon (1999) allows to measure the performance of all these estimators since he proves lower bounds for the minimax rates and gives thus the optimal convergence rates for the estimation of the stationary density and the transition density. Cléménçon also provides an other kind of estimator for the stationary density and for the transition density, that he obtains by projection on wavelet bases. He presents an adaptive procedure which is "quasi-optimal" in the sense that the procedure reaches almost the optimal rate but with a logarithmic loss. He needs other conditions than those we cited above and in particular a minoration condition derived from Nummelin's (1984) works. In this paper, we will use the same condition.

The aim of this paper is to estimate the stationary density of a discrete-time Markov chain and its transition density. We consider an irreducible positive recurrent Markov chain (X_n) with a stationary density denoted by f . We suppose that the initial density is f (hence the process is stationary) and we construct an estimator \tilde{f} from the data X_1, \dots, X_n . Then, we study the mean integrated squared error $\mathbb{E}\|\tilde{f} - f\|_2^2$ and its convergence rate. The same technique enables to estimate the density g of (X_i, X_{i+1}) and so to provide an estimator of the transition density $\pi = g/f$, called the quotient estimator.

An adaptive procedure is proposed for the two estimations and it is proved that both resulting estimators reach the optimal minimax rates without additive logarithmic factor.

We will use here some technical methods known as the Nummelin splitting technique (see Nummelin (1984), Meyn and Tweedie (1993) or Höpfner and Löcherbach (2003)). This method allows to reduce the general state space

Markov chain theory to the countable space theory. Actually, the splitting of the original chain creates an artificial accessible atom and we will use the hitting times to this atom to decompose the chain, as we would have done for a countable space chain.

To build our estimator of f , we use model selection via penalization as described in Barron et al. (1999). First, estimators by projection denoted by \hat{f}_m are considered. The index m denotes the model, i.e. the subspace to which the estimator belongs. Then the model selection technique allows to select automatically an estimator $\hat{f}_{\hat{m}}$ from the collection of estimators (\hat{f}_m) . The estimator of g is built in the same way. The collections of models that we consider here include wavelets but also trigonometric polynomials and piecewise polynomials.

This paper is organized as follows. In Section 2, we present our assumptions on the Markov chain and on the collections of models. We give also examples of chains and models. Section 3 is devoted to estimation of the stationary density and in Section 4 the estimation of the transition density is explained. Some simulations are presented in Section 5. The proofs are gathered in the last section, which contains also a presentation of the Nummelin splitting technique.

2 The framework

2.1 Assumptions on the Markov chain

We consider an irreducible Markov chain (X_n) taking its values in the real line \mathbb{R} . We suppose that (X_n) is positive recurrent, i.e. it admits a stationary probability measure μ (for more details, we refer to Meyn and Tweedie (1993)). We assume that the distribution μ has a density f with respect to the Lebesgue measure and it is this quantity that we want to estimate. Since the number of observations is finite, f is estimated on a compact set only. Without loss of generality, this compact set is assumed to be equal to $[0, 1]$ and, from now, f denotes the transition density multiplied by the indicator function of $[0, 1]$ $f\mathbf{1}_{[0,1]}$. More precisely, the Markov process is supposed to satisfy the following assumptions:

- A1. (X_n) is irreducible and positive recurrent.
- A2. The distribution of X_0 is equal to μ , thus the chain is (strictly) stationary.
- A3. The stationary density f belongs to $L^\infty([0, 1])$ i.e. $\sup_{x \in [0, 1]} |f(x)| < \infty$
- A4. The chain is strongly aperiodic, i.e. it satisfies the following minorization condition: there is some function $h : [0, 1] \mapsto [0, 1]$ with $\int h d\mu > 0$ and a

positive distribution ν such that, for all event A and for all x ,

$$P(x, A) \geq h(x)\nu(A)$$

where P is the transition kernel of (X_n) .

A5. The chain is geometrically ergodic, i.e. there exists a function $V > 0$ finite and a constant $\rho \in (0, 1)$ such that, for all $n \geq 1$

$$\|P^n(x, \cdot) - \mu\|_{TV} \leq V(x)\rho^n$$

where $\|\cdot\|_{TV}$ is the total variation norm.

We can remark that condition A3 implies that f belongs to $L^2([0, 1])$ where $L^2([0, 1]) = \{t : \mathbb{R} \mapsto \mathbb{R}, \text{Supp}(t) \subset [0, 1] \text{ and } \|t\|^2 = \int_0^1 t^2(x)dx < \infty\}$.

Notice that, if the chain is aperiodic, condition A4 holds, at least for some m -skeleton (i.e. a chain with transition probability P^m) (see Theorem 5.2.2 in Meyn and Tweedie (1993)). This minorization condition is used in the Nummelin splitting technique and is also required in Cléménçon (1999).

The last assumption, which is called geometric regularity by Cléménçon (2000), means that the convergence of the chain to the invariant distribution is geometrically fast. In Meyn and Tweedie (1993), we find a slightly different condition (replacing the total variation norm by the V -norm). This condition, which is sufficient for A5, is widely used in Monte Carlo Markov Chain literature because it guarantees central limit theorems and enables to simulate laws via a Markov chain (see for example Jarner and Hansen (2000), Roberts and Rosenthal (1998) or Meyn and Tweedie (1994)).

The following subsection gives some examples of Markov chains satisfying hypotheses A1–A5.

2.2 Examples of chains

2.2.1 Diffusion processes

We consider the process $(X_{i\Delta})_{1 \leq i \leq n}$ where $\Delta > 0$ is the observation step and $(X_t)_{t \geq 0}$ is defined by

$$dX_t = b(X_t)dt + \sigma(X_t)dW_t$$

where W is the standard Brownian motion, b a is a locally bounded Borelian function and σ is a uniformly continuous function such that:

- (1) there exists λ_-, λ_+ such that $\forall x \neq 0, 0 < \lambda_- < \sigma^2(x) < \lambda_+$,
- (2) there exists $M_0, \alpha \geq 0$ and $r > 0$ such that $\forall |x| \geq M_0, xb(x) \leq -r|x|^{\alpha+1}$.

Then, if X_0 follows the stationary distribution, Proposition 1 in Pardoux and Veretennikov (2001) shows that the discretized process $(X_{i\Delta})_{1 \leq i \leq n}$ satisfies Assumptions A1–A5.

2.2.2 Nonlinear AR(1) processes

Let us consider the following process

$$X_n = \varphi(X_{n-1}) + \varepsilon_{X_{n-1},n}$$

where $\varepsilon_{x,n}$ has a positive density l_x with respect to the Lebesgue measure, which does not depend on n . We suppose that φ is bounded on any compact set and that there exist $M > 0$ and $\rho < 1$ such that, for all $|x| > M$, $|\varphi(x)| < \rho|x|$. Mokkadem (1987) proves that if there exists $s > 0$ such that $\sup_x \mathbb{E}|\varepsilon_{x,n}|^s < \infty$, then the chain is geometrically ergodic. If we assume furthermore that l_x has a lower bound then the chain satisfies all the previous assumptions.

2.2.3 ARX (1,1) models

The nonlinear process ARX(1,1) is defined by

$$X_n = F(X_{n-1}, Z_n) + \xi_n$$

where F is bounded and (ξ_n) , (Z_n) are independent sequences of i.i.d. random variables with $\mathbb{E}|\xi_n| < \infty$. We suppose that the distribution of Z_n has a positive density l with respect to the Lebesgue measure. Assume that there exist $\rho < 1$, a locally bounded and measurable function $h : \mathbb{R} \mapsto \mathbb{R}^+$ such that $\mathbb{E}h(Z_n) < \infty$ and positive constants M, c such that

$$\forall |x| > M \quad |F(x, v)| < \rho|x| + h(v) - c \text{ and } \sup_{|x| \leq M} |F(x)| < \infty.$$

Then the process (X_n) satisfies Assumptions A1–A5 (see Doukhan (1994) p.102).

2.2.4 ARCH process

The considered model is

$$X_{n+1} = F(X_n) + G(X_n)\varepsilon_{n+1}$$

where F and G are continuous functions and for all x , $G(x) \neq 0$. We suppose that the distribution of ε_n has a positive and continuous density with respect to the Lebesgue measure and that there exists $s \geq 1$ such that $\mathbb{E}|\varepsilon_n|^s < \infty$.

The chain (X_i) satisfies Assumptions A1–A5 if (see Doukhan (1994) p.106):

$$\limsup_{|x| \rightarrow \infty} \frac{|F(x)| + |G(x)|(\mathbb{E}|\varepsilon_n|^s)^{1/s}}{|x|} < 1.$$

2.3 Assumptions on the models

In order to estimate f , we need to introduce some collections of models. The assumptions on the models are the following:

- M1. Each S_m is a linear subspace of $(L^\infty \cap L^2)([0, 1])$ with dimension $D_m \leq \sqrt{n}$
M2. Let

$$\phi_m = \frac{1}{\sqrt{D_m}} \sup_{t \in S_m \setminus \{0\}} \frac{\|t\|_\infty}{\|t\|}$$

There exists a real r_0 such that for all m , $\phi_m \leq r_0$.

This assumption (L^2 - L^∞ connexion) is introduced by Barron et al. (1999) and can be written:

$$\forall t \in S_m \quad \|t\|_\infty \leq r_0 \sqrt{D_m} \|t\|. \quad (1)$$

We get then a set of models $(S_m)_{m \in \mathcal{M}_n}$ where $\mathcal{M}_n = \{m, D_m \leq \sqrt{n}\}$. We need now a last assumption regarding the whole collection, which ensures that, for m and m' in \mathcal{M}_n , $S_m + S'_m$ belongs to the collection of models.

- M3. The models are nested, that is for all $m, D_m \leq D_{m'} \Rightarrow S_m \subset S_{m'}$.

2.4 Examples of models

We show here that the assumptions M1-M3 are not too restrictive. Indeed, they are verified for the models spanned by the following bases (see Barron et al. (1999)):

- Histogram basis: $S_m = \langle \varphi_1, \dots, \varphi_{2^m} \rangle$ with $\varphi_j = 2^{m/2} \mathbf{1}_{[\frac{j-1}{2^m}, \frac{j}{2^m}[}$ for $j = 1, \dots, 2^m$. Here $D_m = 2^m$, $r_0 = 1$ and $\mathcal{M}_n = \{1, \dots, \lfloor \ln n / 2 \ln 2 \rfloor\}$ where $\lfloor x \rfloor$ denotes the floor of x , i.e. the largest integer less than or equal to x .
- Trigonometric basis: $S_m = \langle \varphi_0, \dots, \varphi_{m-1} \rangle$ with $\varphi_0(x) = \mathbf{1}_{[0,1]}(x)$, $\varphi_{2j} = \sqrt{2} \cos(2\pi j x) \mathbf{1}_{[0,1]}(x)$, $\varphi_{2j-1} = \sqrt{2} \sin(2\pi j x) \mathbf{1}_{[0,1]}(x)$ for $j \geq 1$. For this model $D_m = m$ and $r_0 = \sqrt{2}$ hold.
- Regular piecewise polynomial basis: S_m is spanned by polynomials of degree $0, \dots, r$ (where r is fixed) on each interval $[(j-1)/2^D, j/2^D[$, $j = 1, \dots, 2^D$. In this case, $m = (D, r)$, $D_m = (r+1)2^D$ and $\mathcal{M}_n = \{(D, r), D = 1, \dots, \lfloor \log_2(\sqrt{n}/(r+1)) \rfloor\}$. We can put $r_0 = \sqrt{r+1}$.

- Regular wavelet basis: $S_m = \langle \psi_{jk}, j = -1, \dots, m, k \in \Lambda(j) \rangle$ where $\psi_{-1,k}$ points out the translates of the father wavelet and $\psi_{jk}(x) = 2^{j/2}\psi(2^j x - k)$ where ψ is the mother wavelet. We assume that the support of the wavelets is included in $[0, 1]$ and that $\psi_{-1} = \varphi$ belongs to the Sobolev space W_2^r . In this framework $\Lambda(j) = \{0, \dots, K2^j - 1\}$ (for $j \geq 0$) where K is a constant which depends on the supports of φ and ψ : for example for the Haar basis $K = 1$. We have then $D_m = \sum_{j=-1}^m |\Lambda(j)| = |\Lambda(-1)| + K(2^{m+1} - 1)$. Moreover

$$\begin{aligned} \phi_m &\leq \frac{\sum_k |\psi_{-1,k}| + \sum_{j=0}^m 2^{j/2} \sum_k |\psi_{j,k}|}{\sqrt{D_m}} \\ &\leq \frac{\|\varphi\|_\infty \vee \|\psi\|_\infty (1 + \sum_{j=0}^m 2^{j/2})}{\sqrt{(K \wedge |\Lambda(-1)|)2^{m+1}}} \leq \frac{\|\varphi\|_\infty \vee \|\psi\|_\infty}{K \wedge |\Lambda(-1)|} =: r_0 \end{aligned}$$

3 Estimation of the stationary density

3.1 Decomposition of the risk for the projection estimator

Let

$$\gamma_n(t) = \frac{1}{n} \sum_{i=1}^n [\|t\|^2 - 2t(X_i)]. \quad (2)$$

Notice that $\mathbb{E}(\gamma_n(t)) = \|t - f\|^2 - \|f\|^2$ and therefore $\gamma_n(t)$ is the empirical version of the L^2 distance between t and f . Thus, \hat{f}_m is defined by

$$\hat{f}_m = \arg \min_{t \in S_m} \gamma_n(t) \quad (3)$$

where S_m is a subspace of L^2 which satisfies M2. Although this estimator depends on n , no index n is mentioned in order to simplify the notations. It is also the case for all the estimators in this paper.

A more explicit formula for \hat{f}_m is easy to derive:

$$\hat{f}_m = \sum_{\lambda \in \Lambda} \hat{\beta}_\lambda \varphi_\lambda, \quad \hat{\beta}_\lambda = \frac{1}{n} \sum_{i=1}^n \varphi_\lambda(X_i) \quad (4)$$

where $(\varphi_\lambda)_{\lambda \in \Lambda}$ is an orthonormal basis of S_m . Note that

$$\mathbb{E}(\hat{f}_m) = \sum_{\lambda \in \Lambda} \langle f, \varphi_\lambda \rangle \varphi_\lambda,$$

which is the projection of f on S_m .

In order to evaluate the quality of this estimator, we now compute the mean integrated squared error $\mathbb{E}\|f - \hat{f}_m\|^2$ (often denoted by MISE).

Proposition 1 *Let X_n be a Markov chain which satisfies Assumptions A1–A5 and S_m be a subspace of L^2 with dimension $D_m \leq n$. If S_m satisfies condition M2, then the estimator \hat{f}_m defined by (3) satisfies*

$$\mathbb{E}\|f - \hat{f}_m\|^2 \leq d^2(f, S_m) + C \frac{D_m}{n}$$

where C is a constant which does not depend on n .

To compute the bias term $d(f, S_m)$, we assume that f belongs to the Besov space $B_{2,\infty}^\alpha([0, 1])$. We refer to DeVore and Lorentz (1993) p.54 for the definition of $B_{2,\infty}^\alpha([0, 1])$. Notice that when α is an integer, the Besov space $B_{2,\infty}^\alpha([0, 1])$ contains the Sobolev space W_2^α (see DeVore and Lorentz (1993) p.51–55).

Hence, we have the following corollary.

Corollary 2 *Let X_n be a Markov chain which satisfies Assumptions A1–A5. Assume that the stationary density f belongs to $B_{2,\infty}^\alpha([0, 1])$ and that S_m is one of the spaces mentioned in Section 2.4 (with the regularity of polynomials and wavelets larger than $\alpha - 1$). If we choose $D_m = \lfloor n^{\frac{1}{2\alpha+1}} \rfloor$, then the estimator defined by (3) satisfies*

$$\mathbb{E}\|f - \hat{f}_m\|^2 = O(n^{-\frac{2\alpha}{2\alpha+1}})$$

We can notice that we obtain the same rate than in the i.i.d. case (see Donoho et al. (1996)). Actually, Cléménçon (1999) proves that $n^{-\frac{2\alpha}{2\alpha+1}}$ is the optimal rate in the minimax sense in the Markovian framework. With very different theoretical tools, Tribouley and Viennet (1998) show that this rate is also reached in the case of the univariate density estimation of β -mixing random variables by using a wavelet estimator.

However, the choice $D_m = \lfloor n^{\frac{1}{2\alpha+1}} \rfloor$ is possible only if we know the regularity α of the unknown f . But generally, it is not the case. It is the reason why we construct an adaptive estimator, i.e. an estimator which achieves the optimal rate without requiring the knowledge of α .

3.2 Adaptive estimation

Let $(S_m)_{m \in \mathcal{M}_n}$ be a collection of models as described in Section 2.3. For each S_m , \hat{f}_m is defined as above by (3). Next, we choose \hat{m} among the family \mathcal{M}_n such that

$$\hat{m} = \arg \min_{m \in \mathcal{M}_n} [\gamma_n(\hat{f}_m) + \text{pen}(m)]$$

where pen is a penalty function to be specified later. We denote $\tilde{f} = \hat{f}_{\hat{m}}$ and we bound the L^2 -risk $\mathbb{E}\|f - \tilde{f}\|$ as follows.

Theorem 3 *Let X_n be a Markov chain which satisfies Assumptions A1–A5 and $(S_m)_{m \in \mathcal{M}_n}$ be a collection of models satisfying Assumptions M1–M3. Then the estimator defined by*

$$\tilde{f} = \hat{f}_{\hat{m}} \quad \text{where} \quad \hat{m} = \arg \min_{m \in \mathcal{M}_n} [\gamma_n(\hat{f}_m) + \text{pen}(m)], \quad (5)$$

with

$$\text{pen}(m) = K \frac{D_m}{n} \quad \text{for some } K > K_0 \quad (6)$$

(where K_0 is a constant depending on the chain) satisfies

$$\mathbb{E}\|\tilde{f} - f\|^2 \leq 3 \inf_{m \in \mathcal{M}_n} \{d^2(f, S_m) + \text{pen}(m)\} + \frac{C_1}{n}$$

where C_1 does not depend on n .

Remark 4 *The constant K_0 in the penalty depends only on the distribution of the chain and can be chosen equal to $\max(r_0^2, 1)(C_1 + C_2\|f\|_\infty)$ where C_1 and C_2 are theoretical constants provided by the Nummelin splitting technique. The number r_0 is known and depends on the chosen base (see subsection 2.3). The mention of $\|f\|_\infty$ in the penalty term seems to be a problem, seeing that f is unknown. Actually, we could replace $\|f\|_\infty$ by $\|\hat{f}\|_\infty$ with \hat{f} an estimator of f . This method of random penalty is successfully applied in Birgé and Massart (1997) or Comte (2001) for example. But we choose not to use this method here, since the constants C_1 and C_2 in K_0 are not computable either. Notice that Cléménçon (2000) handle with the same kind of unknown quantities in the threshold of his nonlinear wavelet estimator. Actually it is the price to pay for dealing with dependent variables (see also the mixing constant in the threshold in Tribouley and Viennet (1998)). But this annoyance can be circumvented for practical purposes. Indeed, for the simulations the computation of the penalty is hand-adjusted. Some techniques of calibration can be found in Lebarbier (2005) in the context of multiple change point detection. In a Gaussian framework the practical choice of the penalty for implementation is also discussed in Section 4 of Birgé and Massart (2007).*

Corollary 5 *Let X_n be a Markov chain which satisfies Assumptions A1–A5 and $(S_m)_{m \in \mathcal{M}_n}$ be a collection of models mentioned in Section 2.4 (with the regularity of polynomials and wavelets larger than $\alpha - 1$). If f belongs to $B_{2,\infty}^\alpha([0, 1])$, with $\alpha > 1/2$, then the estimator defined by (5) and (6) satisfies*

$$\mathbb{E}\|\tilde{f} - f\|^2 = O(n^{-\frac{2\alpha}{2\alpha+1}})$$

Remark 6 *When $\alpha > \frac{1}{2}$, $B_{2,\infty}^\alpha([0, 1]) \subset C[0, 1]$ (where $C[0, 1]$ is the set of*

the continuous functions with support in $[0, 1]$) and then the assumption A3 $\|f\|_\infty < \infty$ is superfluous.

We have already noticed that it is the optimal rate in the minimax sense (see the lower bound in Cléménçon (1999)). Note that here the procedure reaches this rate whatever the regularity of f , without needing to know α . This result is thus an improvement of the one of Cléménçon (1999), whose adaptive procedure achieves only the rate $(\log(n)/n)^{\frac{2\alpha}{2\alpha+1}}$. Moreover, our procedure allows to use more bases (not only wavelets) and is easy to implement.

4 Estimation of the transition density

We now suppose that the transition kernel P has a density π . In order to estimate π , we remark that π can be written g/f where g is the density of (X_i, X_{i+1}) . Thus we begin with the estimation of g . As previously, g and π are estimated on a compact set which is assumed to be equal to $[0, 1]^2$, without loss of generality.

4.1 Estimation of the joint density g

We need now a new assumption.

A3'. π belongs to $L^\infty([0, 1]^2)$.

Notice that A3' implies A3. We consider now the following subspaces.

$$S_m^{(2)} = \{t \in L^2([0, 1]^2), \quad t(x, y) = \sum_{\lambda, \mu \in \Lambda_m} \alpha_{\lambda, \mu} \varphi_\lambda(x) \varphi_\mu(y)\}$$

where $(\varphi_\lambda)_{\lambda \in \Lambda_m}$ is an orthonormal basis of S_m . Notice that, if we set

$$\phi_m^{(2)} = \frac{1}{D_m} \sup_{t \in S_m^{(2)} \setminus \{0\}} \frac{\|t\|_\infty}{\|t\|},$$

hypothesis M2 implies that $\phi_m^{(2)}$ is bounded by r_0^2 . The condition M1 must be replaced by the following condition:

M1'. Each $S_m^{(2)}$ is a linear subspace of $(L^\infty \cap L^2)([0, 1]^2)$ with dimension $D_m^2 \leq \sqrt{n}$.

Let now

$$\gamma_n^{(2)}(t) = \frac{1}{n-1} \sum_{i=1}^{n-1} \{\|t\|^2 - 2t(X_i, X_{i+1})\}.$$

We define as above

$$\hat{g}_m = \arg \min_{t \in S_m^{(2)}} \gamma_n^{(2)}(t)$$

and $\hat{m}^{(2)} = \arg \min_{m \in \mathcal{M}_n} [\gamma_n^{(2)}(\hat{g}_m) + \text{pen}^{(2)}(m)]$ where $\text{pen}^{(2)}(m)$ is a penalty function which would be specified later. Lastly, we set $\tilde{g} = \hat{g}_{\hat{m}^{(2)}}$.

Theorem 7 *Let X_n be a Markov chain which satisfies Assumptions A1-A2-A3'-A4-A5 and $(S_m)_{m \in \mathcal{M}_n}$ be a collection of models satisfying Assumptions M1'-M2-M3. Then the estimator defined by*

$$\tilde{g} = \hat{g}_{\hat{m}^{(2)}} \quad \text{where} \quad \hat{m}^{(2)} = \arg \min_{m \in \mathcal{M}_n} [\gamma_n^{(2)}(\hat{g}_m) + \text{pen}^{(2)}(m)], \quad (7)$$

with

$$\text{pen}^{(2)}(m) = K^{(2)} \frac{D_m^2}{n} \text{ for some } K^{(2)} > K_0^{(2)} \quad (8)$$

(where $K_0^{(2)}$ is a constant depending on the chain) satisfies

$$\mathbb{E} \|\tilde{g} - g\|^2 \leq 3 \inf_{m \in \mathcal{M}_n} \{d^2(g, S_m^{(2)}) + \text{pen}^{(2)}(m)\} + \frac{C_1}{n}$$

where C_1 does not depend on n .

The constant $K_0^{(2)}$ in the penalty is similar to the constant K_0 in Theorem 3 (replacing r_0 by r_0^2 and $\|f\|_\infty$ by $\|g\|_\infty$). We refer the reader to Remark 4 for considerations related to these constants.

Corollary 8 *Let X_n be a Markov chain which satisfies Assumptions A1-A2-A3'-A4-A5 and $(S_m)_{m \in \mathcal{M}_n}$ be a collection of models mentioned in Section 2.4 (with the regularity of polynomials and wavelets larger than $\alpha - 1$). If g belongs to $B_{2,\infty}^\alpha([0, 1]^2)$, with $\alpha > 1$, then*

$$\mathbb{E} \|\tilde{g} - g\|^2 = O(n^{-\frac{2\alpha}{2\alpha+2}})$$

This rate of convergence is the minimax rate for density estimation in dimension 2 in the case of i.i.d. random variables (see for instance Ibragimov and Has'minskiĭ (1980)). Let us now proceed to the estimation of the transition density.

4.2 Estimation of π

The estimator of π is defined in the following way. Let

$$\tilde{\pi}(x, y) = \begin{cases} \frac{\tilde{g}(x, y)}{f(x)} & \text{if } |\tilde{g}(x, y)| \leq a_n |\tilde{f}(x)| \\ 0 & \text{else} \end{cases}$$

with $a_n = n^\beta$ and $\beta < 1/8$.

We introduce a new assumption:

A6. There exists a positive constant χ such that $\forall x \in [0, 1], f(x) \geq \chi$.

Theorem 9 *Let X_n be a Markov chain which satisfies Assumptions A1-A2-A3'-A4-A5-A6 and $(S_m)_{m \in \mathcal{M}_n}$ be a collection of models mentioned in Section 2.4 (with the regularity of polynomials and wavelets larger than $\alpha - 1$). We suppose that the dimension D_m of the models is such that*

$$\forall m \in \mathcal{M}_n \quad \ln n \leq D_m \leq n^{1/4}.$$

If f belongs to $B_{2,\infty}^\alpha([0, 1])$, with $\alpha > 1/2$, then for n large enough

- *there exists C_1 and C_2 such that*

$$\mathbb{E}\|\pi - \tilde{\pi}\|^2 \leq C_1 \mathbb{E}\|g - \tilde{g}\|^2 + C_2 \mathbb{E}\|f - \tilde{f}\|^2 + o\left(\frac{1}{n}\right)$$

- *if furthermore g belongs to $B_{2,\infty}^\beta([0, 1]^2)$ (with $\beta > 1$), then*

$$\mathbb{E}\|\pi - \tilde{\pi}\|^2 = O\left(\sup\left(n^{-\frac{2\beta}{2\beta+2}}, n^{-\frac{2\alpha}{2\alpha+1}}\right)\right)$$

Cl  men  on (2000) proved that $n^{-2\beta/(2\beta+2)}$ is the minimax rate for f and g of same regularity β . Notice that in this case the procedure is adaptive and there is no logarithmic loss in the estimation rate contrary to the result of Cl  men  on (2000).

But it should be remembered that we consider only the restriction of f or π since the observations are in a compact set. And the restriction of the stationary density to $[0, 1]$ may be less regular than the restriction of the transition density. The previous procedure has thus the disadvantage that the resulting rate does not depend only on the regularity of π but also on the one of f .

However, if the chain lives on $[0, 1]$ and if g belongs to $B_{2,\infty}^\beta([0, 1]^2)$ (that is to say that we consider the regularity of g on its whole support and not only on the compact of the observations) then equality $f(y) = \int g(x, y)dx$ yields

that f belongs to $B_{2,\infty}^\beta([0, 1])$ and then $\mathbb{E}\|\pi - \tilde{\pi}\|^2 = O(n^{-\frac{2\beta}{2\beta+2}})$. Moreover, if π belongs to $B_{2,\infty}^\beta([0, 1]^2)$, formula $f(y) = \int f(x)\pi(x, y)dx$ implies that f belongs to $B_{2,\infty}^\beta([0, 1])$. Then, by using properties of Besov spaces (see Runst and Sickel (1996) p.192), $g = f\pi$ belongs to $B_{2,\infty}^\beta([0, 1]^2)$. So in this case of a chain with compact support the minimax rate is achieved as soon as π belongs to $B_{2,\infty}^\beta([0, 1]^2)$ with $\beta > 1$.

5 Simulations

The computation of the previous estimator is very simple. We use the following procedure in 3 steps:

First step:

- For each m , compute $\gamma_n(\hat{f}_m) + \text{pen}(m)$. Notice that $\gamma_n(\hat{f}_m) = -\sum_{\lambda \in \Lambda_m} \hat{\beta}_\lambda^2$ where $\hat{\beta}_\lambda$ is defined by (4) and is quickly computed.
- Select the argmin \hat{m} of $\gamma_n(\hat{f}_m) + \text{pen}(m)$.
- Choose $\tilde{f} = \sum_{\lambda \in \Lambda_{\hat{m}}} \hat{\beta}_\lambda \varphi_\lambda$.

Second step:

- For each m such that $D_m^2 \leq \sqrt{n}$ compute $\gamma_n^{(2)}(\hat{g}_m) + \text{pen}^{(2)}(m)$, with $\gamma_n^{(2)}(\hat{g}_m) = -\sum_{\lambda, \mu \in \Lambda_m} \hat{a}_{\lambda, \mu}^2$ where $\hat{a}_{\lambda, \mu} = (1/n) \sum_{i=1}^n \varphi_\lambda(X_i) \varphi_\mu(X_{i+1})$.
- Select the argmin $\hat{m}^{(2)}$ of $\gamma_n^{(2)}(\hat{g}_m) + \text{pen}^{(2)}(m)$.
- Choose $\tilde{g}(x, y) = \sum_{\lambda, \mu \in \Lambda_{\hat{m}^{(2)}}} \hat{a}_{\lambda, \mu} \varphi_\lambda(x) \varphi_\mu(y)$.

Third step: Compute $\tilde{\pi}(x, y) = \tilde{g}(x, y) / \tilde{f}(x)$ if $|\tilde{g}(x, y)| \leq n^{1/10} |\tilde{f}(x)|$ and 0 otherwise.

The bases are here adjusted with an affin transform in order to be defined on the estimation interval $[c, d]$ instead of $[0, 1]$. We consider 2 different bases (see Section 2.4): trigonometric basis and histogram basis.

We found that a good choice for the penalty functions is $\text{pen}(m) = 5D_m/n$ and $\text{pen}^{(2)}(m) = 0.02D_m^2/n$.

We consider several kinds of Markov chains :

- An autoregressive process denoted by AR and defined by:

$$X_{n+1} = aX_n + b + \varepsilon_{n+1}$$

where the ε_{n+1} are independent and identical distributed random variables, with centered Gaussian distribution with variance σ^2 . For this process, the stationary distribution is a Gaussian with mean $b/(1-a)$ and variance $\sigma^2/(1-a^2)$. By denoting by $\varphi(z) = 1/(\sigma\sqrt{2\pi}) \exp(-z^2/2\sigma^2)$ the Gaussian

density, the transition density can be written $\pi(x, y) = \varphi(y - ax - b)$. We consider the following parameter values :

- (i) $a = 2/3, b = 0, \sigma^2 = 5/9$, estimated on $[-2, 2]^2$. The stationary density of this chain is the standard Gaussian distribution.
- (ii) $a = 0.5, b = 3, \sigma^2 = 1$, and then the process is estimated on $[4, 8]^2$.
- A radial Ornstein-Uhlenbeck process (in its discrete version). For $j = 1, \dots, \delta$, we define the processes: $\xi_{n+1}^j = a\xi_n^j + \beta\varepsilon_n^j$ where the ε_n^j are i.i.d. standard Gaussian. The chain is then defined by $X_n = \sqrt{\sum_{i=1}^{\delta} (\xi_n^i)^2}$. The transition density is given in Chaleyat-Maurel and Genon-Catalot (2006) where this process is studied in detail:

$$\pi(x, y) = \mathbb{1}_{y>0} \exp\left(-\frac{y^2 + a^2x^2}{2\beta^2}\right) I_{\delta/2-1}\left(\frac{axy}{\beta^2}\right) \frac{ax}{\beta^2} \left(\frac{y}{ax}\right)^{\delta/2}$$

and $I_{\delta/2-1}$ is the Bessel function with index $\delta/2 - 1$. The invariant density is $f(x) = C\mathbb{1}_{x>0} \exp(-x^2/2\rho^2)x^{\delta-1}$ with $\rho^2 = \beta^2/(1 - a^2)$ and C such that $\int f = 1$. This process (with here $a = 0.5, \beta = 3, \delta = 3$) is denoted by $\sqrt{\text{CIR}}$ since its square is actually a Cox-Ingersoll-Ross process. The estimation domain for this process is $[2, 10]^2$.

- A Cox-Ingersoll-Ross process, which is exactly the square of the previous process. It follows a Gamma density for invariant distribution with scale parameter $l = 1/2\rho^2$ and shape parameter $a = \delta/2$. The transition density is

$$\pi(x, y) = \frac{1}{2\beta^2} \exp\left(-\frac{y + a^2x}{2\beta^2}\right) I_{\delta/2-1}\left(\frac{a\sqrt{xy}}{\beta^2}\right) \left(\frac{y}{a^2x}\right)^{\delta/4-1/2}$$

The used parameters are the following:

- (iii) $a = 3/4, b = \sqrt{7/48}$ (so that $l = 3/2$) and $\delta = 4$, estimated on $[0.1, 3]^2$.
- (iv) $a = 1/3, b = 3/4$ and $\delta = 2$. This chain is estimated on $[0, 2]^2$.
- An ARCH process defined by $X_{n+1} = \sin(X_n) + (\cos(X_n) + 3)\varepsilon_{n+1}$ where the ε_{n+1} are i.i.d. standard Gaussian. The transition density of this chain is

$$\pi(x, y) = \varphi\left(\frac{y - \sin(x)}{\cos(x) + 3}\right) \frac{1}{\cos(x) + 3}$$

and we estimate this process on $[-5, 5]^2$.

For this last chain, the stationary density is not explicit. So we simulate $n+500$ variables and we estimate only from the last n to ensure the stationarity of the process. For the other chains, it is sufficient to simulate an initial variable X_0 with density f .

Figure 1 illustrates the performance of the method and Table 1 shows the L^2 -risk for different values of n .

The results in Table 1 are roughly good and illustrate that we can not pretend that a basis among the others gives better results. We can then imagine a

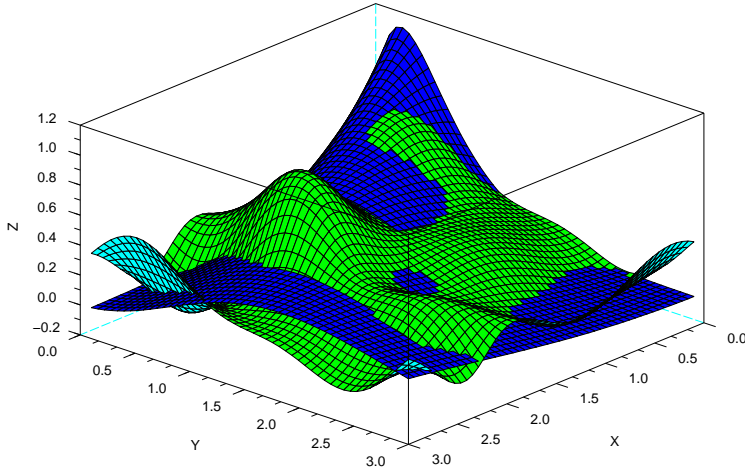


Fig. 1. Estimator (light surface) and true transition (dark surface) for the process CIR(iii) estimated with a trigonometric basis, $n=1000$

n	50	100	250	500	1000	basis
AR(i)	0.7280	0.5442	0.2773	0.1868	0.1767	H
	0.5262	0.4682	0.2223	0.1797	0.1478	T
AR(ii)	0.4798	0.3252	0.2249	0.1160	0.0842	H
	0.2867	0.2393	0.1770	0.1342	0.1083	T
$\sqrt{\text{CIR}}$	0.3054	0.2324	0.1724	0.1523	0.1278	H
	0.2157	0.1939	0.1450	0.1284	0.0815	T
CIR(iii)	0.5086	0.3082	0.2113	0.1760	0.1477	H
	0.4170	0.3959	0.2843	0.2565	0.2265	T
CIR(iv)	0.3381	0.2101	0.1205	0.0756	0.0458	H
	0.2273	0.2212	0.1715	0.1338	0.1328	T
ARCH	0.3170	0.3013	0.2420	0.2124	0.1610	H
	0.2553	0.2541	0.2075	0.1884	0.1689	T

Table 1

MISE $\mathbb{E}\|\pi - \tilde{\pi}\|^2$ averaged over $N = 200$ samples. H: histogram basis, T: trigonometric basis.

mixed strategy, i.e. a procedure which uses several kinds of bases and which can choose the best basis or, for instance, the best degree for a polynomial basis. These techniques are successfully used in regression frameworks by Comte and Rozenholc (2002, 2004).

The results for the stationary density are given in Table 2.

n	50	100	250	500	1000	basis
AR(i)	0.0658	0.0599	0.0329	0.0137	0.0122	H
	0.0569	0.0538	0.0246	0.0040	0.0026	T
AR(ii)	0.0388	0.0354	0.0309	0.0147	0.0081	H
	0.0342	0.0342	0.0327	0.0195	0.0054	T
$\sqrt{\text{CIR}}$	0.0127	0.0115	0.0105	0.0102	0.0096	H
	0.0169	0.0169	0.0168	0.0166	0.0107	T
CIR(iii)	0.0335	0.0268	0.0229	0.0222	0.0210	H
	0.0630	0.0385	0.0216	0.0211	0.0191	T
CIR(iv)	0.0317	0.0249	0.0223	0.0185	0.0103	H
	0.0873	0.0734	0.0572	0.0522	0.0458	T

Table 2

MISE $\mathbb{E}\|f - \tilde{f}\|^2$ averaged over $N = 200$ samples. H: histogram basis, T: trigonometric basis.

We can compare results of Table 2 with those of Dalelane (2005) who gives results of simulations for i.i.d. random variables. For density estimation, she uses three types of kernel: Gauss kernel, sinc-kernel (where $\text{sinc}(x) = \sin(x)/x$) and her Cross Validation optimal kernel (denoted by Dal). Table 3 gives her results for the Gaussian density and the Gamma distribution with the same parameters that we used (2 and $3/2$). If we compare the results that she obtains with her optimal kernel and our results with the trigonometric basis, we observe that her risks are about 5 times less than ours. However this kernel is particularly effective and if we consider the classical kernels, we notice that the results are almost comparable, with a reasonable price for dependency.

6 Proofs

6.1 The Nummelin splitting technique

This whole subsection is summarized from Höpfner and Löcherbach (2003) p.60–63 and is detailed for the sake of completeness.

The interest of the Nummelin splitting technique is to create a two-dimensional chain (the "split chain"), which contains automatically an atom. Let us recall the definition of an atom. Let A be a set such that $\psi(A) > 0$ where ψ is an

n	100	500	1000	kernel
	0.0065	0.0013	0.0008	Dal
Gaussian	0.0127	0.0028	0.0016	Gauss
(=AR(i))	0.0114	0.0026	0.0010	sinc
	0.0148	0.0052	0.0027	Dal
Gamma	0.0209	0.0061	0.0031	Gauss
(=CIR(iii))	0.0403	0.0166	0.0037	sinc

Table 3

MISE obtained by Dalelane (2005) for i.i.d. data, averaged over 50 samples

irreducibility measure. The set A is called an atom for the chain (X_n) with transition kernel P if there exists a measure ν such that $P(x, B) = \nu(B)$, for all x in A and for all event B .

Let us now describe the splitting method. Let $E = [0, 1]$ the state space and \mathcal{E} the associated σ -field. Each point x in E is splitted in $x_0 = (x, 0) \in E_0 = E \times \{0\}$ and $x_1 = (x, 1) \in E_1 = E \times \{1\}$. Each set A in \mathcal{E} is splitted in $A_0 = A \times \{0\}$ and $A_1 = A \times \{1\}$. Thus, we have defined a new probability space (E^*, \mathcal{E}^*) where $E^* := E_0 \cup E_1$ and $\mathcal{E}^* = \sigma(A_0, A_1 : A \in \mathcal{E})$. Using h defined in A4, a measure λ on (E, \mathcal{E}) splits according to

$$\begin{cases} \lambda^*(A_1) &= \int \mathbb{1}_A(x)h(x)\lambda(dx) \\ \lambda^*(A_0) &= \int \mathbb{1}_A(x)(1-h)(x)\lambda(dx) \end{cases}$$

Notice that $\lambda^*(A_0 \cup A_1) = \lambda(A)$. Now the aim is to define a new transition probability $P^*(., .)$ on (E^*, \mathcal{E}^*) to replace the transition kernel P of (X_n) . Let

$$P^*(x_i, .) = \begin{cases} \frac{1}{1-h(x)}(P - h \otimes \nu)^*(x, .) & \text{if } i = 0 \text{ and } h(x) > 1 \\ \nu^* & \text{else} \end{cases}$$

where ν is the measure introduced in A4 and $h \otimes \nu$ is a kernel defined by $h \otimes \nu(x, dy) = h(x)\nu(dy)$. Consider now a chain (X_n^*) on (E^*, \mathcal{E}^*) with one-step transition P^* and with starting law μ^* . The split chain (X_n^*) has the following properties:

P1. For all $(A_p)_{0 \leq p \leq N} \in \mathcal{E}^N$ and for all measure λ

$$P_\lambda(X_p \in A_p, 0 \leq p \leq N) = P_{\lambda^*}(X_p^* \in A_p \times \{0, 1\}, 0 \leq p \leq N).$$

P2. The split chain is irreducible positive recurrent with stationary distribution μ^* .

P3. The set E_1 is an atom for (X_n^*) .

We can also extend functions $g : E \mapsto \mathbb{R}$ to E^* via $g^*(x_0) = g(x) = g^*(x_1)$. Then, the property P1 can be written: for all function \mathcal{E} -measurable $g : E^N \mapsto \mathbb{R}$

$$\mathbb{E}_\lambda(g(X_1, \dots, X_N)) = \mathbb{E}_{\lambda^*}(g^*(X_1^*, \dots, X_N^*)).$$

We can say that (X_n) is a marginal chain of (X_n^*) . When necessary, the following proofs are decomposed in two steps: first, we assume that the Markov chain has an atom, next we extend the result to the general chain by introducing the artificial atom E_1 .

6.2 Proof of Proposition 1

First step: We suppose that (X_n) has an atom A .

Let f_m be the orthogonal projection of f on S_m . Pythagoras theorem gives us:

$$\mathbb{E}\|f - \hat{f}_m\|^2 = d^2(f, S_m) + \mathbb{E}\|f_m - \hat{f}_m\|^2.$$

We recognize in the right member a bias term and a variance term. According to the expression (4) of \hat{f}_m the variance term can be written:

$$\mathbb{E}\|f_m - \hat{f}_m\|^2 = \sum_{\lambda \in \Lambda_m} \text{Var}(\hat{\beta}_\lambda) = \sum_{\lambda \in \Lambda_m} \mathbb{E}(\nu_n^2(\varphi_\lambda)) \quad (9)$$

where $\nu_n(t) = (1/n) \sum_{i=1}^n [t(X_i) - \langle t, f \rangle]$. By denoting $\tau = \tau(1) = \inf\{n \geq 1, X_n \in A\}$ and $\tau(j) = \inf\{n > \tau(j-1), X_n \in A\}$ for $j \geq 2$, we can decompose $\nu_n(t)$ in the classic following way:

$$\nu_n(t) = \nu_n^{(1)}(t) + \nu_n^{(2)}(t) + \nu_n^{(3)}(t) + \nu_n^{(4)}(t) \quad (10)$$

with $\nu_n^{(1)}(t) = \nu_n(t) \mathbf{1}_{\tau > n}$,

$$\nu_n^{(2)}(t) = \frac{1}{n} \sum_{i=1}^{\tau} [t(X_i) - \langle t, f \rangle] \mathbf{1}_{\tau \leq n},$$

$$\nu_n^{(3)}(t) = \frac{1}{n} \sum_{i=1+\tau(1)}^{\tau(l_n)} [t(X_i) - \langle t, f \rangle] \mathbf{1}_{\tau \leq n},$$

$$\nu_n^{(4)}(t) = \frac{1}{n} \sum_{i=\tau(l_n)+1}^n [t(X_i) - \langle t, f \rangle] \mathbf{1}_{\tau \leq n},$$

and $l_n = \sum_{i=1}^n \mathbf{1}_A(X_i)$ (number of visits to the atom A). Hence,

$$\nu_n(t)^2 \leq 4\{\nu_n^{(1)}(t)^2 + \nu_n^{(2)}(t)^2 + \nu_n^{(3)}(t)^2 + \nu_n^{(4)}(t)^2\}.$$

- To bound $\nu_n^{(1)}(t)^2$, notice that $|\nu_n(t)| \leq 2\|t\|_\infty$. And then, by using M2 and (1), $|\nu_n^{(1)}(t)| \leq 2r_0\sqrt{D_m}\|t\|\mathbf{1}_{\tau>n}$. Thus,

$$\mathbb{E}(\nu_n^{(1)}(t)^2) \leq 4r_0^2\|t\|^2 D_m P(\tau > n) \leq 4r_0^2\|t\|^2 \mathbb{E}(\tau^2) \frac{D_m}{n^2}.$$

- We bound the second term in the same way. Since $|\nu_n^{(2)}(t)| \leq 2(\tau/n)\|t\|_\infty$, we obtain $|\nu_n^{(2)}(t)| \leq 2\|t\|r_0\tau\sqrt{D_m}/n$ and then

$$\mathbb{E}(\nu_n^{(2)}(t)^2) \leq 4r_0^2\|t\|^2 \mathbb{E}(\tau^2) \frac{D_m}{n^2}.$$

- Let us study now the fourth term. As

$$|\nu_n^{(4)}(t)| \leq 2\frac{n - \tau(l_n)}{n}\|t\|_\infty \mathbf{1}_{\tau \leq n} \leq 2(n - \tau(l_n))\frac{\sqrt{D_m}}{n}r_0\|t\| \mathbf{1}_{\tau \leq n},$$

we get $\mathbb{E}(\nu_n^{(4)}(t)^2) \leq 4r_0^2\|t\|^2 \frac{D_m}{n^2} \mathbb{E}((n - \tau(l_n))^2 \mathbf{1}_{\tau \leq n})$.

It remains to bound $\mathbb{E}((n - \tau(l_n))^2 \mathbf{1}_{\tau \leq n})$:

$$\begin{aligned} \mathbb{E}_\mu((n - \tau(l_n))^2 \mathbf{1}_{\tau \leq n}) &= \sum_{k=1}^n \mathbb{E}_\mu((n - k)^2 \mathbf{1}_{\tau(l_n)=k} \mathbf{1}_{\tau \leq n}) \\ &= \sum_{k=1}^n (n - k)^2 P_\mu(X_{k+1} \notin A, \dots, X_n \notin A | X_k \in A) P_\mu(X_k \in A) \\ &= \sum_{k=1}^n (n - k)^2 P_A(X_1 \notin A, \dots, X_{n-k} \notin A) \mu(A) \end{aligned}$$

by using the stationarity of X and the Markov property. Hence

$$\begin{aligned} \mathbb{E}_\mu((n - \tau(l_n))^2 \mathbf{1}_{\tau \leq n}) &= \sum_{k=1}^n (n - k)^2 P_A(\tau > n - k) \mu(A) \\ &\leq \sum_{k=1}^{n-1} \frac{\mathbb{E}_A(\tau^4)}{(n - k)^2} \mu(A). \end{aligned}$$

Therefore $\mathbb{E}_\mu((n - \tau(l_n))^2 \mathbf{1}_{\tau \leq n}) \leq 2\mathbb{E}_A(\tau^4)\mu(A)$. Finally

$$\mathbb{E}(\nu_n^{(4)}(t)^2) \leq 8r_0^2\|t\|^2 \mu(A) \mathbb{E}_A(\tau^4) \frac{D_m}{n^2}$$

and we can summarize the last three results by

$$\mathbb{E}(\nu_n^{(1)}(t)^2 + \nu_n^{(2)}(t)^2 + \nu_n^{(4)}(t)^2) \leq 8r_0^2\|t\|^2 [\mathbb{E}_\mu(\tau^2) + \mu(A)\mathbb{E}_A(\tau^4)] \frac{D_m}{n^2}. \quad (11)$$

In particular, if $t = \varphi_\lambda$, using that $D_m \leq n$,

$$\mathbb{E} \left(\nu_n^{(1)}(\varphi_\lambda)^2 + \nu_n^{(2)}(\varphi_\lambda)^2 + \nu_n^{(4)}(\varphi_\lambda)^2 \right) \leq 8r_0^2 \frac{\mathbb{E}_\mu(\tau^2) + \mu(A)\mathbb{E}_A(\tau^4)}{n}.$$

• Last we can write $\nu_n^{(3)}(t) = (1/n) \sum_{j=1}^{l_n-1} S_j(t) \mathbb{1}_{\tau \leq n}$ where

$$S_j(t) = \sum_{i=1+\tau(j)}^{\tau(j+1)} (t(X_i) - \langle t, f \rangle). \quad (12)$$

We remark that, according to the Markov property, the $S_j(t)$ are independent identically distributed and centered. Thus,

$$\mathbb{E}(\nu_n^{(3)}(\varphi_\lambda)^2) \leq \frac{1}{n^2} \sum_{j=1}^{l_n-1} \mathbb{E}|S_j(\varphi_\lambda)|^2.$$

Then, we use Lemma 10 below to bound the expectation of $\nu_n^{(3)}(\varphi_\lambda)^2$:

Lemma 10 For all $m \geq 2$, $\mathbb{E}_\mu |S_j(t)|^m \leq (2\|t\|_\infty)^{m-2} \|f\|_\infty \|t\|^2 \mathbb{E}_A(\tau^m)$.

We can then give the bound

$$\mathbb{E}(\nu_n^{(3)}(\varphi_\lambda)^2) \leq \frac{1}{n^2} \sum_{j=1}^n \|f\|_\infty \|\varphi_\lambda\|^2 \mathbb{E}_A(\tau^2) \leq \frac{\|f\|_\infty \mathbb{E}_A(\tau^2)}{n}.$$

Finally

$$\mathbb{E}(\nu_n^2(\varphi_\lambda)) \leq \frac{4}{n} [8r_0^2(\mathbb{E}_\mu(\tau^2) + \mu(A)\mathbb{E}_A(\tau^4)) + \|f\|_\infty \mathbb{E}_A(\tau^2)].$$

Let $C = 4[8r_0^2(\mathbb{E}_\mu(\tau^2) + \mu(A)\mathbb{E}_A(\tau^4)) + \|f\|_\infty \mathbb{E}_A(\tau^2)]$. We obtain with (9)

$$\mathbb{E}\|f_m - \hat{f}_m\|^2 \leq C \frac{D_m}{n}.$$

Second step: We do not suppose any more that (X_n) has an atom.

Let us apply the Nummelin splitting technique to the chain (X_n) and let

$$\gamma_n^*(t) = \frac{1}{n} \sum_{i=1}^n [\|t\|^2 - 2t^*(X_i^*)]. \quad (13)$$

We define also

$$\hat{f}_m^* = \arg \min_{t \in S_m} \gamma_n^*(t). \quad (14)$$

Then the property P1 in Section 6.1 yields $\mathbb{E}\|f - \hat{f}_m^*\|^2 = \mathbb{E}\|f - \hat{f}_m\|^2$. The split chain having an atom (property P3), we can use the first step to deduce $\mathbb{E}\|f - \hat{f}_m^*\|^2 \leq d^2(f, S_m) + CD_m/n$. It follows that

$$\mathbb{E}\|f - \hat{f}_m\|^2 \leq d^2(f, S_m) + CD_m/n.$$

□

Proof of Lemma 10: For all j , $\mathbb{E}_\mu|S_j(t)|^m = \mathbb{E}_\mu|S_1(t)|^m = \mathbb{E}_\mu|\sum_{i=\tau+1}^{\tau(2)} \bar{t}(X_i)|^m$ where $\bar{t} = t- < t, f >$. Thus

$$\begin{aligned} \mathbb{E}_\mu|S_j(t)|^m &= \sum_{k<l} \mathbb{E} \left(\left| \sum_{i=k+1}^l \bar{t}(X_i) \right|^m \middle| \tau = k, \tau(2) = l \right) P(\tau = k, \tau(2) = l) \\ &\leq \sum_{k<l} (2\|t\|_\infty(l-k))^{m-2} \mathbb{E} \left(\left| \sum_{i=k+1}^l \bar{t}(X_i) \right|^2 \middle| \tau = k, \tau(2) = l \right) P(\tau = k, \tau(2) = l) \\ &\leq \sum_{k<l} (2\|t\|_\infty)^{m-2} (l-k)^{m-1} \sum_{i=k+1}^l \mathbb{E} \left(\left| \bar{t}(X_i) \right|^2 \middle| \tau = k, \tau(2) = l \right) P(\tau = k, \tau(2) = l) \end{aligned}$$

using the Schwarz inequality. Then, since the X_i have the same distribution under μ .

$$\begin{aligned} \mathbb{E}_\mu|S_j(t)|^m &\leq \sum_{k<l} (2\|t\|_\infty)^{m-2} (l-k)^m \mathbb{E}(t^2(X_1)) P(\tau = k, \tau(2) = l) \\ &\leq \sum_{k<l} (2\|t\|_\infty)^{m-2} (l-k)^m \|f\|_\infty \|t\|^2 P(\tau = k, \tau(2) = l) \\ &\leq (2\|t\|_\infty)^{m-2} \mathbb{E}(|\tau(2) - \tau|^m) \|f\|_\infty \|t\|^2. \end{aligned}$$

We conclude by using the Markov property. □

6.3 Proof of Corollary 2

According to Proposition 1 $\mathbb{E}\|f - \hat{f}_m\|^2 \leq d^2(f, S_m) + CD_m/n$. Then we use Lemma 12 in Barron et al. (1999) which ensures that (for piecewise polynomials or wavelets having a regularity larger than $\alpha - 1$ and for trigonometric polynomials) $d^2(f, S_m) = O(D_m^{-2\alpha})$. Thus,

$$\mathbb{E}\|f - \hat{f}_m\|^2 = O(D_m^{-2\alpha} + \frac{D_m}{n})$$

In particular, if $D_m = \lfloor n^{\frac{1}{1+2\alpha}} \rfloor$, then $\mathbb{E}\|f - \hat{f}_m\|^2 = O(n^{-\frac{2\alpha}{1+2\alpha}})$. □

6.4 Proof of Theorem 3

First step: We suppose that (X_n) has an atom A .

Let m in \mathcal{M}_n . The definition of \hat{m} yields that $\gamma_n(\hat{f}_{\hat{m}}) + \text{pen}(\hat{m}) \leq \gamma_n(f_m) + \text{pen}(m)$. This leads to

$$\|\hat{f}_{\hat{m}} - f\|^2 \leq \|f_m - f\|^2 + 2\nu_n(\hat{f}_{\hat{m}} - f_m) + \text{pen}(m) - \text{pen}(\hat{m}) \quad (15)$$

where $\nu_n(t) = (1/n) \sum_{i=1}^n [t(X_i) - \langle t, f \rangle]$.

Remark 11 *If t is deterministic, $\nu_n(t)$ can actually be written $\nu_n(t) = (1/n) \sum_{i=1}^n [t(X_i) - \mathbb{E}(t(X_i))]$.*

We set $B(m, m') = \{t \in S_m + S_{m'}, \|t\| = 1\}$. Let us write now

$$\begin{aligned} 2\nu_n(\hat{f}_{\hat{m}} - f_m) &= 2\|\hat{f}_{\hat{m}} - f_m\| \nu_n\left(\frac{\hat{f}_{\hat{m}} - f_m}{\|\hat{f}_{\hat{m}} - f_m\|}\right) \\ &\leq 2\|\hat{f}_{\hat{m}} - f_m\| \sup_{t \in B(m, \hat{m})} \nu_n(t) \leq \frac{1}{5}\|\hat{f}_{\hat{m}} - f_m\|^2 + 5 \sup_{t \in B(m, \hat{m})} \nu_n(t)^2 \end{aligned}$$

by using inequality $2xy \leq \frac{1}{5}x^2 + 5y^2$. Thus,

$$2\mathbb{E}|\nu_n(\hat{f}_{\hat{m}} - f_m)| \leq \frac{1}{5}\mathbb{E}\|\hat{f}_{\hat{m}} - f_m\|^2 + 5\mathbb{E}\left(\sup_{t \in B(m, \hat{m})} \nu_n(t)^2\right). \quad (16)$$

Consider decomposition (10) of $\nu_n(t)$ again and let

$$Z_n(t) = \frac{1}{n} \sum_{j=1+\tau(1)}^{\tau(l_n)} [t(X_j) - \langle t, f \rangle]. \quad (17)$$

Since $|\nu_n^{(3)}(t)| \leq |Z_n(t)|$, we can write

$$\sup_{t \in B(m, \hat{m})} \nu_n^{(3)}(t)^2 \leq p(m, \hat{m}) + \sum_{m' \in \mathcal{M}_n} \left[\sup_{t \in B(m, m')} Z_n(t)^2 - p(m, m') \right]_+$$

where $p(\cdot, \cdot)$ is a function specified in Proposition 12 on page 24. Then, the bound (11) combined with M1, (15) and (16) gives

$$\begin{aligned}\mathbb{E}\|\hat{f}_{\hat{m}} - f\|^2 &\leq \|f_m - f\|^2 + \frac{1}{5}\mathbb{E}\|\hat{f}_{\hat{m}} - f_m\|^2 + 160r_0^2 \frac{\mathbb{E}(\tau^2) + \mu(A)\mathbb{E}_A(\tau^4)}{n} \\ &\quad + 20 \sum_{m' \in \mathcal{M}_n} \mathbb{E}[\sup_{t \in B(m, m')} Z_n(t)^2 - p(m, m')]_+ \\ &\quad + \mathbb{E}(20p(m, \hat{m}) + \text{pen}(m) - \text{pen}(\hat{m})).\end{aligned}$$

We choose $\text{pen}(m)$ such that $20p(m, m') \leq \text{pen}(m) + \text{pen}(m')$. Thus $20p(m, \hat{m}) + \text{pen}(m) - \text{pen}(\hat{m}) \leq 2\text{pen}(m)$. Let

$$W(m, m') = [\sup_{t \in B(m, m')} Z_n^2(t) - p(m, m')]_+. \quad (18)$$

We use now the inequality $\frac{1}{5}(x + y)^2 \leq \frac{1}{3}x^2 + \frac{1}{2}y^2$ to deduce

$$\mathbb{E}\|\hat{f}_{\hat{m}} - f\|^2 \leq \frac{1}{3}\mathbb{E}\|\hat{f}_{\hat{m}} - f\|^2 + \frac{3}{2}\|f_m - f\|^2 + 20 \sum_{m' \in \mathcal{M}_n} \mathbb{E}W(m, m') + 2\text{pen}(m) + \frac{C}{n}$$

and thus

$$\mathbb{E}\|\hat{f}_{\hat{m}} - f\|^2 \leq \frac{9}{4}\|f_m - f\|^2 + 30 \sum_{m' \in \mathcal{M}_n} \mathbb{E}W(m, m') + 3\text{pen}(m) + \frac{3C}{2n}.$$

We need now to bound $\mathbb{E}W(m, m')$ to complete the proof. Proposition 12 below implies

$$\mathbb{E}W(m, m') \leq K' e^{-D_{m'}} (r_0 \vee 1)^2 K_3 \frac{1 + K_2 \|f\|_\infty}{n}$$

where K' is a numerical constant and K_2, K_3 depend on the chain and with

$$p(m, m') = K \frac{\dim(S_m + S_{m'})}{n} (r_0 \vee 1)^2 K_3 (1 + K_2 \|f\|_\infty). \quad (19)$$

The notation $a \vee b$ means $\max(a, b)$.

Assumption M3 yields $\sum_{m' \in \mathcal{M}_n} e^{-D_{m'}} \leq \sum_{k \geq 1} e^{-k} = 1/(e - 1)$. Thus, by summation on m' in \mathcal{M}_n

$$\sum_{m' \in \mathcal{M}_n} \mathbb{E}W(m, m') \leq K' \frac{1}{e - 1} (r_0 \vee 1)^2 K_3 \frac{1 + K_2 \|f\|_\infty}{n}.$$

It remains to specify the penalty, which has to satisfy $20p(m, m') \leq \text{pen}(m) + \text{pen}(m')$. The value of $p(m, m')$ is given by (19), so we set

$$\text{pen}(m) \geq 20K \frac{D_m}{n} (r_0 \vee 1)^2 K_3 (1 + K_2 \|f\|_\infty)$$

Finally

$$\forall m \quad \mathbb{E}\|\hat{f}_{\hat{m}} - f\|^2 \leq 3\|f_m - f\|^2 + 3\text{pen}(m) + \frac{C_1}{n}$$

where C_1 depends on $r_0, \|f\|_\infty, \mu(A), \mathbb{E}_\mu(\tau^2), \mathbb{E}_A(\tau^4), K_2, K_3$. Since it is true for all m , we obtain the result.

Second step: We do not suppose any more that (X_n) has an atom.

The Nummelin splitting technique allows us to create the chain (X_n^*) and to define $\gamma_n^*(t)$ and \hat{f}_m^* as above by (13),(14). Set now

$$\hat{m}^* = \arg \min_{m \in \mathcal{M}_n} [\gamma_n^*(\hat{f}_m^*) + \text{pen}(m)]$$

and $\tilde{f}^* = \hat{f}_{\hat{m}^*}$. The property P1 in Section 6.1 gives $\mathbb{E}\|f - \tilde{f}^*\|^2 = \mathbb{E}\|f - \tilde{f}^*\|^2$. The split chain having an atom, we can use the first step to deduce

$$\mathbb{E}\|f - \tilde{f}^*\|^2 \leq 3 \inf_{m \in \mathcal{M}_n} \{d^2(f, S_m) + \text{pen}(m)\} + \frac{C_1}{n}.$$

And then the result is valid when replacing \tilde{f}^* by \tilde{f} .

□

Proposition 12 *Let (X_n) be a Markov chain which satisfies A1–A5 and $(S_m)_{m \in \mathcal{M}_n}$ be a collection of models satisfying M1–M3. We suppose that (X_n) has an atom A . Let $Z_n(t)$ and $W(m, m')$ defined by (17) and (18) with*

$$p(m, m') = K \frac{\dim(S_m + S_{m'})}{n} (r_0 \vee 1)^2 \frac{1 + \|f\|_\infty \mathbb{E}_A(s^\tau)}{(\ln s)^2}$$

(where K is a numerical constant and s is a real depending on the chain). Then

$$\mathbb{E}W(m, m') \leq K' e^{-D_{m'}} (r_0 \vee 1)^2 \frac{1 + \|f\|_\infty \mathbb{E}_A(s^\tau)}{(\ln s)^2 n}$$

Proof of Proposition 12: We can write $Z_n(t) = (1/n) \sum_{j=1}^{l_n-1} S_j(t)$ where $S_j(t)$ is defined by (12). According to Lemma 10: $\mathbb{E}_\mu |S_j(t)|^m \leq (2\|t\|_\infty)^{m-2} \|f\|_\infty \|t\|^2 \mathbb{E}_A(\tau^m)$. Now, we use condition A5 of geometric ergodicity. The proof of Theorem 15.4.2 in Meyn and Tweedie (1993) shows that A is a Kendall set, i.e. there exists $s > 1$ (depending on A) such that $\sup_{x \in A} \mathbb{E}_x(s^\tau) < \infty$. Then $\mathbb{E}_A(\tau^m) \leq [m! / (\ln s)^m] \mathbb{E}_A(s^\tau)$. Indeed

$$\begin{aligned} \mathbb{E}_A(\tau^m) &= \int_0^\infty m x^{m-1} P_A(\tau > x) dx \\ &\leq \int_0^\infty m x^{m-1} s^{-x} \mathbb{E}_A(s^\tau) dx = \frac{m!}{(\ln s)^m} \mathbb{E}_A(s^\tau) \end{aligned}$$

Thus

$$\forall m \geq 2 \quad \mathbb{E}_\mu |S_j(t)|^m \leq m! \left(\frac{2\|t\|_\infty}{\ln s} \right)^{m-2} \frac{\|f\|_\infty \|t\|^2}{(\ln s)^2} \mathbb{E}_A(s^\tau). \quad (20)$$

We use now the following inequality (see Petrov (1975) p.49):

$$P\left(\max_{1 \leq l \leq n} \sum_{j=1}^l S_j(t) \geq y\right) \leq 2P\left(\sum_{j=1}^n S_j(t) \geq y - \sqrt{2B_n}\right)$$

where $B_n \geq \sum_{j=1}^n \mathbb{E}S_j(t)^2$. The inequality (20) gives us $B_n = 2n \frac{\|f\|_\infty \|t\|^2}{(\ln s)^2} \mathbb{E}_A(s^\tau)$

and

$$P\left(\sum_{j=1}^{l_n-1} S_j(t) \geq y\right) \leq P\left(\max_{1 \leq l \leq n} \sum_{j=1}^l S_j(t) \geq y\right) \leq 2P\left(\sum_{j=1}^n S_j(t) \geq y - 2\sqrt{n}\|t\|M/\ln s\right)$$

where $M^2 = \|f\|_\infty \mathbb{E}_A(s^\tau)$. We use then the Bernstein inequality given by Birgé and Massart (1998).

$$P\left(\sum_{j=1}^n S_j(t) \geq n\varepsilon\right) \leq e^{-nx}$$

with $\varepsilon = \frac{2\|t\|_\infty}{\ln s}x + \frac{2\|t\|M}{\ln s}\sqrt{x}$. Indeed, according to (20),

$$\frac{1}{n} \sum_{j=1}^n \mathbb{E}|S_j(t)|^m \leq \frac{m!}{2} \left(\frac{2\|t\|_\infty}{\ln s} \right)^{m-2} \left(\frac{\sqrt{2}\|t\|M}{\ln s} \right)^2.$$

Finally

$$P\left(Z_n(t) \geq \frac{2}{\ln s} \left[\|t\|_\infty x + M\|t\|\sqrt{x} + M\|t\|/\sqrt{n} \right] \right) \leq 2e^{-nx}. \quad (21)$$

We will now use a chaining technique used in Barron et al. (1999). Let us recall first the following lemma (Lemma 9 p.400 in Barron et al. (1999), see also Proposition 1 in Birgé and Massart (1998)).

Lemma 13 *Let \bar{S} a subspace of L^2 with dimension D spanned by $(\varphi_\lambda)_{\lambda \in \Lambda}$ (orthonormal basis). Let*

$$r = \frac{1}{\sqrt{D}} \sup_{\beta \neq 0} \frac{\left\| \sum_{\lambda \in \Lambda} \beta_\lambda \varphi_\lambda \right\|_\infty}{\sup_{\lambda \in \Lambda} |\beta_\lambda|}.$$

Then, for all $\delta > 0$, we can find a countable set $T \subset \bar{S}$ and a mapping π from \bar{S} to T such that :

- for all ball \mathcal{B} with radius $\sigma \geq 5\delta$

$$|T \cap \mathcal{B}| \leq (5\sigma/\delta)^D \quad (22)$$

- $\|u - \pi(u)\| \leq \delta, \forall u \in \bar{S}$ and $\sup_{u \in \pi^{-1}(t)} \|u - t\|_\infty \leq r\delta, \forall t \in T$.

We apply this lemma to the subspace $S_m + S_{m'}$ with dimension $D_m \vee D_{m'}$ denoted by $D(m, m')$ and $r = r(m, m')$ defined by

$$r(m, m') = \frac{1}{\sqrt{D(m, m')}} \sup_{\beta \neq 0} \frac{\|\sum_{\lambda \in \Lambda(m, m')} \beta_\lambda \varphi_\lambda\|_\infty}{\sup_{\lambda \in \Lambda(m, m')} |\beta_\lambda|}$$

where $(\varphi_\lambda)_{\lambda \in \Lambda(m, m')}$ is an orthonormal basis of $S_m + S_{m'}$. Notice that this quantity satisfy $\phi_{m''} \leq r(m, m') \leq \sqrt{D(m, m')} \phi_{m''}$ where m'' is such that $S_m + S_{m'} = S_{m''}$ and then, using M2,

$$r(m, m') \leq r_0 \sqrt{D(m, m')}.$$

We consider $\delta_0 \leq 1/5$, $\delta_k = \delta_0 2^{-k}$, and the $T_k = T \cap B(m, m')$ where T is defined by Lemma 13 with $\delta = \delta_k$ and $B(m, m')$ is the unit ball of $S_m + S_{m'}$. Inequality (22) gives us $|T \cap B(m, m')| \leq (5/\delta_k)^{D(m, m')}$. By letting $H_k = \ln(|T_k|)$, we obtain

$$H_k \leq D(m, m') [\ln(\frac{5}{\delta_0}) + k \ln 2]. \quad (23)$$

Thus, for all u in $B(m, m')$, we can find a sequence $\{u_k\}_{k \geq 0}$ with $u_k \in T_k$ such that $\|u - u_k\| \leq \delta_k$ and $\|u - u_k\|_\infty \leq r(m, m') \delta_k$. Hence, we have the following decomposition:

$$u = u_0 + \sum_{k=1}^{\infty} (u_k - u_{k-1})$$

with $\|u_0\| \leq 1$ and $\|u_0\|_\infty \leq r_0 \sqrt{D(m, m')} \|u_0\| \leq r_0 \sqrt{D(m, m')}$ and for all $k \geq 1$,

$$\begin{aligned} \|u_k - u_{k-1}\| &\leq \delta_k + \delta_{k-1} = 3\delta_{k-1}/2, \\ \|u_k - u_{k-1}\|_\infty &\leq 3r(m, m') \delta_{k-1}/2 \leq 3r_0 \sqrt{D(m, m')} \delta_{k-1}/2. \end{aligned}$$

Then

$$\begin{aligned} P\left(\sup_{u \in B(m, m')} Z_n(u) > \eta\right) &= P(\exists (u_k)_{k \geq 0} \in \prod_{k \geq 0} T_k, Z_n(u_0) + \sum_{k=1}^{\infty} Z_n(u_k - u_{k-1}) > \eta_0 + \sum_{k=1}^{\infty} \eta_k) \\ &\leq \sum_{u_0 \in T_0} P(Z_n(u_0) > \eta_0) + \sum_{k=1}^{\infty} \sum_{\substack{u_k \in T_k \\ u_{k-1} \in T_{k-1}}} P(Z_n(u_k - u_{k-1}) > \eta_k) \end{aligned}$$

with $\eta_0 + \sum_{k=1}^{\infty} \eta_k \leq \eta$. We use the exponential inequality (21) to obtain

$$\begin{aligned} \sum_{u_0 \in T_0} P(Z_n(u_0) > \eta_0) &\leq 2e^{H_0 - nx_0} \\ \sum_{\substack{u_k \in T_k \\ u_{k-1} \in T_{k-1}}} P(Z_n(u_k - u_{k-1}) > \eta_k) &\leq 2e^{H_k + H_{k-1} - nx_k} \end{aligned}$$

by choosing
$$\begin{cases} \eta_0 = \frac{2}{\ln s} \left(r_0 \sqrt{D(m, m')} x_0 + M \sqrt{x_0} + \frac{M}{\sqrt{n}} \right) \\ \eta_k = \frac{3}{\ln s} \left(r_0 \sqrt{D(m, m')} \delta_{k-1} x_k + M \delta_{k-1} \sqrt{x_k} + \frac{M \delta_{k-1}}{\sqrt{n}} \right). \end{cases}$$

Let us choose now the $(x_k)_{k \geq 0}$ such that $nx_0 = H_0 + D_{m'} + v$ and for $k \geq 1$,

$$nx_k = H_{k-1} + H_k + kD_{m'} + D_{m'} + v$$

Thus

$$P\left(\sup_{u \in B(m, m')} Z_n(u) > \eta\right) \leq 2e^{-D_{m'} - v} \left(1 + \sum_{k \geq 1} e^{-kD_{m'}}\right) \leq 3.2e^{-D_{m'} - v}$$

It remains to bound $\sum_{k=0}^{\infty} \eta_k$:

$$\sum_{k=0}^{\infty} \eta_k \leq \frac{1}{(\ln s)} (A_1 + A_2 + A_3).$$

where
$$\begin{cases} A_1 = r_0 \sqrt{D(m, m')} (2x_0 + 3 \sum_{k=1}^{\infty} \delta_{k-1} x_k) \\ A_2 = 2M \sqrt{x_0} + 3M \sum_{k=1}^{\infty} \delta_{k-1} \sqrt{x_k} \\ A_3 = 2 \frac{M}{\sqrt{n}} + \sum_{k=1}^{\infty} \frac{3M \delta_{k-1}}{\sqrt{n}} \end{cases}$$

- Regarding the third term, just write

$$A_3 = \frac{M}{\sqrt{n}} \left(2 + 3 \sum_{k=1}^{\infty} \delta_{k-1}\right) = \frac{M}{\sqrt{n}} (6\delta_0 + 2) \leq c_1(\delta_0) \frac{M}{\sqrt{n}}$$

with $c_1(\delta_0) = 6\delta_0 + 2$.

- Let us bound the first term. First, recall that $D(m, m') \leq \sqrt{n}$ and then

$$A_1 \leq r_0 \sqrt{\frac{n}{D(m, m')}} \left(2 \frac{H_0 + D_{m'} + v}{n} + 3 \sum_{k=1}^{\infty} \delta_{k-1} \frac{H_{k-1} + H_k + kD_{m'} + D_{m'} + v}{n} \right).$$

Observing that $\sum_{k=1}^{\infty} \delta_{k-1} = 2\delta_0$ and $\sum_{k=1}^{\infty} k\delta_{k-1} = 4\delta_0$ and using (23), we get

$$A_1 \leq c_1(\delta_0) r_0 \frac{v}{\sqrt{nD(m, m')}} + c_2(\delta_0) r_0 \sqrt{\frac{D(m, m')}{n}}$$

with $c_2(\delta_0) = c_1(\delta_0) + \ln(5/\delta_0)(2 + 12\delta_0) + 6\delta_0(2 + 3 \ln 2)$

• To bound the second term, we use the Schwarz inequality and the inequality $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$. We obtain

$$A_2 \leq c_1(\delta_0) M \sqrt{\frac{v}{n}} + c_3(\delta_0) M \sqrt{\frac{D(m, m')}{n}}$$

with $c_3(\delta_0) = 2\sqrt{1 + \ln(5/\delta_0)} + 3\sqrt{2\delta_0} \sqrt{6\delta_0(1 + \ln 2) + 4\delta_0 \ln(5/\delta_0)}$

We get so

$$\begin{aligned} \left(\sum_{k=0}^{\infty} \eta_k \right) &\leq \left(\frac{r_0 \vee 1}{\ln s} \right) c_1 \left(\frac{v}{\sqrt{nD(m, m')}} + M \sqrt{\frac{v}{n}} \right) \\ &\quad + \sqrt{\frac{D(m, m')}{n}} \left(\frac{r_0 \vee 1}{\ln s} \right) [c_2 + c_3 M + c_1 M] \\ \left(\sum_{k=0}^{\infty} \eta_k \right)^2 &\leq c_4(\delta_0) \left(\frac{r_0 \vee 1}{\ln s} \right)^2 \left[\frac{v^2}{nD(m, m')} \vee M^2 \frac{v}{n} \right] \\ &\quad + c_5(\delta_0) \frac{D(m, m')}{n} \left(\frac{r_0 \vee 1}{\ln s} \right)^2 (1 + M)^2 \end{aligned}$$

where $\begin{cases} c_4(\delta_0) = 6c_1^2 \\ c_5(\delta_0) = (6/5) \sup(c_2, c_3 + c_1)^2 \end{cases}$

Let us choose now $\delta_0 = 0.024$ and then $c_4 = 28$, $c_5 = 268$. Let $K_1 = c_4(r_0 \vee 1/\ln s)^2$. Then

$$\eta^2 = K_1 \left[\frac{v^2}{nD(m, m')} \vee M^2 \frac{v}{n} \right] + p(m, m')$$

where

$$p(m, m') = c_5(r_0 \vee 1)^2 \frac{D(m, m')}{n} \frac{1 + \|f\|_{\infty} \mathbb{E}_A(s^{\tau})}{(\ln s)^2}$$

We get

$$\begin{aligned}
& P\left(\sup_{u \in B(m, m')} Z_n^2(u) > K_1 \left[\frac{v^2}{nD(m, m')} \vee M^2 \frac{v}{n} \right] + p(m, m')\right) \\
&= P\left(\sup_{u \in B(m, m')} Z_n^2(u) > \eta^2\right) \\
&\leq P\left(\sup_{u \in B(m, m')} Z_n(u) > \eta\right) + P\left(\sup_{u \in B(m, m')} Z_n(u) < -\eta\right)
\end{aligned}$$

Now

$$\begin{aligned}
P\left(\sup_{u \in B(m, m')} Z_n(u) < -\eta\right) &\leq \sum_{u_0 \in T_0} P(Z_n(u_0) < -\eta_0) + \sum_{k=1}^{\infty} \sum_{\substack{u_k \in T_k \\ u_{k-1} \in T_{k-1}}} P(Z_n(u_k - u_{k-1}) < -\eta_k) \\
&\leq \sum_{u_0 \in T_0} P(Z_n(-u_0) > \eta_0) + \sum_{k=1}^{\infty} \sum_{\substack{u_k \in T_k \\ u_{k-1} \in T_{k-1}}} P(Z_n(-u_k + u_{k-1}) > \eta_k) \\
&\leq 3.2e^{-D_{m'}-v}.
\end{aligned}$$

Hence

$$P\left(\sup_{u \in B(m, m')} Z_n^2(u) > K_1 \left[\frac{v^2}{nD(m, m')} \vee M^2 \frac{v}{n} \right] + p(m, m')\right) \leq 6.4e^{-D_{m'}-v}.$$

We obtain then

$$\begin{aligned}
& \mathbb{E}\left[\sup_{t \in B(m, m')} Z_n^2(t) - p(m, m')\right]_+ \leq \int_0^{\infty} P\left(\sup_{u \in B(m, m')} Z_n^2(u) > p(m, m') + z\right) dz \\
&\leq \int_0^{M^2 D(m, m')} P\left(\sup_{u \in B(m, m')} Z_n^2(u) > p(m, m') + K_1 M^2 \frac{v}{n}\right) K_1 \frac{M^2}{n} dv \\
&+ \int_{M^2 D(m, m')}^{\infty} P\left(\sup_{u \in B(m, m')} Z_n^2(u) > p(m, m') + K_1 \frac{v^2}{nD(m, m')}\right) K_1 \frac{2v}{nD(m, m')} dv \\
&\leq \frac{K_1}{n} \left[M^2 \int_0^{\infty} 6.4e^{-D_{m'}-v} dv + \frac{2}{D(m, m')} \int_0^{\infty} 6.4e^{-D_{m'}-v} v dv \right] \\
&\leq \frac{6.4K_1}{n} e^{-D_{m'}} \left(M^2 + \frac{2}{D(m, m')} \right) \leq 12.8K_1 e^{-D_{m'}} \frac{1 + M^2}{n}.
\end{aligned}$$

By replacing M^2 by its value, we get so

$$\mathbb{E}W(m, m') \leq K' \left(\frac{r_0 \vee 1}{\ln s} \right)^2 e^{-D_{m'}} \frac{1 + \|f\|_{\infty} \mathbb{E}_A(s^{\tau})}{n}$$

where K' is a numerical constant □

6.5 Proof of Corollary 5

According to Theorem 3, $\mathbb{E}\|\tilde{f} - f\|^2 \leq C_2 \inf_{m \in \mathcal{M}_n} \{d^2(f, S_m) + D_m/n\}$. Since $d^2(f, S_m) = O(D_m^{-2\alpha})$ (see Lemma 12 in Barron et al. (1999)),

$$\mathbb{E}\|\tilde{f} - f\|^2 \leq C_3 \inf_{m \in \mathcal{M}_n} \left\{ D_m^{-2\alpha} + \frac{D_m}{n} \right\}$$

In particular, if m_0 is such that $D_{m_0} = \lfloor n^{\frac{1}{1+2\alpha}} \rfloor$, then

$$\mathbb{E}\|\tilde{f} - f\|^2 \leq C_3 \left\{ D_{m_0}^{-2\alpha} + \frac{D_{m_0}}{n} \right\} \leq C_4 n^{-\frac{2\alpha}{1+2\alpha}}.$$

The condition $D_m \leq \sqrt{n}$ allows this choice of m only if $\alpha > \frac{1}{2}$. \square

6.6 Proof of Theorem 7

The proof is identical to the one of Theorem 3. \square

6.7 Proof of Corollary 8

It is sufficient to prove that $d(g, S_m^{(2)}) \leq D_m^{-\alpha}$ if g belongs to $B_{2,\infty}^\alpha([0, 1]^2)$. It is done in the following lemma. \square

Lemma 14 *Let g in the Besov space $B_{2,\infty}^\alpha([0, 1]^2)$. We consider the following spaces of dimension D^2 :*

- S_1 is a space of piecewise polynomials of degree bounded by $s > \alpha - 1$ based on a partition with square of vertice $1/D$,
- S_2 is a space of orthonormal wavelets of regularity $s > \alpha - 1$,
- S_3 is the space of trigonometric polynomials.

Then, there exist positive constants C_i such that

$$d(g, S_i) \leq C_i D^{-\alpha} \quad \text{for } i = 1, 2, 3.$$

Proof of Lemme 14: Let us recall the definition of $B_{2,\infty}^\alpha([0, 1]^2)$. Let

$$\Delta_h^r g(x, y) = \sum_{k=0}^r (-1)^{r-k} \binom{r}{k} g(x + kh_1, y + kh_2)$$

the r th difference operator with step h and $\omega_r(g, t) = \sup_{|h| \leq t} \|\Delta_h^r g\|_2$ the r th modulus of smoothness of g . We say g is in the Besov space $B_{2,\infty}^\alpha([0, 1]^2)$ if $\sup_{t>0} t^{-\alpha} \omega_r(g, t) < \infty$ for $r = \lfloor \alpha \rfloor + 1$, or equivalently, for r an integer larger than α .

DeVore (1998) proved that $d(g, S_1) \leq C\omega_{s+1}(g, D^{-1})$, so

$$d(g, S_1) \leq CD^{-\alpha}.$$

For the wavelets case, we use the fact that f belongs to $B_{2,\infty}^\alpha([0, 1]^2)$ if and only if $\sup_{j \geq -1} 2^{j\alpha} \|\beta_j\| < \infty$ (see Meyer (1990) chapter 6, section 10). If g_D is the orthogonal projection of g on S_2 , it follows from Bernstein's inequality that

$$\|g - g_D\|^2 = \sum_{j>m} \sum_{k,l} |\beta_{jkl}|^2 \leq C \sum_{j>m} 2^{-2j\alpha} \leq C' D^{-j\alpha}$$

where m is such that $2^m = D$.

For the trigonometric case, it is proved in Nikol'skiĭ (1975) (p. 191 and 200) that $d(g, S_3) \leq C\omega_{s+1}(g, D^{-1})$ so that $d(g, S_3) \leq C' D^{-\alpha}$. \square

6.8 Proof of Theorem 9

Let us prove first the first item. Let $E_n = \{\|f - \tilde{f}\|_\infty \leq \chi/2\}$ and E_n^c its complementary. On E_n , $\tilde{f}(x) = \tilde{f}(x) - f(x) + f(x) \geq \chi/2$ and for n large enough, $\tilde{\pi}(x, y) = \frac{\tilde{g}(x, y)}{\tilde{f}(x)}$. For all $(x, y) \in [0, 1]^2$,

$$\begin{aligned} |\tilde{\pi}(x, y) - \pi(x, y)|^2 &\leq \left| \frac{\tilde{g}(x, y) - \tilde{f}(x)\pi(x, y)}{\tilde{f}(x)} \right|^2 \mathbb{1}_{E_n} + (\|\tilde{\pi}\|_\infty + \|\pi\|_\infty)^2 \mathbb{1}_{E_n^c} \\ &\leq \frac{|\tilde{g}(x, y) - g(x, y) + \pi(x, y)(f(x) - \tilde{f}(x))|^2}{\chi^2/4} \\ &\quad + (a_n + \|\pi\|_\infty)^2 \mathbb{1}_{E_n^c} \\ \mathbb{E}\|\pi - \tilde{\pi}\|^2 &\leq \frac{8}{\chi^2} [\mathbb{E}\|g - \tilde{g}\|^2 + \|\pi\|_\infty^2 \mathbb{E}\|f - \tilde{f}\|^2] + (a_n + \|\pi\|_\infty)^2 P(E_n^c) \end{aligned}$$

It remains to bound $P(E_n^c)$. To do this, we observe that

$$\|f - \tilde{f}\|_\infty \leq \|f - f_{\hat{m}}\|_\infty + \|f_{\hat{m}} - \tilde{f}_{\hat{m}}\|_\infty$$

Let $\gamma = \alpha - \frac{1}{2}$, then $B_{2,\infty}^\alpha([0, 1]) \subset B_{\infty,\infty}^\gamma([0, 1])$ (see DeVore and Lorentz (1993) p.182). Thus f belongs to $B_{\infty,\infty}^\gamma([0, 1])$ and Lemma 12 in Barron et al. (1999)

gives

$$\|f - f_{\hat{m}}\|_{\infty} \leq D_{\hat{m}}^{-\gamma} \leq (\ln n)^{-\gamma}$$

Thus $\|f - f_{\hat{m}}\|_{\infty}$ decreases to 0 and $\|f - f_{\hat{m}}\|_{\infty} \leq \chi/4$ for n large enough. So

$$P(E_n^c) \leq P(\|f_{\hat{m}} - \hat{f}_{\hat{m}}\|_{\infty} > \frac{\chi}{4})$$

But $\|f_{\hat{m}} - \hat{f}_{\hat{m}}\|_{\infty} \leq r_0 \sqrt{D_{\hat{m}}} \|f_{\hat{m}} - \hat{f}_{\hat{m}}\| \leq r_0 n^{1/8} \|f_{\hat{m}} - \hat{f}_{\hat{m}}\|$ and $\|f_{\hat{m}} - \hat{f}_{\hat{m}}\|^2 = \sum_{\lambda \in \Lambda_{\hat{m}}} \nu_n^2(\varphi_{\lambda})$. Thus,

$$\begin{aligned} P(E_n^c) &\leq P\left(\sum_{\lambda \in \Lambda_{\hat{m}}} \nu_n^2(\varphi_{\lambda}) > \frac{\chi^2}{16r_0^2 n^{1/4}}\right) \\ &\leq P\left(\sum_{\lambda \in \Lambda_{\hat{m}}} \nu_n^{(1)}(\varphi_{\lambda})^2 + \nu_n^{(2)}(\varphi_{\lambda})^2 + \nu_n^{(4)}(\varphi_{\lambda})^2 > \frac{\chi^2}{32r_0^2 n^{1/4}}\right) \\ &\quad + P\left(\sum_{\lambda \in \Lambda_{\hat{m}}} Z_n^2(\varphi_{\lambda}) > \frac{\chi^2}{32r_0^2 n^{1/4}}\right) \\ &\leq \frac{32r_0^2 n^{1/4}}{\chi^2} \mathbb{E}\left(\sum_{\lambda \in \Lambda_{\hat{m}}} \nu_n^{(1)}(\varphi_{\lambda})^2 + \nu_n^{(2)}(\varphi_{\lambda})^2 + \nu_n^{(4)}(\varphi_{\lambda})^2\right) \\ &\quad + \sup_{m \in \mathcal{M}_n} \sum_{\lambda \in \Lambda_m} P(Z_n^2(\varphi_{\lambda}) > \frac{\chi^2}{32r_0^2 n^{1/2}}) \end{aligned}$$

We need then to bound two terms. For the first term, let S_{m_0} the maximum model with cardinal $D_{m_0} \leq n^{1/4}$. Since $\Lambda_{\hat{m}} \subset \Lambda_{m_0}$ and using inequality (11) and the assumption $\forall m \quad D_m \leq n^{1/4}$, we obtain

$$\frac{32r_0^2 n^{1/4}}{\chi^2} \mathbb{E}\left(\sum_{\lambda \in \Lambda_{\hat{m}}} \nu_n^{(1)}(\varphi_{\lambda})^2 + \nu_n^{(2)}(\varphi_{\lambda})^2 + \nu_n^{(4)}(\varphi_{\lambda})^2\right) \leq C' n^{-5/4}$$

Besides, for all x and for all λ , using (21),

$$P(Z_n(\varphi_{\lambda}) \geq 2r_0 n^{1/8} x + 2M\sqrt{x} + 2\frac{M}{\sqrt{n}}) \leq 2e^{-nx}$$

and so

$$P(Z_n^2(\varphi_{\lambda}) \geq (2r_0 n^{1/8} x + 2M\sqrt{x} + 2\frac{M}{\sqrt{n}})^2) \leq 4e^{-nx}$$

Let now $x = n^{-3/4}$, x verifies (for n large enough)

$$2r_0 n^{3/8} x + 2M n^{1/4} \sqrt{x} + 2M n^{-1/4} \leq \frac{\chi}{r_0 \sqrt{32}}$$

that yields

$$(2r_0 n^{1/8} x + 2M\sqrt{x} + 2\frac{M}{\sqrt{n}})^2 \leq \frac{\chi^2}{32r_0^2 n^{1/2}}$$

The previous inequality gives then

$$P\left(Z_n^2(\varphi_\lambda) > \frac{\chi^2}{32r_0^2 n^{1/4}}\right) \leq 4e^{-nx} \leq 4e^{-n^{1/4}}$$

Finally

$$P(E_n^c) \leq 4n^{1/4}e^{-n^{1/4}} + C'n^{-5/4} \leq C''n^{-5/4}$$

for n great enough. And then, for n large enough, $(a_n + \|\pi\|_\infty)^2 P(E_n^c) \leq Ca_n^2 n^{-5/4}$. So, since $a_n = o(n^{1/8})$, $(a_n + \|\pi\|_\infty)^2 P(E_n^c) = o(n^{-1})$.

Following result in Theorem 9 is provided by using Corollary 5 and Corollary 8. \square

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