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NONPARAMETRIC ADAPTIVE ESTIMATION FOR PURE JUMP LÉVY PROCESSES.

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Abstract. This paper is concerned with nonparametric estimation of the Lévy density of a pure jump Lévy process. The sample path is observed at n discrete instants with fixed sampling interval. We construct a collection of estimators obtained by deconvolution methods and deduced from appropriate estimators of the characteristic function and its first derivative. We obtain a bound for the $\mathbb{L}^2$-risk, under general assumptions on the model. Then we propose a penalty function that allows to build an adaptive estimator. The risk bound for the adaptive estimator is obtained under additional assumptions on the Lévy density. Examples of models fitting in our framework are described and rates of convergence of the estimator are discussed. **June 20, 2008**

Keywords. Adaptive Estimation; Deconvolution; Lévy process; Nonparametric Projection Estimator.

1. Introduction

In recent years, the use of Lévy processes for modelling purposes has become very popular in many areas and especially in the field of finance (see *e.g.* Eberlein and Keller (1995), Barndorff-Nielsen and Shephard (2001), Cont and Tankov (2004); see also Bertoin (1996) or Sato (1999) for a comprehensive study for these processes). The distribution of a Lévy process is usually specified by its characteristic triple (drift, Gaussian component and Lévy measure) rather than by the distribution of its independent increments. Indeed, the exact distribution of these increments is most often intractable or even has no closed form formula. For this reason, the standard parametric approach by likelihood methods is a difficult task and many authors have rather considered nonparametric methods. For Lévy processes, estimating the Lévy measure is of crucial importance since this measure specifies the jumps behavior. Nonparametric estimation of the Lévy measure has been the subject of several recent contributions. The statistical approaches depend on the way observations are performed. For instance, Basawa and Brockwell (1982) consider non decreasing Lévy processes and observations of jumps with size larger than some positive ε, or discrete observations with fixed sampling interval. They build nonparametric estimators of a distribution function linked with the Lévy measure. More recently, Figueroa-López and Houdré (2006) consider a continuous-time observation of a general Lévy process and study penalized projection estimators of the Lévy density based on integrals of functions with respect to the random Poisson measure associated with the jumps of the process. However, their approach remains theoretical since these Poisson integrals are hardly accessible.

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In this paper, we consider nonparametric estimation of the Lévy measure for real-valued Lévy processes of pure jump type, *i.e.* without drift and Gaussian component. We rely on the common assumption that the Lévy measure admits a density $n(x)$ on $\mathbb{R}$ and assume that the process is discretely observed with fixed sampling interval Δ. Let (L_t) denote the underlying Lévy process and $(Z_k^\Delta = L_{k\Delta} - L_{(k-1)\Delta}, k = 1, \dots, n)$ be the observed random variables which are independent and identically distributed. Under our assumption, the characteristic function of $L_\Delta = Z_1^\Delta$ is given by the following simple formula:

$$\psi_\Delta(u) = \mathbb{E}(\exp iuZ_1^\Delta) = \exp(\Delta \int_{\mathbb{R}} (e^{iux} - 1)n(x)dx) \tag{1}$$

where the unknown function is the Lévy density $n(x)$. It is therefore natural to investigate the nonparametric estimation of $n(x)$ using empirical estimators of the charasteristic functions and its derivatives and then recover the Lévy density by Fourier inversion. This approach is illustrated by Watteel and Kulperger (2003) and Neumann and Reiss (2000). However, these authors consider general Lévy processes, with drift and Gaussian component. Hence, at least two derivatives of the characteristic function are necessary to reach the Lévy density. Moreover, the way Fourier inversion is done in concrete is not detailed in these papers. In our case, under the assumption that $\int_{\mathbb{R}} |x|n(x)dx < \infty$, we get the simple relation:

$$g^*(u) = \int e^{iux} g(x)dx = -i\frac{\psi'_\Delta(u)}{\Delta\psi_\Delta(u)}, \tag{2}$$

with $g(x) = xn(x)$. This equation indicates that we can estimate $g^*(u)$ by using empirical counterparts of $\psi_\Delta(u)$ and $\psi'_\Delta(u)$ only. Then, the problem of recovering an estimator of g looks like a classical deconvolution problem. We have at hand the methods used for estimating unknown densities of random variables observed with additive independent noise. This requires the additional assumption that g belongs to $\mathbb{L}^2(\mathbb{R})$. However, the problem of deconvolution set by equation (2) is not standard and looks more like deconvolution in presence of unknown errors densities. This is due to the fact that both the numerator and the denominator are unknown and have to be estimated from the same data. This is why our estimator of $\psi_\Delta(u)$ is not a simple empirical counterpart. Instead, we use a truncated version analogous to the one used in Neumann (1997) and Neumann and Reiss (2000).

Below, we show how to adapt the deconvolution method described in Comte *et al.* (2006). We consider an adequate sequence $(S_m, m = 1, \dots, m_n)$ of subspaces of $\mathbb{L}^2(\mathbb{R})$ and build a collection of projection estimators $(\hat{g}_m)$. Then using a penalization device, we select through a data-driven procedure the best estimator in the collection. We study the $\mathbb{L}^2$-risk of the resulting estimator under the asymptotic framework that n tends to infinity. Although the sampling interval Δ is fixed, we keep it as much as possible in all formulae since the distributions of the observed random variables highly depend on Δ.

In Section 2, we give assumptions and some preliminary properties. Section 3 contains examples of models included in our framework. Section 4 describes the statistical strategy. We present the projection spaces and define the collection of estimators. Proposition 4.1 gives the upper bound for the risk of a projection estimator on a fixed projection space. This proposition guides the choice of the penalty function and allows to discuss the rates of convergence of the projection estimators. Afterwards, we introduce a theoretical penalty (depending on the unknown characteristic function ψ_Δ) and study the risk bound of a false estimator (actually not an estimator) (Theorem 4.1). Then, we replace the theoretical penalty by an estimated counterpart and give the upper bound of the risk of the resulting penalized estimator (Theorem 4.2). Section 6 gives some conclusions and open problems. Proofs are gathered in Section 6. In the Appendix, a fondamental result used in our proofs is recalled.

2. Framework and assumptions.

Recall that we consider the discrete time observation with sample step Δ of a Lévy process L_t with Lévy density n and characteristic function given by (1). We assume that (L_t) is a pure jump process with finite variation on compacts. When the Lévy measure $n(x)dx$ is concentrated on $(0, +\infty)$, then (L_t) has increasing paths and is called a subordinator. We focus on the estimation of the real valued function

$$g(x) = xn(x), \tag{3}$$

and introduce the following assumptions on the function g:

(H1) $\int_{\mathbb{R}} |x|n(x)dx < \infty$.
(H2(p)) For p integer, $\int_{\mathbb{R}} |x|^{p-1}|g(x)|dx < \infty$.
(H3) The function g belongs to $\mathbb{L}_2(\mathbb{R})$.

Note that (H1) is stronger than the usual assumption $\int(|x| \wedge 1)n(x)dx < +\infty$, and is also a moment assumption for L_t. Under the usual assumption, (H2(p)) for $p \geq 1$ implies (H1) and (H2(k)) for $k \leq p$.

Our estimation procedure is based on the random variables

$$Z_i^\Delta = L_{i\Delta} - L_{(i-1)\Delta}, i = 1, \dots, n, \tag{4}$$

which are independent, identically distributed, with common characteristic function $\psi_\Delta(u)$.

The moments of Z_1^Δ are linked with the function g. More precisely, we have:

Proposition 2.1. *Let $p \geq 1$ integer. Under (H2)(p), $\mathbb{E}|Z_1^\Delta|^p < \infty$. Moreover, setting, for $k = 1, \dots p$, $M_k = \int_{\mathbb{R}} x^{k-1}g(x)dx$, we have $\mathbb{E}(Z_1^\Delta) = \Delta M_1$, $\mathbb{E}[(Z_1^\Delta)^2] = \Delta M_2 + \Delta^2 M_1$, and more generally, $\mathbb{E}[(Z_1^\Delta)^l] = \Delta\ M_l + o(\Delta)$ for all $l = 1, \dots, p$.*

Proof. By the assumption, the exponent of the exponential in (1) is p times differentiable and, by derivating ψ_Δ, we get the result. □

Assumption (H1) yields the relation (2), which is the basis of our estimation procedure. We need a precise control of ψ_Δ. For this, we introduce the assumption that, for m_n an integer to be defined later, the following holds:

(H4) $\forall x \in \mathbb{R},$ we have $c_\psi(1 + x^2)^{-\Delta\beta/2} \leq |\psi_\Delta(x)| \leq C_\psi(1 + x^2)^{-\Delta\beta/2}$,

for some given constants c_ψ, C_ψ and $\beta \geq 0$. Note that an assumption of this type is also considered in Neumann and Reiss (2007).

For the adaptive version of our estimator, we need additional assumptions for g:

(H5) There exists some positive a such that $\int |g^*(x)|^2(1 + x^2)^a dx < +\infty$,

and

(H6) $\int x^2 g^2(x)dx < +\infty$.

We must set independent assumptions for ψ_Δ and g, since there may be no relation at all between these two functions (see the examples). Note that, in Assumption (H5), which is a classical regularity assumption, the knowledge of a is not required.

3. Examples.

3.1. **Compound Poisson processes.** Let $L_t = \sum_{i=1}^{N_t} Y_i$, where (N_t) is a Poisson process with constant intensity c and (Y_i) is a sequence of i.i.d. random variables with density f independent of the process (N_t). Then, (L_t) is a compound Poisson process with characteristic function

$$\psi_t(u) = \exp ct \int_{\mathbb{R}} (e^{iux} - 1) f(x) dx. \tag{5}$$

Its Lévy density is $n(x) = cf(x)$. Assumptions (H1)-(H2)(p) are equivalent to $\mathbb{E}(|Y_1|^p) < \infty$. Assumption (H3) is equivalent to $\int_{\mathbb{R}} x^2 f^2(x) dx < \infty$, which holds for instance if $\sup_x f(x) < +\infty$ and $\mathbb{E}(Y_1^2) < +\infty$. We can compute the distribution of $Z_1^\Delta = L_\Delta$ as follows:

$$P_{Z_1^\Delta}(dz) = e^{-c\Delta}(\delta_0(dz) + \sum_{n\geq 1} f^{*n}(z) \frac{(c\Delta)^n}{n!} dz). \tag{6}$$

We have the following bound:

$$1 \geq |\psi_\Delta(u)| \geq e^{-2c\Delta}. \tag{7}$$

On this example, it appears clearly that we can not link the regularity assumption on g and (H4) which holds with $\beta = 0$.

3.2. **The Lévy gamma process.** Let $\alpha > 0, \beta > 0$. The Lévy gamma process (L_t) with parameters (β, α) is a subordinator such that, for all $t > 0$, L_t has distribution Gamma with parameters $(\beta t, \alpha)$, *i.e.* has density:

$$\frac{\alpha^{\beta t}}{\Gamma(\beta t)} x^{\beta t - 1} e^{-\alpha x} 1_{x \geq 0}. \tag{8}$$

The characteristic function of Z_1^Δ is equal to:

$$\psi_\Delta(u) = \left(\frac{\alpha}{\alpha - iu}\right)^{\beta\Delta}. \tag{9}$$

The Lévy density is $n(x) = \beta x^{-1} e^{-\alpha x} \mathbf{1}_{\{x>0\}}$ so that $g(x) = \beta e^{-\alpha x} \mathbf{1}_{\{x>0\}}$ satisfies our assumptions. We have:

$$\frac{\psi'_\Delta(u)}{\psi_\Delta(u)} = i\Delta \frac{\beta}{\alpha - iu}, \qquad |\psi_\Delta(u)| = \frac{\alpha^{\beta\Delta}}{(\alpha^2 + u^2)^{\beta\Delta/2}} \tag{10}$$

3.3. **Another class of subordinators.** Consider the Lévy process (L_t) with Lévy density

$$n(x) = cx^{\delta-1/2}x^{-1}e^{-\beta x}1_{x>0},$$

where (δ, β, c) are positive parameters. If $\delta > 1/2$, $\int_0^{+\infty} n(x)dx < +\infty$, and we recover compound Poisson processes. If $0 < \delta \leq 1/2$, $\int_0^{+\infty} n(x)dx = +\infty$ and $g(x) = xn(x)$ belongs to $\mathbb{L}^2(\mathbb{R}) \cap \mathbb{L}^1(\mathbb{R})$. The case $\delta = 0$, which corresponds to the Lévy inverse Gaussian process does not fit in our framework. For $0 < \delta < 1/2$, we find

$$g^*(x) = c\frac{\Gamma(\delta + 1/2)}{(\beta - ix)^{\delta+1/2}},$$

and

$$|\psi_\Delta(x)| = \exp\left(-c\frac{\Delta\Gamma(\delta + 1/2)}{1/2 - \delta}[(\beta^2 + x^2)^{-(\delta-1/2)/2} - \beta^{-(\delta-1/2)}]\right).$$

It is important to mention that ψ_Δ above does not satisfy assumption (H4) since

$$|\psi_\Delta(x)| \sim_{x\to+\infty} K(\beta, \delta)\exp(-c\Delta\frac{\Gamma(\delta + 1/2)}{1/2 - \delta}x^{-\delta+1/2}) \tag{11}$$

where $K(\beta, \delta) = \exp\left(c\frac{\Delta\Gamma(\delta+1/2)}{1/2-\delta}\beta^{-(\delta-1/2)}\right)$. Thus, it has an exponential rate of decrease.

3.4. **The bilateral Gamma process.** This process has been recently introduced by Küchler and Tappe (2008). Consider X, Y two independent random variables, X with distribution $\Gamma(\beta, \alpha)$ and Y with distribution $\Gamma(\beta', \alpha')$. Then, $Z = X - Y$ has distribution bilateral gamma with parameters $(\beta, \alpha, \beta', \alpha')$, that we denote by $\Gamma(\beta, \alpha; \beta', \alpha')$. The characteristic function of Z is equal to:

$$\psi(u) = \left(\frac{\alpha}{\alpha - iu}\right)^\beta \left(\frac{\alpha'}{\alpha' + iu}\right)^{\beta'} = \exp\left(\int_{\mathbb{R}}(e^{iux} - 1)n(x)dx\right), \tag{12}$$

with

$$n(x) = x^{-1}g(x),$$

and, for $x \in \mathbb{R}$,

$$g(x) = \beta e^{-\alpha x}1_{(0,+\infty)(x)} - \beta' e^{-\alpha'|x|}1_{(-\infty,0)}(x).$$

The bilateral Gamma process (L_t) has characteristic function $\psi_t(u) = \psi(u)^t$.

The method can be generalized and we may consider Lévy processes on $\mathbb{R}$ obtained by bilateralisation of two subordinators.

3.5. **Subordinated Processes.** Let (W_t) be a Brownian motion, and let (Z_t) be an increasing Lévy process (subordinator), independent of (W_t). Assume that the observed process is

$$L_t = W_{Z_t}.$$

We have

$$\psi_\Delta(u) = \mathbb{E}(e^{iuL_\Delta}) = \mathbb{E}(e^{-\frac{u^2}{2}Z_\Delta}).$$

As Z_t is positive, we consider, for $\lambda \geq 0$,

$$\vartheta_\Delta(\lambda) = \mathbb{E}(e^{-\lambda Z_\Delta}) = \exp\left(-\Delta\int_0^{+\infty}(1 - e^{-\lambda x})n_Z(x)dx\right),$$

where n_Z denotes the Lévy density of (Z_t). Now let us assume that $g_Z(x) = xn_Z(x)$ is integrable over $(0, +\infty)$. We have:

$$\begin{aligned}\log(\vartheta_\Delta(\lambda)) &= -\Delta \int_0^{+\infty} \frac{1-e^{-\lambda x}}{x} x n_Z(x)dx = -\Delta \int_0^{+\infty} (\int_0^\lambda e^{-sx}ds) x n_Z(x)dx \\ &= -\Delta \int_0^\lambda \left(\int_0^{+\infty} e^{-sx} x n_Z(x)dx\right) ds.\end{aligned}$$

Hence,

$$\psi_\Delta(u) = \exp\left(-\Delta \int_0^{u^2/2} \left(\int_0^{+\infty} e^{-sx} g_Z(x)dx\right) ds\right).$$

Moreover, it is possible to relate the Lévy density n_L of (L_t) with the Lévy density n_Z of (Z_t) as follows. Consider f a non negative function on $\mathbb{R}$, with $f(0) = 0$. Given the whole path (Z_t), the jumps $\delta L_s = W_{Z_s} - W_{Z_{s-}}$ are centered Gaussian with variance δZ_s. Hence,

$$\begin{aligned}\mathbb{E}(\sum_{s\le t} f(\delta L_s)) &= \sum_{s\le t} \mathbb{E}(\int_{\mathbb{R}} f(u)\exp(-u^2/2\delta Z_s)\frac{du}{\sqrt{2\pi\delta Z_s}}) \\ &= t\int_{\mathbb{R}} f(u)du\left(\int_0^{+\infty} \exp(-u^2/2x)\frac{n_Z(x)dx}{\sqrt{2\pi x}})\right).\end{aligned}$$

This gives $n_L(u) = \int_0^{+\infty} \exp(-u^2/2x)\frac{n_Z(x)dx}{\sqrt{2\pi x}}$. By the same tools, we see that

$$\mathbb{E}(\sum_{s\le t} |\delta L_s|) = \sqrt{2/\pi}\,\mathbb{E}(\sum_{s\le t}\sqrt{\delta Z_s}) = t\int_0^{+\infty} \sqrt{x} n_Z(x)dx.$$

Therefore, if the above integral is finite, the process (L_t) has finite variation on compact sets and it holds that $\int_{\mathbb{R}} |u| n_L(u)du < \infty$.

With (Z_t) a Lévy-Gamma process, $g_Z(x) = \beta e^{-\alpha x}\mathbb{1}_{x>0}$. Then $\int_0^{+\infty} e^{-sx}\beta e^{-\alpha x}dx = \beta/(\alpha + s)$, and

$$\psi_\Delta(u) = \left(\frac{\alpha}{\alpha + \frac{u^2}{2}}\right)^{\Delta\beta}.$$

This model is the Variance Gamma stochastic volatility model described by Madan and Seneta (1990). As noted in Küchler and Tappe (2008), the Variance Gamma distributions are special cases of bilateral Gamma distributions. The condition $\int_0^{+\infty} \sqrt{x} n_Z(x)dx < \infty$ holds. We can compute, for instance using the norming constant for an inverse Gaussian density,

$$n_L(u) = \int_0^{+\infty} \exp(-\frac{1}{2}(\frac{u^2}{x} + 2\alpha x)\frac{\beta x^{-3/2}dx}{\sqrt{2\pi}} = \beta(2\alpha)^{1/4})|u|^{-1}\exp(-(2\alpha)^{1/2}|u|)$$

4. Statistical strategy

4.1. **Notations.** Subsequently we denote by u^* the Fourier transform of the function u defined as $u^*(y) = \int e^{iyx}u(x)dx$, and by $\|u\|$, $< u, v >$, $u * v$ the quantities

$$\|u\|^2 = \int |u(x)|^2 dx,$$

$$< u, v >= \int u(x)\overline{v}(x)dx \text{ with } z\overline{z} = |z|^2 \text{ and } u \star v(x) = \int u(y)\overline{v}(x-y)dy.$$

Moreover, we recall that for any integrable and square-integrable functions u, u_1, u_2,

$$(u^*)^*(x) = 2\pi u(-x) \text{ and } \langle u_1, u_2\rangle = (2\pi)^{-1}\langle u_1^*, u_2^*\rangle. \tag{13}$$

4.2. **The projection spaces.** As we use projection estimators, we describe now the projection spaces. Let us define

$$\varphi(x) = \frac{\sin(\pi x)}{\pi x} \text{ and } \varphi_{m,j}(x) = \sqrt{m}\varphi(mx - j),$$

where m is an integer, that can be taken equal to 2^ℓ. It is well known (see Meyer (1990), p.22) that $\{\varphi_{m,j}\}_{j\in\mathbb{Z}}$ is an orthonormal basis of the space of square integrable functions having Fourier transforms with compact support included into $[-\pi m, \pi m]$. Indeed an elementary computation yields

$$\varphi^*_{m,j}(x) = \frac{e^{ixj/m}}{\sqrt{m}}\mathbf{1}_{[-\pi m,\pi m]}(x). \tag{14}$$

We denote by S_m such a space:

$$S_m \;=\; \text{Span}\{\varphi_{m,j},\ j\in\mathbb{Z}\} \;= \{h \in \mathbb{L}^2(\mathbb{R}), \text{supp}(h^*) \subset [-m\pi, m\pi]\}.$$

We denote by $(S_m)_{m\in\mathcal{M}_n}$ the collection of linear spaces, where

$$\mathcal{M}_n = \{1, \ldots, m_n\}$$

and $m_n \le n$ is the maximal admissible value of m, subject to constraints to be precised later.

In practice, we should consider the truncated spaces $S_m^{(n)} = \text{Span}\{\varphi_{m,j},\ \ j\in\mathbb{Z},\ \ |j| \le K_n\}$, where K_n is an integer depending on n, and the associated estimators. Under assumption (H6), it is possible and does not change the main part of the study (see Comte *et al.* (2006)). For the sake of simplicity, we consider here sums over $\mathbb{Z}$.

4.3. **Estimation strategy.** We want to estimate g such that

$$g^*(x) = -i\frac{\psi'_\Delta(x)}{\Delta\psi_\Delta(x)} = \frac{\theta_\Delta(x)}{\Delta\psi_\Delta(x)}, \tag{15}$$

with

$$\psi_\Delta(x) = \mathbb{E}(e^{ixZ_1^\Delta}),\ \ \theta_\Delta(x) = -i\psi'_\Delta(x) = \mathbb{E}(Z_1^\Delta e^{ixZ_1^\Delta}).$$

The orthogonal projection g_m of g on S_m is given by

$$g_m = \sum_{j\in\mathbb{Z}} a_{m,j}(g)\varphi_{m,j} \text{ with } a_{m,j}(g) = \int_{\mathbb{R}} \varphi_{m,j}(x)g(x)dx = \langle\varphi_{m,j}, g\rangle. \tag{16}$$

We have at hand the empirical versions of ψ_Δ and θ_Δ:

$$\hat{\psi}_\Delta(x) = \frac{1}{n}\sum_{k=1}^n e^{ixZ_k^\Delta},\ \ \hat{\theta}_\Delta(x) = \frac{1}{n}\sum_{k=1}^n Z_k^\Delta e^{ixZ_k^\Delta}.$$

Following Neumann (1997) and Neumann and Reiss (2007), we truncate $1/\hat{\psi}_\Delta$ and set

$$\frac{1}{\tilde{\psi}_\Delta(x)} = \frac{1}{\hat{\psi}_\Delta(x)}\mathbf{1}_{|\hat{\psi}_\Delta(x)|>\kappa_\psi n^{-1/2}}. \tag{17}$$

Now, for t belonging to a space S_m of the collection $(S_m)_{m\in\mathcal{M}_n}$, let us define

$$\gamma_n(t) = \frac{1}{n}\sum_{k=1}^{n}\left(\|t\|^2 - \frac{1}{\pi\Delta}Z_k^\Delta \int e^{ixZ_k^\Delta}\frac{t^*(-x)}{\tilde{\psi}_\Delta(x)}dx\right), \tag{18}$$

Consider $\gamma_n(t)$ as an approximation of the theoretical contrast

$$\gamma_n^{th}(t) = \frac{1}{n}\sum_{k=1}^{n}\left(\|t\|^2 - \frac{1}{\pi\Delta}Z_k^\Delta \int e^{ixZ_k^\Delta}\frac{t^*(-x)}{\psi_\Delta(x)}dx\right),$$

The following sequence of equalities, relying on (13), explains the choice of the contrast:

$$\mathbb{E}(\frac{1}{2\pi\Delta}Z_k^\Delta \int e^{ixZ_k^\Delta}\frac{t^*(-x)}{\psi_\Delta(x)}dx) = \frac{1}{2\pi\Delta}\int \theta_\Delta(x)\frac{t^*(-x)}{\psi_\Delta(x)}dx = \frac{1}{2\pi}\langle t^*, g^*\rangle = \langle t, g\rangle.$$

Therefore, we find that $\mathbb{E}(\gamma_n^{th}(t)) = \|t\|^2 - 2\langle g, t\rangle = \|t-g\|^2 - \|g\|^2$ is minimal when $t = g$. Thus, we define the estimator belonging to S_m by

$$\hat{g}_m = \text{Argmin}_{t\in S_m}\gamma_n(t) \tag{19}$$

This estimator can also be written

$$\hat{g}_m = \sum_{j\in\mathbb{Z}}\hat{a}_{m,j}\varphi_{m,j}, \text{ with } \hat{a}_{m,j} = \frac{1}{2\pi n\Delta}\sum_{k=1}^{n}Z_k^\Delta\int e^{ixZ_k^\Delta}\frac{\varphi_{m,j}^*(-x)}{\tilde{\psi}_\Delta(x)}dx, \tag{20}$$

or

$$\hat{a}_{m,j} = \frac{1}{2\pi\Delta}\int \hat{\theta}_\Delta(x)\frac{\varphi_{m,j}^*(-x)}{\tilde{\psi}_\Delta(x)}dx.$$

4.4. **Risk bound of the collection of estimators.** First, we recall a key Lemma, borrowed from Neumann (1997) (see his Lemma 2.1):

Lemma 4.1. *It holds that, for any $p \geq 1$,*

$$\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^{2p}\right) \leq C\left(\frac{1}{|\psi_\Delta(x)|^{2p}} \wedge \frac{n^{-p}}{|\psi_\Delta(x)|^{4p}}\right),$$

where $1/\tilde{\psi}_\Delta$ is defined by (17).

Neumann's result is for $p = 1$ but the extension to any p is straighforward. See also Neumann and Reiss (2007). This lemma allows to prove the following risk bound.

Proposition 4.1. *Under Assumptions* (H1)-(H2)(4)-(H3)*, then for all m:*

$$\mathbb{E}(\|g - \hat{g}_m\|^2) \leq \|g - g_m\|^2 + K\frac{\mathbb{E}^{1/2}[(Z_1^\Delta)^4]\int_{-\pi m}^{\pi m}dx/|\psi_\Delta(x)|^2}{n\Delta^2}. \tag{21}$$

where K is a constant.

It is worth stressing that (H4) is not required for the above result. Therefore, it holds even for exponential decay of ψ_Δ.

Proof of Proposition 4.1. First with Pythagoras Theorem, we have

$$\|g - \hat{g}_m\|^2 = \|g - g_m\|^2 + \|\hat{g}_m - g_m\|^2. \tag{22}$$

Let

$$a_{m,j}(g) = \frac{1}{2\pi\Delta}\int \theta_\Delta(x)\frac{\varphi^*_{m,j}(-x)}{\psi_\Delta(x)}dx.$$

Then, using Parseval's formula and (14), we obtain

$$\|\hat{g}_m - g_m\|^2 = \sum_{j\in\mathbb{Z}} |\hat{a}_{m,j} - a_{m,j}(g)|^2 = \frac{1}{2\pi\Delta^2}\int_{-\pi m}^{\pi m}\left|\frac{\hat{\theta}_\Delta(x)}{\tilde{\psi}_\Delta(x)} - \frac{\theta_\Delta(x)}{\psi_\Delta(x)}\right|^2 dx.$$

It follows that

$$\begin{aligned}
\mathbb{E}(\|\hat{g}_m - g_m\|^2) \;&\leq\; \frac{c}{\Delta^2}\left\{\int_{-\pi m}^{\pi m}\mathbb{E}\left|\hat{\theta}_\Delta(x)\left(\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right)\right|^2 dx\right. \\
&\qquad \left. + \int_{-\pi m}^{\pi m}\frac{\mathbb{E}|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^2}{|\psi_\Delta(x)|^2}dx\right\} \\
&\leq\; \frac{c}{\Delta^2}\left\{\int_{-\pi m}^{\pi m}\left(\mathbb{E}(|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^2\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right)dx\right. \qquad (23) \\
&\qquad \left. + \int_{-\pi m}^{\pi m}\left(\Delta^2|g^*(x)\psi_\Delta(x)|^2\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right) + \frac{1}{n}\frac{\mathbb{E}[(Z_1^\Delta)^2]}{|\psi_\Delta(x)|^2}\right)dx\right\}
\end{aligned}$$

The Schwarz Inequality yields

$$\mathbb{E}\left(|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^2\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right) \leq \mathbb{E}^{1/2}(|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^4)\mathbb{E}^{1/2}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^4\right).$$

Then, with the Rosenthal inequality $\mathbb{E}(|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^4) \leq c\mathbb{E}[(Z_1^\Delta)^4]/n^2$ and by using Lemma 4.1,

$$\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^4\right) \leq \frac{C}{|\psi_\Delta(x)|^4}$$

so that

$$\int_{-\pi m}^{\pi m}\left(\mathbb{E}^{1/2}(|\hat{\theta}_\Delta(x) - \theta_\Delta(x)|^4)\mathbb{E}^{1/2}\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^4\right)dx \leq \frac{c\mathbb{E}^{1/2}[(Z_1^\Delta)^4]}{n}\int_{-\pi m}^{\pi m}\frac{dx}{|\psi_\Delta(x)|^2}.$$

For the second term, we use Lemma 4.1, to get

$$\mathbb{E}\left(\left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2\right) \leq \frac{Cn^{-1}}{|\psi_\Delta(x)|^4}.$$

We obtain

$$\mathbb{E}(\|\hat{g}_m - g_m\|^2) \leq \frac{c}{n\Delta^2}(\mathbb{E}^{1/2}[(Z_1^\Delta)^4] + \Delta^2\|g\|_1^2 + \mathbb{E}[(Z_1^\Delta)^2])\int_{-\pi m}^{\pi m}\frac{dx}{|\psi_\Delta(x)|^2}dx, \qquad (24)$$

where $\|g\|_1 = \int |g(x)|dx$. Therefore, gathering (22) and (24) implies the result. □

Remark 4.1. *In papers concerned with deconvolution in presence of unknown error densities, the error characteristic function is estimated using a preliminary and independent set of data. This solution is possible here: we may split the sample and use the first half* *to obtain a preliminary and independent estimator of ψ_Δ, and then estimate g from the second half. This would simplify the above proof, but not the study of the adaptive case.*

4.5. **Discussion about the rates.** Let us study some examples and use (21) to get a relevant choice of m. We have $\|g - g_m\|^2 = \int_{|x|\geq \pi m} |g^*(x)|^2 dx$. Suppose that g belongs to the Sobolev class

$$\mathcal{S}(a, L) = \{f, \int |f^*(x)|^2 (x^2+1)^a dx \leq L\}.$$

Then, the bias term satisfies

$$\|g - g_m\|^2 = O(m^{-2a}).$$

Under (H4), the bound of the variance term satisfies

$$\frac{\int_{-\pi m}^{\pi m} dx/|\psi_\Delta(x)|^2}{n\Delta} = O\left(\frac{m^{2\beta\Delta+1}}{n\Delta}\right).$$

The optimal choice for m is $O((n\Delta)^{1/(2\beta\Delta+2a+1}))$ and the resulting rate for the risk is $(n\Delta)^{-2a/(2\beta\Delta+2a+1})$. It is worth noting that the sampling interval Δ explicitely appears in the exponent of the rate. Therefore, for positive β, the rate is worse for large Δ that for small Δ.

• Let us consider the example of the compound process. In this case $\beta = 0$, the upper bound of the mean integrated squared error is of order $O((n\Delta)^{-2a/(2a+1)})$, if g belongs to the Sobolev class $\mathcal{S}(a, L)$. Note that if g is analytic i.e. belongs to a class

$$\mathcal{A}(\gamma, Q) = \{f, \int (e^{\gamma x} + e^{-\gamma x})^2 |f^*(x)|^2 dx \leq Q\},$$

then the risk is of order $O(\ln(n\Delta)/(n\Delta))$ (choose $m = O(\ln(n\Delta))$).

• For the Levy Gamma process, we have a more precise result since we have

$$|\psi_\Delta(u)| = \frac{\alpha^{\beta\Delta}}{(\alpha^2+u^2)^{\beta\Delta/2}}, \quad g^*(x) = \frac{\beta}{\alpha - ix}.$$

Therefore $\int_{|x|\geq \pi m} |g^*(x)|^2 dx = O(m^{-1})$ and $\int_{[-\pi m, \pi m]} dx/|\psi_\Delta(x)|^2 = O(m^{2\beta\Delta+1})$. The resulting rate is of order $(n\Delta)^{-1/(2\beta\Delta+2)}$ for a choice of m of order $O((n\Delta)^{1/(2\beta\Delta+2)})$.

• For the Bilateral Gamma process with $(\beta, \alpha) = (\beta', \alpha')$, we have

$$\psi_\Delta(u) = \frac{\alpha^{\beta\Delta}}{(\alpha^2+u^2)^{\beta\Delta}}, \quad g^*(x) = \frac{\beta}{\alpha^2 + x^2}.$$

Therefore $\int_{|x|\geq \pi m} |g^*(x)|^2 dx = O(m^{-3})$ and $\int_{[-\pi m, \pi m]} dx/|\psi_\Delta(x)|^2 = O(m^{4\beta\Delta+1})$. The resulting rate is of order $(n\Delta)^{-3/(4\beta\Delta+4)}$ for a choice of m of order $O((n\Delta)^{1/(4\beta\Delta+4)})$.

These examples illustrate that the relevant choice of m depends on the unknown function, in particular on its smoothness. The model selection procedure proposes a data driven criterion to select m.

• Consider now the process described in Section 3.3. In that case, it follows from (11) that $\int_{[-\pi m, \pi m]} dx/|\psi_\Delta(x)|^2 = O(m^{\delta+1/2}\exp(\kappa m^{1/2-\delta}))$ and $\int_{|x|\geq \pi m} |g^*(x)|^2 dx = O(m^{-2\delta})$. In this case, choosing $\kappa m^{1/2-\delta} = \ln(n\Delta)/2$ gives the rate $[\ln(n\Delta)]^{-2\delta}$ which is thus very slow, but known to be optimal in the usual deconvolution setting (see Fan (1991)). This case is not considered in the following for the adaptative strategy since it does not satisfy (H4).

4.6. **Study of the adaptive estimator.** We have to select an adequate value of m. For this, we start by defining the term

$$\Phi_\psi(m) = \int_{-\pi m}^{\pi m} \frac{dx}{|\psi_\Delta(x)|^2}, \tag{25}$$

and the following theoretical penalty

$$\mathrm{pen}(m) = \kappa(1 + \mathbb{E}[(Z_1^\Delta)^2]/\Delta)\frac{\Phi_\psi(m)}{n\Delta}. \tag{26}$$

We set

$$\hat{m} = \arg\min_{m\in\mathcal{M}_n} \{\gamma_n(\hat{g}_m) + \mathrm{pen}(m)\},$$

and study first the “risk” of $\hat{g}_{\hat{m}}$.
Moreover we need the following assumption on the collection of models $\mathcal{M}_n = \{1, \dots, m_n\}$, $m_n \le n$:

$$\text{(H7)} \qquad \exists\varepsilon, 0 < \varepsilon < 1, \;\; m_n^{2\beta\Delta} \le Cn^{1-\varepsilon},$$

where C is a fixed constant and β is defined by (H4).
For instance, Assumption (H7) is fulfilled if:

(1) $\mathrm{pen}(m_n) \le C$. In such a case, we have $m_n \le C(n\Delta)^{1/(2\beta\Delta+1)}$.
(2) Δ is small enough to ensure $2\beta\Delta < 1$. In such a case we can take $\mathcal{M}_n = \{1, \dots, n\}$.

Remark 4.2. *Assumption (H7) raises a problem since it depends on the unknown β and concrete implementation requires the knowledge of m_n. It is worth stressing that the analogous difficulty arises in deconvolution with unknown error density (see Comte and Lacour (2008)). In the compound Poisson model, $\beta = 0$ and nothing is needed. Otherwise one should at least know if ψ_Δ is in a class of polynomial decay. The estimator $\hat{\psi}_\Delta$ may be used to that purpose and to provide an estimator of β (see e.g. Diggle et Hall (1993)).*

Let us define

$$\theta_\Delta^{(1)}(x) = \mathbb{E}(Z_1^\Delta \mathbf{1}_{|Z_1^\Delta|\le k_n\sqrt{\Delta}} e^{ixZ_1^\Delta}), \quad \theta_\Delta^{(2)}(x) = \mathbb{E}(Z_1^\Delta \mathbf{1}_{|Z_1^\Delta|> k_n\sqrt{\Delta}} e^{ixZ_1^\Delta})$$

so that $\theta_\Delta = \theta_\Delta^{(1)} + \theta_\Delta^{(2)}$ and analogously $\hat{\theta}_\Delta = \hat{\theta}_\Delta^{(1)} + \hat{\theta}_\Delta^{(2)}$. For any two functions t, s in S_m, the contrast γ_n satisfies:

$$\begin{aligned} \gamma_n(t) - \gamma_n(s) &= \|t-g\|^2 - \|s-g\|^2 - 2\nu_n^{(1)}(t-s) - 2\nu_n^{(2)}(t-s) \\ &\quad -2\sum_{i=1}^4 R_n^{(i)}(t-s), \end{aligned} \tag{27}$$

with

$$\begin{aligned}
\nu_n^{(1)}(t) &= \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\hat{\theta}_\Delta^{(1)}(x)-\theta_\Delta^{(1)}(x)}{\psi_\Delta(x)}dx,\\
\nu_n^{(2)}(t) &= \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\theta_\Delta(x)}{[\psi_\Delta(x)]^2}(\psi_\Delta(x)-\hat{\psi}_\Delta(x))dx,\\
R_n^{(1)}(t) &= \frac{1}{2\pi\Delta}\int t^*(-x)(\hat{\theta}_\Delta(x)-\theta_\Delta(x))\left(\frac{1}{\tilde{\psi}_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\right)dx\\
R_n^{(2)}(t) &= \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\theta_\Delta(x)}{\psi_\Delta(x)}(\psi_\Delta(x)-\hat{\psi}_\Delta(x))\left(\frac{1}{\tilde{\psi}_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\right)dx,\\
R_n^{(3)}(t) &= \frac{1}{2\pi\Delta}\int t^*(-x)\frac{\hat{\theta}_\Delta^{(2)}(x)-\theta_\Delta^{(2)}(x)}{\psi_\Delta(x)}dx,\\
R_n^{(4)}(t) &= -\frac{1}{2\pi\Delta}\int t^*(-x)\frac{\theta_\Delta(x)}{\psi_\Delta(x)}\mathbf{I}_{|\hat{\psi}_\Delta(x)|\le\kappa_\psi/\sqrt{n}}dx.
\end{aligned}$$

Using this decomposition and Talagrand's inequality, we can prove

Theorem 4.1. *Assume that assumptions* (H1)-(H2)(8)-(H3)-(H7) *hold. Then*

$$\mathbb{E}(\|\hat{g}_{\hat{m}}-g\|^2)\le C\inf_{m\in\mathcal{M}_n}\left(\|g-g_m\|^2+\mathrm{pen}(m)\right)+K\frac{\ln^2(n)}{n\Delta},$$

where K is a constant.

Remark 4.3. *Assumption (H6) is satisfied for the Levy-Gamma process. For the compound Poisson process, it is equivalent to $\int x^4 f^2(x)dx<+\infty$, where f denotes the density of Y_i (see Section 3).*

To get an estimator, we replace the theoretical penalty by:

$$\widehat{\mathrm{pen}}(m)=\kappa'\left(1+\frac{1}{n\Delta^2}\sum_{i=1}^n(Z_i^\Delta)^2\right)\frac{\int_{-\pi m}^{\pi m}dx/|\tilde{\psi}_\Delta(x)|^2dx}{n}.$$

In that case we can prove:

Theorem 4.2. *Assume that assumptions* (H1)-(H2)(8)-(H3)-(H7) *hold and let $\tilde{g}=\hat{g}_{\widehat{\widehat{m}}}$ be the estimator defined with $\widehat{\widehat{m}}=\arg\min_{m\in\mathcal{M}_n}(\gamma_n(\hat{g}_m)+\widehat{\mathrm{pen}}(m))$. Then*

$$\mathbb{E}(\|\tilde{g}-g\|^2)\le C\inf_{m\in\mathcal{M}_n}\left(\|g-g_m\|^2+\mathrm{pen}(m)\right)+K'_\Delta\frac{\ln^2(n)}{n}$$

where K'_Δ is a constant depending on Δ (and on fixed quantities but not on n).

Theorem 4.2 shows that the adaptive estimator automatically achieves the best rate that can be hoped. If g belongs to the Sobolev ball $\mathcal{S}(a,L)$, and under (H4), the rate is automatically of order $O((n\Delta)^{-2a/(2\beta\Delta+2a+1)})$. See Section 4.5.

Remark 4.4. (1) *It is possible to extend our study of the adaptive estimator to the case ψ_Δ having exponential decay. Note that the faster $|\psi_\Delta|$ decays, the more difficult it will be to estimate g.*

(2) *Few results on rates of convergence are available in the literature for this problem. The results of Neumann and Reiss (2007) are difficult to compare with ours since the point of view is different.*

5. Proofs

5.1. **Proof of Theorem 4.1.** Writing that $\gamma_n(\hat g_{\hat m})+\mathrm{pen}(\hat m)\le \gamma_n(g_m)+\mathrm{pen}(m)$ in view of (27) implies that

$$\begin{aligned}\|\hat g_{\hat m}-g\|^2 &\le \|g_m-g\|^2+2\nu_n^{(1)}(\hat g_{\hat m}-g_m)+2\nu_n^{(2)}(\hat g_{\hat m}-g_m)+2\sum_{i=1}^4 R_n^{(i)}(\hat g_{\hat m}-g_m)\\ &\quad +\mathrm{pen}(m)-\mathrm{pen}(\hat m).\end{aligned}$$

Let us take expectations of both sides and bound each r.h.s. term.

$$\begin{aligned}|\mathbb{E}(\nu_n^{(1)}(\hat g_{\hat m}-g_m))| &\le \frac{1}{16}\mathbb{E}(\|g_m-\hat g_{\hat m}\|^2)+16\mathbb{E}\left[\sup_{t\in S_m+S_{\hat m},\|t\|=1}|\nu_n^{(1)}(t)|^2\right]\\ &\le \frac18\mathbb{E}(\|g-\hat g_{\hat m}\|^2)+\frac18\|g-g_m\|^2\\ &\quad +16\mathbb{E}\left(\sup_{t\in S_{m\vee\hat m},\|t\|=1}|\nu_n^{(1)}(t)|^2-p_1(m,\hat m)\right)_+ +16\mathbb{E}(p_1(m,\hat m)).\end{aligned}$$

The same kind of bounds are obtained for $\nu_n^{(2)}$ and the residuals leading to

$$\begin{aligned}\frac28\mathbb{E}(\|\hat g_{\hat m}-g\|^2) &\le \frac{14}{8}\|g-g_m\|^2+16\sum_{m'\in\mathcal{M}_n}\mathbb{E}\left(\sup_{t\in S_{m\vee m'},\|t\|=1}|\nu_n^{(1)}(t)|^2-p_1(m,m')\right)_+\\ &\quad +16\mathbb{E}\left(\sup_{t\in S_{m\vee\hat m},\|t\|=1}|\nu_n^{(2)}(t)|^2-p_2(m,\hat m)\right)_+\\ &\quad +16\sum_{i=1}^2\mathbb{E}\left(\sup_{t\in S_{m\vee\hat m},\|t\|=1}|R_n^{(i)}(t)|^2-p_1(m,\hat m)\right)\\ &\quad +16\sum_{i=3}^4\mathbb{E}\left(\sup_{t\in S_{m_n},\|t\|=1}|R_n^{(i)}(t)|^2\right)\\ &\quad +\mathrm{pen}(m)+\mathbb{E}(48p_1(m,\hat m)+16p_2(m,\hat m)-\mathrm{pen}(\hat m)).\end{aligned}\tag{28}$$

Next, definition of pen(.) comes from the following constraint:

$$48p_1(m,m')+16p_2(m,m')\le \mathrm{pen}(m')+\mathrm{pen}(m).\tag{29}$$

This leads to

$$\mathrm{pen}(m)+\mathbb{E}(48p_1(m,\hat m)+16p_2(m,\hat m)-\mathrm{pen}(\hat m))\le 2\mathrm{pen}(m).$$

First, we apply Talagrand's Inequality recalled in Lemma 6.1 to prove the following result:

Proposition 5.1. *Under the assumptions of Theorem 4.1, define*

$$p_1(m,m')=(4\mathbb{E}[(Z_1^\Delta)^2]\int_{-\pi(m\vee m')}^{\pi(m\vee m')}|\psi_\Delta(x)|^{-2}dx)/(\pi n\Delta^2),$$

then

$$\sum_{m'\in\mathcal{M}_n} \mathbb{E}\left(\sup_{t\in S_{m\vee m'},\|t\|=1} |\nu_n^{(1)}(t)|^2 - p_1(m,m')\right)_+ \leq \frac{c}{n}. \tag{30}$$

Next we prove:

Proposition 5.2. *Under the assumptions of Theorem 4.1, define* $p_2(m,m')=0$ *if* $-a+\beta\Delta\leq 0$ *and* $p_2(m,m') = (\int_{-\pi(m\vee m')}^{\pi(m\vee m')} |\psi_\Delta(x)|^{-2}dx)/n$ *otherwise. Then*

$$\mathbb{E}\left(\sup_{t\in S_{m\vee \hat m},\|t\|=1} |\nu_n^{(2)}(t)|^2 - p_2(m,\hat m)\right)_+ \leq \frac{c}{n}. \tag{31}$$

For the residual terms, two type of results can be obtained.

Proposition 5.3. *Under the assumptions of Theorem 4.1, for* $i=1,2$*,*

$$\mathbb{E}\left(\sup_{t\in S_{m\vee \hat m},\|t\|=1} [R_n^{(i)}(t)]^2 - p_1(m,\hat m)\right) \leq \frac{C}{n\Delta}.$$

and

Proposition 5.4. *Under the assumptions of theorem 4.1, for* $i=3,4$

$$\mathbb{E}\left(\sup_{t\in S_{m_n},\|t\|=1} [R_n^{(i)}(t)]^2\right) \leq c\frac{\ln^2(n)}{n\Delta}.$$

Then the choice $\mathrm{pen}(m)$ given by (26) gives, following (28) and (29),

$$\frac{1}{4}\mathbb{E}(\|\hat g_{\hat m} - g\|^2) \leq \frac{7}{4}\|g-g_m\|^2 + 2\mathrm{pen}(m) + C\frac{\ln^2(n)}{n\Delta},$$

which is the result. □

5.2. **Proof of Proposition 5.1.** Let

$$\omega_t(z) = \frac{z\mathbf{I}_{\{|z|\leq k_n\sqrt{\Delta}\}}}{2\pi\Delta}\int e^{izx}\frac{t^*(-x)}{\psi_\Delta(x)}dx$$

and notice that

$$\nu_n^{(1)}(t) = \frac{1}{n}\sum_{k=1}^n \left[\omega_t(Z_k^\Delta) - \mathbb{E}(\omega_t(Z_k^\Delta))\right].$$

To apply Lemma 6.1, we compute M_1, H_1 and v_1 defined therein. First, we have

$$\begin{aligned}
\mathbb{E}\left(\sup_{t\in S_m,\|t\|=1} |\nu_n^{(1)}(t)|^2\right) &\leq \mathbb{E}\left(\sum_{j\in\mathbb{Z}} |\nu_n^{(1)}(\varphi_{m,j})|^2\right)\\
&= \mathbb{E}\left(\frac{1}{2\pi\Delta^2}\int_{-\pi m}^{\pi m}\left|\frac{\hat\theta_\Delta^{(1)}(x)-\theta_\Delta^{(1)}(x)}{\psi_\Delta(x)}\right|^2 dx\right)\\
&\leq \frac{\mathbb{E}[(Z_1^\Delta)^2]}{2\pi n\Delta^2}\Phi_\psi(m),
\end{aligned}$$

where $\Phi_\psi(m)$ is defined in (25). We can take, for $m^\star = m \vee m'$,

$$H_1^2 = \frac{\mathbb{E}[(Z_1^\Delta)^2]}{2\pi n \Delta^2}\Phi_\psi(m^\star).$$

Then it is easy to see that if $\|t\| = 1$ and $t \in S_{m^\star}$, then

$$|\omega_t(z)| \leq \frac{k_n}{2\pi\sqrt{\Delta}}\int \left|\frac{t^*(-x)}{\psi_\Delta(x)}\right| dx \leq \frac{k_n}{2\pi\sqrt{\Delta}}\sqrt{\Phi_\psi(m^\star)} := M_1.$$

Lastly, for $t \in S_m$, $\|t\| = 1$, $t = \sum_{j\in\mathbb{Z}} t_{m,j}\varphi_{m,j}$

$$\begin{aligned}\mathrm{Var}(\omega_t(Z_1^\Delta)) &\leq \frac{1}{(2\pi)^2\Delta^2}\iint \mathbb{E}\left(e^{i(u-v)Z_1^\Delta}(Z_1^\Delta \mathbf{1}_{|Z_1^\Delta|\leq k_n\sqrt{\Delta}})^2\right)\frac{t^*(-u)t^*(v)}{\psi_\Delta(u)\psi_\Delta(-v)}dudv \\ &= \frac{1}{(2\pi\Delta)^2}\sum_{j,k} t_{m,j}t_{m,k}\iint \mathbb{E}\left(e^{i(u-v)Z_1^\Delta}(Z_1^\Delta \mathbf{1}_{|Z_1^\Delta|\leq k_n\sqrt{\Delta}})^2\right)\frac{\varphi_{m,j}^*(-u)\varphi_{m,k}^*(v)}{\psi_\Delta(u)\psi_\Delta(-v)}dudv.\end{aligned}$$

Denoting by

$$h_\Delta^*(u) = \mathbb{E}[e^{iuZ_1^\Delta}(Z_1^\Delta \mathbf{1}_{|Z_1^\Delta|\leq k_n\sqrt{\Delta}})^2], \tag{32}$$

we obtain:

$$\begin{aligned}\mathrm{Var}(\omega_t(Z_1^\Delta)) \leq &\leq \frac{1}{(2\pi\Delta)^2}\left(\sum_{j,k}\left|\iint h_\Delta^*(u-v)\frac{\varphi_{m,j}^*(-u)\varphi_{m,k}^*(v)}{\psi_\Delta(u)\psi_\Delta(-v)}dudv\right|^2\right)^{1/2} \\ &= \frac{1}{2\pi\Delta^2}\left(\iint_{[-\pi m,\pi m]^2}\left|\frac{h_\Delta^*(u-v)}{\psi_\Delta(u)\psi_\Delta(-v)}\right|^2 dudv\right)^{1/2}\end{aligned}$$

where the last equality follows from the Parseval equality. Next with the Schwarz inequality and the Fubini theorem, we obtain

$$\begin{aligned}\mathrm{Var}(\omega_t(Z_1^\Delta)) &\leq \frac{1}{2\pi\Delta^2}\left(\iint_{[-\pi m,\pi m]^2}\frac{|h_\Delta^*(u-v)|^2}{|\psi_\Delta(u)|^4}dudv\right)^{1/2} \\ &= \frac{1}{2\pi\Delta^2}\left(\int_{[-\pi m,\pi m]}\left|\frac{du}{\psi_\Delta(u)}\right|^4 du\int |h_\Delta^*(z)|^2 dz\right)^{1/2} \\ &\leq \frac{\sqrt{\int_{-\pi m}^{\pi m} dx/|\psi_\Delta(x)|^4}}{2\pi\Delta}\frac{\|h_\Delta^*\|}{\Delta}.\end{aligned}$$

Now we use the following Lemma:

Lemma 5.1. *Under the assumptions of Theorem 4.1,*

$$\|h_\Delta^*\|/\Delta \leq 2\sqrt{\pi}\left(\int x^2g^2(x)dx + \mathbb{E}[(Z_1^\Delta)^2]\|g\|^2\right)^{1/2} := \xi.$$

Thus, under (H5), ξ is finite. We set

$$v_1 = \frac{\xi\sqrt{\int_{-\pi m^\star}^{\pi m^\star} dx/|\psi_\Delta(x)|^4}}{2\pi\Delta}.$$

Therefore, setting $\epsilon^2 = 1/2$,

$$p_1(m,m') = 4\mathbb{E}[(Z_1^\Delta)^2/\Delta]\frac{\Phi_\psi(m^\star)}{2\pi n\Delta}(= 2(1+2\epsilon^2)H_1^2).$$

Using (H4) and the fact that $\mathbb{E}[(Z_1^\Delta)^2/\Delta]$ is bounded, we find

$$\mathbb{E}\left(\sup_{t\in S_{m^\star},\|t\|=1}|\nu_n^{(1)}(t)|^2 - p_1(m,m')\right)_+ \leq C\left(\frac{(m^\star)^{2\beta\Delta+1/2}}{n\Delta}e^{-K\sqrt{m^\star}} + \frac{k_n^2\Phi_\psi(m^\star)}{n^2\Delta}e^{-K'\sqrt{n}/k_n}\right).$$

Here $K = K(c_\psi, C_\psi)$. Moreover, we take

$$k_n = K'\sqrt{n}/((2\beta\Delta+3)\ln(n)) \tag{33}$$

and we obtain

$$\sum_{m'\in\mathcal{M}_n}\mathbb{E}\left(\sup_{t\in S_{m^\star},\|t\|=1}[\nu_n^{(1)}(t)]^2 - p_1(m,m')\right)_+ \leq \frac{K"}{n\Delta}.$$

5.3. **Proof of Proposition 5.2.** The study of $\nu_n^{(2)}$ is slightly different.

$$\mathbb{E}\left(\sup_{t\in S_m,\|t\|=1}|\nu_n^{(2)}(t)|^2\right) \leq \frac{1}{2\pi n\Delta^2}\int_{-\pi m}^{\pi m}\frac{|\theta_\Delta(x)|^2}{|\psi_\Delta(x)|^4}dx = \frac{1}{2\pi n}\int_{-\pi m}^{\pi m}\frac{|g^*(x)|^2}{|\psi_\Delta(x)|^2}dx.$$

With assumptions (H4) and (H5), we can see that if $-a+\beta\Delta \leq 0$, then

$$\int_{-\pi m}^{\pi m}\frac{|g^*(x)|^2}{|\psi_\Delta(x)|^2}dx \leq \int_{-\pi m}^{\pi m}|g^*(x)|^2(1+x^2)^a\frac{(1+x^2)^{-a+\beta\Delta}}{c_\psi^2}dx \leq \frac{1}{c_\psi^2}\int|g^*(x)|^2(1+x^2)^a dx \leq \frac{L}{c_\psi^2}.$$

In that case, we simply take $p_2(m,m') = 0$ and write

$$\mathbb{E}\left(\sup_{t\in S_{m\vee\hat{m}},\|t\|=1}[\nu_n^{(2)}]^2(t)\right) \leq \mathbb{E}\left(\sup_{t\in S_{m_n},\|t\|=1}[\nu_n^{(2)}]^2(t)\right) \leq \frac{L}{nc_\psi^2}.$$

Now we study the case $-a+\beta\Delta > 0$ and find the constants $H = H_2, v = v_2, \epsilon = \epsilon_2$ to apply Lemma 6.1. Consider

$$\tilde{\omega}_t(z) = (1/2\pi\Delta)\int e^{izu}t^*(-u)\{\theta_\Delta(u)/[\psi_\Delta(u)]^2\}du.$$

As

$$\int_{-\pi m}^{\pi m}\frac{|g^*(x)|^2}{|\psi_\Delta(x)|^2}dx \leq \frac{L}{c_\psi^2}m^{-2a+2\beta\Delta},$$

we take

$$H_2^2 = \frac{L}{2\pi c_\psi^2}\frac{(m^\star)^{-2a+2\beta\Delta}}{n}.$$

Next, we have

$$M_2 = \sqrt{n}H_2$$

and we use the rough bound $v_2 = nH_2^2$. Moreover, we take $\epsilon_2^2 = (-2a+2\beta\Delta+2)\ln(m^\star)/K_1$. There exists m_0, such that for $m^\star \geq m_0$,

$$2(1+2\epsilon_2^2)H_2^2 \leq \Phi_\psi(m^\star)/n.$$

We set $p_2(m,m') = \Phi_\psi(m^\star)/n$. Introducing

$$W_n(m,m') = \left[\sup_{t\in S_{m\vee m'},\|t\|=1} |\nu_n^{(2)}|^2(t) - p_2(m,m')\right]_+,$$

we find that

$$\begin{aligned}
\sum_{m'\in\mathcal{M}_n} \mathbb{E}(W_n(m,m')) &= \sum_{m'|m^\star\leq m_0} \mathbb{E}(W_n(m,m')) + \sum_{m'|m^\star>m_0} \mathbb{E}(W_n(m,m')) \\
&\leq \sum_{m'|m^\star\leq m_0} [\mathbb{E}(\sup_{t\in S_{m^\star},\|t\|=1} |\nu_n^{(2)}(t)|^2 - 2(1+2\epsilon_2^2)H_2^2]_+) \\
&\quad + \sum_{m'|m^\star\leq m_0} |p_2(m,m') - 2(1+2\epsilon_2^2)H_2^2| \\
&\quad + \sum_{m'|m^\star>m_0} \mathbb{E}([\sup_{t\in S_{m^\star},\|t\|=1} |\nu_n^{(2)}(t)|^2 - 2(1+2\epsilon_2^2)H_2^2]_+).
\end{aligned}$$

Therefore

$$\begin{aligned}
\sum_{m'\in\mathcal{M}_n} \mathbb{E}(W_n(m,m')) &\leq 2\sum_{m'\in\mathcal{M}_n} \mathbb{E}([\sup_{t\in S_{m^\star},\|t\|=1} |\nu_n^{(2)}(t)|^2 - 2(1+2\epsilon_2^2)H_2^2]_+) \\
&\quad + \sum_{m'|m^\star\leq m_0} |p_2(m,m') - 2(1+2\epsilon_2^2)H_2^2| \\
&\leq 2\sum_{m'\in\mathcal{M}_n} \mathbb{E}([\sup_{t\in S_{m^\star},\|t\|=1} |\nu_n^{(2)}(t)|^2 - 2(1+2\epsilon_2^2)H_2^2]_+) + \frac{C(m_0)}{n}.
\end{aligned}$$

Talagrand's Inequality again can be then applied and gives that

$$\sum_{m'\in\mathcal{M}_n} \mathbb{E}([\sup_{t\in S_{m^\star},\|t\|=1} |\nu_n^{(2)}(t)|^2 - 2(1+2\epsilon_2^2)H_2^2]_+) \leq \frac{C}{n}.$$

The result for $\nu_n^{(2)}$ in this case follows then by saying as for $\nu_n^{(1)}$ that

$$\mathbb{E}\left(W_n(m,\hat{m})\right) \leq \sum_{m'\in\mathcal{M}_n} \mathbb{E}(W_n(m,m')).$$

5.4. **Proof of Proposition 5.3.** First define $\Omega(x) = \Omega_1(x)\cap\Omega_2(x)$ with

$$\begin{aligned}
\Omega_1(x) &= \left\{|\hat\theta_\Delta(x) - \theta_\Delta(x)| \leq 8\mathbb{E}^{1/2}[(Z_1^\Delta)^2](\log^{1/2}(n)n^{-1/2}\right\}, \\
\Omega_2(x) &= \left\{\left|\frac{1}{\tilde\psi_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right| \leq 1/(\log^{1/2}(n)n^\omega|\psi_\Delta(x)|^2)\right\}.
\end{aligned}$$

Then split: $R_n^{(1)}(t) = R_n^{(1,1)}(t) + R_n^{(1,2)}(t)$ where

$$R_n^{(1,1)}(t) = \frac{1}{2\pi\Delta}\int t^*(-x)(\hat\theta_\Delta - \theta_\Delta)(x)\left(\frac{1}{\tilde\psi_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right)\mathbf{1}_{\Omega(x)}dx$$

and $R_n^{(1,2)}(t)$ the integral on the complement of $\Omega(x)$.

$$\mathbb{E}\left(\sup_{t\in S_{m\vee\hat m},\|t\|=1}|R_n^{(1)}(t)|^2\right)\le 2\mathbb{E}\left(\sup_{t\in S_{m\vee\hat m},\|t\|=1}|R_n^{(1,1)}(t)|^2\right)+2\mathbb{E}\left(\sup_{t\in S_{m_n},\|t\|=1}|R_n^{(1,2)}(t)|^2\right)$$

$$\begin{aligned}
&\mathbb{E}\left(\sup_{t\in S_{m\vee\hat m},\|t\|=1}|R_n^{(1,1)}(t)|^2\right)\\
\le\;& \frac{1}{2\pi\Delta^2}\mathbb{E}\left(\int_{-\pi(m\vee\hat m)}^{\pi(m\vee\hat m)}|\hat\theta_\Delta(x)-\theta_\Delta(x)|^2\left|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\right|^2\mathbf{I}_{\Omega(x)}dx\right)\\
\le\;& \frac{8(\mathbb{E}[(Z_1^\Delta)^2]/\Delta)}{2\pi n\Delta}\mathbb{E}\left(\int_{-\pi(m\vee\hat m)}^{\pi(m\vee\hat m)}n^{-2\omega}\frac{dx}{|\psi_\Delta(x)|^4}\right)\le\frac{4\mathbb{E}[(Z_1^\Delta)^2]}{\pi\Delta}\mathbb{E}(\frac{\Phi_\psi(m\vee\hat m)}{n\Delta})\le\mathbb{E}(p_1(m,\hat m)),
\end{aligned}$$

under the condition $-2\omega+(1-\varepsilon)\le 0$. Therefore we choose $\omega=(1-\varepsilon)/2$. Note that if $\beta=0$ the decomposition is useless and the residual is straightforwardly negligible.

On the other hand, Lemma (4.1) yields:

$$\mathbb{E}^{1/4}\left[\left|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\right|^8\right]\le\frac{C_\Delta}{n|\psi_\Delta(x)|^4}.$$

Now, we find

$$\begin{aligned}
&\mathbb{E}\left(\sup_{t\in S_{m_n},\|t\|=1}|R_n^{(1,2)}(t)|^2\right)\\
\le\;& \frac{1}{2\pi\Delta^2}\int_{-\pi m_n}^{\pi m_n}\mathbb{P}^{1/2}(\Omega(x)^c)\mathbb{E}^{1/4}[(\hat\theta_\Delta(x)-\theta_\Delta(x))^8]\mathbb{E}^{1/4}\left[\left|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\right|^8\right]dx\\
\le\;& \frac{C\mathbb{E}^{1/4}[(Z_1^\Delta)^8]}{2\pi n^2}\int_{-\pi m_n}^{\pi m_n}\frac{\mathbb{P}^{1/2}(\Omega(x)^c)}{|\psi_\Delta(x)|^4}dx\\
\le\;& \frac{C\mathbb{E}^{1/4}[(Z_1^\Delta)^8]n^{2(1-\varepsilon)+1-b}}{n^2}\le\frac{C'_\Delta}{n}\text{ if }\mathbb{P}(\Omega(x)^c)\le n^{-2b}\text{ and }2(1-\varepsilon)-b\le 0.
\end{aligned}$$

We take $b=2(1-\varepsilon)$. In fact,

$$\mathbb{P}(\Omega(x)^c)\le\mathbb{P}(\Omega_1(x)^c)+\mathbb{P}(\Omega_2(x)^c).$$

We use the Markov Inequality to bound $\mathbb{P}(\Omega_2(x)^c)$:

$$\begin{aligned}
\mathbb{P}(\Omega_2(x)^c)\;&\le\;\log^p(n)n^{2p\omega}|\psi_\Delta(x)|^{4p}\mathbb{E}\left(\left|\frac{1}{\tilde\psi_\Delta(x)}-\frac{1}{\psi_\Delta(x)}\right|^{2p}\right)\\
&\le\;\log^p(n)n^{2p\omega-p}.
\end{aligned}$$

The choice of p is thus constrained by $2p\omega-p=-p(1-2\omega)<-4(1-\varepsilon)$ that is $p>4(1-\varepsilon)/\varepsilon$, e.g. $p=5(1-\varepsilon)/\varepsilon$.

We use the decomposition of $\theta_\Delta(x)=\theta_\Delta^{(1)}(x)+\theta_\Delta^{(2)}(x)$ with

$$k_n\sqrt{\Delta}=\frac{\sqrt{n\mathbb{E}[(Z_1^\Delta)^2]}}{8\sqrt{\log(n)}}.$$

We use the Bernstein Inequality to bound $\mathbb{P}(\Omega_1(x)^c)$. If $X_1, \dots, X_n$ are i.i.d. variables with variance less than v^2 and such that $|X_i| \le c$, then for $S_n = \sum_{i=1}^n X_i$, we have:

$$\mathbb{P}(|S_n - \mathbb{E}(S_n)| \ge n\epsilon) \le 2\exp\left(-\frac{n\epsilon^2/2}{v^2 + c\epsilon}\right).$$

This yields

$$\begin{aligned}
\mathbb{P}(\Omega_1(x)^c) &\le \mathbb{P}\left(|\hat{\theta}_\Delta^{(1)}(x) - \theta_\Delta^{(1)}(x)| \ge 4\sqrt{\mathbb{E}[(Z_1^\Delta)^2]\log(n)/n}\right) \\
&\quad + \mathbb{P}\left(|\hat{\theta}_\Delta^{(2)}(x) - \theta_\Delta^{(2)}(x)| \ge 4\sqrt{\mathbb{E}[(Z_1^\Delta)^2]\log(n)/n}\right) \\
&\le n^{-16/3} + \frac{n}{16\mathbb{E}[(Z_1^\Delta)^2]\log(n)}\mathbb{E}(|\hat{\theta}_\Delta^{(2)}(x) - \theta_\Delta^{(2)}(x)|^2) \\
&\le n^{-16/3} + \frac{\mathbb{E}[(Z_1^\Delta)^2 \mathbf{1}_{|Z_1^\Delta| \ge k_n\sqrt{\Delta}}]}{16\mathbb{E}[(Z_1^\Delta)^2]\log(n)} \\
&\le n^{-16/3} + \frac{8^4\mathbb{E}[(Z_1^\Delta)^6]\log^2(n)}{16\mathbb{E}^3[(Z_1^\Delta)^2]n^2} \\
&\le n^{-16/3} + \frac{c}{n^2\Delta^2}.
\end{aligned}$$

This gives the result of Proposition 5.3 for $R_n^{(1)}$. The study of $R_n^{(2)}$ follows the same line and is omitted.

5.5. **Proof of Proposition 5.4.** First we study $R_n^{(3)}$.

$$\begin{aligned}
\mathbb{E}\left(\sup_{t\in S_{m_n}, \|t\|=1} |R_n^{(3)}(t)|^2\right) &\le \frac{1}{4\pi^2\Delta^2}\mathbb{E}\left[\sup_{t\in S_{m_n}, \|t\|=1}\left|\int (\hat{\theta}_\Delta^{(2)}(x) - \theta_\Delta^{(2)}(x))\frac{t^*(-x)}{\psi_\Delta(x)}dx\right|^2\right] \\
&\le \frac{1}{2\pi\Delta^2}\int_{-\pi m_n}^{\pi m_n} \mathbb{E}[|\hat{\theta}_\Delta^{(2)}(x) - \theta_\Delta^{(2)}(x)|^2]\frac{dx}{|\psi_\Delta(x)|^2} \\
&= \frac{1}{2\pi\Delta^2}\int_{-\pi m_n}^{\pi m_n} \frac{\mathrm{Var}(Z_1^\Delta \mathbf{1}_{|Z_1^\Delta| \ge k_n\sqrt{\Delta}})}{n}\frac{dx}{|\psi_\Delta(x)|^2} \\
&\le \frac{\mathbb{E}[(Z_1^\Delta)^8]\Phi_\psi(m_n)}{2\pi n k_n^6 \Delta^4} \\
&\le \frac{K\mathbb{E}[(Z_1^\Delta)^8]\ln^6(n)}{n^{2+\varepsilon}\Delta^4},
\end{aligned}$$

using the choice of k_n given by (33).
Next,

$$\mathbb{E}\left(\sup_{t\in S_{m_n}, \|t\|=1} |R_n^{(4)}(t)|^2\right) \le \frac{1}{2\pi\Delta}\int_{-\pi m_n}^{\pi m_n} |g^*(x)|^2\mathbb{P}(|\hat{\psi}_\Delta(x)| \le \kappa_\psi/\sqrt{n})dx \le \frac{c}{n\Delta}.$$

If $|\psi_\Delta(x)| \geq 2\kappa_\psi/\sqrt{n}$, then

$$\begin{aligned}
\mathbb{P}(|\hat{\psi}_\Delta(u)| \leq \kappa_\psi n^{-1/2}) &\leq \mathbb{P}(|\hat{\psi}_\Delta(u) - \psi_\Delta(u)| \leq |\psi_\Delta(u)| - \kappa_\psi n^{-1/2}) \\
&\leq \mathbb{P}(|\hat{\psi}_\Delta(u) - \psi_\Delta(u)| \geq \frac{1}{2}|\psi_\Delta(u)|) \\
&\leq \exp(-cn|\psi_\Delta(u)|^2)
\end{aligned}$$

for some $c > 0$, where the last inequality follows from Bernstein's Inequality.

Now, it follows from (H4) that $|\psi_\Delta(u)| \geq c_\psi(1+u^2)^{-\Delta\beta/2}$. Therefore, for $|u| \leq \pi m_n$ with $m_n^{2\beta\Delta} \leq Cn^{1-\varepsilon}$ by (H7),

$$|\psi_\Delta(u)| \geq c' m_n^{-\beta\Delta} \geq 2\kappa_\psi n^{-1/2}.$$

Moreover, with the previous remarks, $\exp(-cn|\psi_\Delta(u)|^2) \leq \exp(-cn^\varepsilon)$ and thus

$$\int_{-\pi m_n}^{\pi m_n} |g^*(x)|^2 \mathbb{P}(|\hat{\psi}_\Delta(x)| \leq \kappa/\sqrt{n}) dx \leq \|g^*\|^2 \exp(-cn^\varepsilon).$$

Therefore

$$\mathbb{E}\left(\sup_{t \in S_{m_n}, \|t\|=1} |R_n^{(4)}(t)|^2\right) \leq \frac{c}{n\Delta}.$$

5.6. **Proof of Lemma 5.1.** Let us denote by P_Δ the distribution of Z_1^Δ and define $\mu_\Delta(dz) = \Delta^{-1} z P_\Delta(dz)$. Let us set $\mu(dx) = g(x)dx$. Equation (15) states that

$$\mu_\Delta^* = \mu^* P_\Delta^*.$$

Hence, $\mu_\Delta = \mu \star P_\Delta$. Therefore, μ_Δ has a density given by

$$\int g(z-y) P_\Delta(dy) = \mathbb{E} g(z - Z_1^\Delta).$$

Moreover, we have, for any compactly supported function t:

$$\frac{1}{\Delta}\mathbb{E}(Z_1^\Delta t(Z_1^\Delta)) = \int t(z) \mathbb{E} g(z - Z_1^\Delta) dz = \int \mathbb{E}(t(x + Z_1^\Delta) g(x) dx.$$

Hence, we apply first Parseval formula:

$$\begin{aligned}
\|h_\Delta^*\|^2 &= \int |h_\Delta^*(x)|^2 dx = 2\pi \int h_\Delta^2(x) dx = 2\pi\Delta \int z^2 \mathbf{1}_{|z| \leq k_n\sqrt{\Delta}} \mathbb{E}^2(g(z - Z_1^\Delta)) dz \\
&\leq 2\pi\Delta \mathbb{E}\left(\int z^2 \mathbf{1}_{|z| \leq k_n\sqrt{\Delta}} g^2(z - Z_1^\Delta) dz\right) \\
&\leq 2\pi\Delta \mathbb{E}\left(\int (x + Z_1^\Delta)^2 g^2(x) dx\right) \leq 4\pi\Delta \mathbb{E}\left(\int (x^2 + (Z_1^\Delta)^2) g^2(z) dz\right) \\
&\leq 4\pi\Delta\left(\int x^2 g^2(x) + \mathbb{E}[(Z_1^\Delta)^2] \|g\|^2\right).
\end{aligned}$$

This ends the proof. □

5.7. **Proof of Theorem 4.2.** Let us define the sets

$$\Omega_1 = \left\{\forall m \in \mathcal{M}_n, \int_{-\pi m}^{\pi m} \left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2 dx \le k_1 \int_{-\pi m}^{\pi m} \frac{dx}{|\psi_\Delta(x)|^2}\right\}$$

and

$$\Omega_2 = \left\{\left|\frac{\frac{1}{n}\sum_{i=1}^n [Z_i^\Delta]^2}{\mathbb{E}[(Z_i^\Delta)^2]} - 1\right| \le k_2\right\}.$$

Take $0 < k_1 < 1/2$ and $0 < k_2 < 1$. On Ω_1, we have, $\forall m \in \mathcal{M}_n$,

$$\int_{-\pi m}^{\pi m} \frac{dx}{|\tilde{\psi}_\Delta(x)|^2} \le (2k_1+2)\int_{-\pi m}^{\pi m} \frac{dx}{|\psi_\Delta(x)|^2} \text{ and } \int_{-\pi m}^{\pi m} \frac{dx}{|\psi_\Delta(x)|^2} \le \frac{2}{1-2k_1}\int_{-\pi m}^{\pi m} \frac{dx}{|\tilde{\psi}_\Delta(x)|^2}$$

and on Ω_2, we find

$$\frac{1}{n}\sum_{i=1}^n [Z_i^\Delta]^2 \le (1+k_2)\mathbb{E}[(Z_1^\Delta)^2] \text{ and } \mathbb{E}[(Z_1^\Delta)^2] \le \frac{1}{1-k_2}\frac{1}{n}\sum_{i=1}^n [Z_i^\Delta]^2.$$

Il follows that, on $\Omega_1 \cap \Omega_2 := \Omega_{1,2}$, we can choose κ' large enough to ensure

$$48p_1(m,\hat{\hat{m}}) + 16p_2(m,\hat{\hat{m}}) + \widehat{\mathrm{pen}}(m) - \widehat{\mathrm{pen}}(\hat{\hat{m}}) \le C(a,b)\mathrm{pen}(m).$$

This allows to extend the result of Theorem 4.1 as follows: $\forall m \in \mathcal{M}_n$,

$$\mathbb{E}\left(\|\tilde{g}-g\|^2 \mathbf{I}_{\Omega_{1,2}}\right) \le C\left(\|g-g_m\|^2 + \mathrm{pen}(m)\right) + \frac{K\ln^2(n)}{n\Delta}.$$

Next we need to prove that

$$\mathbb{E}\left(\|\tilde{g}-g\|^2 \mathbf{I}_{\Omega_{1,2}^c}\right) \le \frac{K'}{n}. \tag{34}$$

First, we prove that $\mathbb{P}(\Omega_{1,2}^c) \le c/n^2$ by proving that $\mathbb{P}(\Omega_1^c) \le c/n^2$ and $\mathbb{P}(\Omega_2^c) \le c/n$.

$$\begin{aligned}
\mathbb{P}((\Omega_1)^c) &\le \sum_{m\in\mathcal{M}_n} \mathbb{P}\left(\int_{-\pi m}^{\pi m} \left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2 dx > k_1 \int_{-\pi m}^{\pi m} \frac{dx}{|\psi_\Delta(x)|^2}\right) \\
&\le \sum_{m\in\mathcal{M}_n} \mathbb{E}\left[\left(\frac{\int_{-\pi m}^{\pi m} \left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^2 dx}{k_1\Phi_\psi(m)}\right)^p\right] \\
&\le \sum_{m\in\mathcal{M}_n} \frac{(2\pi m)^{p-1}}{(k_1\Phi_\psi(m))^p}\mathbb{E}\left(\int_{-\pi m}^{\pi m} \left|\frac{1}{\tilde{\psi}_\Delta(x)} - \frac{1}{\psi_\Delta(x)}\right|^{2p} dx\right) \\
&\le \sum_{m\in\mathcal{M}_n} C_p m^{p-1} n^{-p} \frac{\int_{-\pi m}^{\pi m} dx/|\psi_\Delta(x)|^{4p}}{(\Phi_\psi(m))^p} \\
&\le \sum_{m\in\mathcal{M}_n} C'_p n^{-p} m^{(p-1)-p(2\beta\Delta+1)+4p\beta\Delta+1} = \sum_{m\in\mathcal{M}_n} C'_p m^{2p\beta\Delta} n^{-p} \\
&\le C" n^{1-p+p(1-\varepsilon)} \le C" n^{1-p\varepsilon}.
\end{aligned}$$

As $m^{2\beta\Delta+1}/(n\Delta)$ is bounded $m^{2p\beta\Delta}n^{-p} = O(n^{2p\beta\Delta/(2\beta\Delta+1)-p}) = O(n^{-p/(2\beta\Delta+1)})$. Therefore, choosing $p = 3/\varepsilon$ ensures that $n^{1-p\varepsilon)} = n^{-2}$ and $\mathbb{P}(\Omega_1^c) \le C/n^2$.

On the other hand,

$$\mathbb{P}[\Omega_2^c] \leq \frac{1}{k_2^p \mathbb{E}^p[(Z_1^\Delta)^2]} \mathbb{E}\left(\left| \frac{1}{n}\sum_{i=1}^n [(Z_i^\Delta)^2 - \mathbb{E}[(Z_1^\Delta)^2]] \right|^p \right).$$

Here the choice $p = 4$ gives $\mathbb{P}[\Omega_2^c] = O(1/n^2)$ with a simple variance inequality, provided that $\mathbb{E}[(Z_1^\Delta)^8] < +\infty$.
Next, we write that

$$\|g - \tilde{g}\|^2 = \|g - g_{\widehat{\widehat{m}}}\|^2 + \|g_{\widehat{\widehat{m}}} - \hat{g}_{\widehat{\widehat{m}}}\|^2 \leq \|g\|^2 + \sum_{j\in\mathbb{Z}} |\hat{a}_{\widehat{\widehat{m}},j} - a_{\widehat{\widehat{m}},j}(g)|^2$$

and

$$\begin{aligned}
\sum_{j\in\mathbb{Z}} |\hat{a}_{\widehat{\widehat{m}},j} - a_{\widehat{\widehat{m}},j}(g)|^2 &= \sum_{j\in\mathbb{Z}} |\nu_n^{(1)}(\varphi_{\widehat{\widehat{m}},j}) + \nu_n^{(2)}(\varphi_{\widehat{\widehat{m}},j}) + \sum_{k=1}^4 R_n^{(k)}(\varphi_{\widehat{\widehat{m}},j})|^2 \\
&\leq C\sum_{j\in\mathbb{Z}} \{|\nu_n^{(1)}(\varphi_{\widehat{\widehat{m}},j})|^2 + |\nu_n^{(2)}(\varphi_{\widehat{\widehat{m}},j})|^2 + \sum_{k=1}^4 |R_n^{(k)}(\varphi_{\widehat{\widehat{m}},j})|^2\} \\
&= C\left\{ \sup_{t\in S_{\widehat{\widehat{m}}}, \|t\|=1} |\nu_n^{(1)}(t)|^2 + \sup_{t\in S_{\widehat{\widehat{m}}}, \|t\|=1} |\nu_n^{(2)}(t)|^2 \right. \\
&\quad \left. + \sum_{k=1}^4 \sup_{t\in S_{\widehat{\widehat{m}}}, \|t\|=1} |R_n^{(k)}(t)|^2 \right\}
\end{aligned}$$

It follows that, $\mathbb{E}(\|g\|^2 \mathbf{I}_{\Omega_{1,2}^c}) = \|g\|^2\mathbb{P}(\Omega_{1,2}^c) \leq c/n$, and for $k = 3, 4$,

$$\mathbb{E}\left(\sup_{t\in S_{\widehat{\widehat{m}}}, \|t\|=1} |R_n^{(k)}(t)|^2 \mathbf{I}_{\Omega_{1,2}^c} \right) \leq \mathbb{E}\left(\sup_{t\in S_{m_n}, \|t\|=1} |R_n^{(k)}(t)|^2 \right) \leq C/n$$

as it has been proved previously. Lastly,

$$\begin{aligned}
\mathbb{E}\left(\sup_{t\in S_{\widehat{\widehat{m}}}, \|t\|=1} |\nu_n^{(1)}(t)|^2 \mathbf{I}_{\Omega_{1,2}^c} \right) &\leq \mathbb{E}\left(\sup_{t\in S_{\widehat{\widehat{m}}}, \|t\|=1} \left\{ |\nu_n^{(1)}(t)|^2 - \mathrm{pen}(\widehat{\widehat{m}}) \right\} \right)_+ \\
&\quad + \mathbb{E}\left(\mathrm{pen}(\widehat{\widehat{m}}) \mathbf{I}_{\Omega_{1,2}^c} \right) \\
&\leq c(\frac{1}{n\Delta} + n\mathbb{P}(\Omega_{1,2}^c)) \leq \frac{c'}{n}
\end{aligned}$$

using the proof of Theorem 4.1 and the fact that pen(.) is less than $O(n)$. The same line can be followed for the other terms.

6. Appendix

Lemma 6.1. *Let $Y_1, \ldots, Y_n$ be independent random variables, let $\nu_{n,Y}(f) = (1/n)\sum_{i=1}^n [f(Y_i) - \mathbb{E}(f(Y_i))]$ and let $\mathcal{F}$ be a countable class of uniformly bounded measurable functions. Then for $\epsilon^2 > 0$*

$$\mathbb{E}\Big[\sup_{f\in\mathcal{F}} |\nu_{n,Y}(f)|^2 - 2(1+2\epsilon^2)H^2 \Big]_+ \leq \frac{4}{K_1}\left(\frac{v}{n} e^{-K_1\epsilon^2 \frac{nH^2}{v}} + \frac{98M^2}{K_1 n^2 C^2(\epsilon^2)} e^{-\frac{2K_1 C(\epsilon^2)\epsilon}{7\sqrt{2}} \frac{nH}{M}} \right),$$

with $C(\epsilon^2) = \sqrt{1+\epsilon^2} - 1$, $K_1 = 1/6$, *and*

$$\sup_{f\in\mathcal{F}} \|f\|_\infty \le M, \quad \mathbb{E}\Big[\sup_{f\in\mathcal{F}} |\nu_{n,Y}(f)|\Big] \le H, \ \sup_{f\in\mathcal{F}} \frac{1}{n}\sum_{k=1}^{n} \mathrm{Var}(f(Y_k)) \le v.$$

This result follows from the concentration inequality given in Klein and Rio (2005) and arguments in Birgé and Massart (1998) (see the proof of their Corollary 2 page 354). It can be extended to the case where $\mathcal{F}$ is a unit ball of a linear space.

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