

Solving BSDE with adaptive control variate.

A note on the rate of convergence of the operator \mathcal{P}^k

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This note is a complement of the paper "Solving BSDE with adaptive control variate" [1]. It deals with the convergence of the approximating operator \mathcal{P} , based on a non parametric regression technique called local averaging, and defined in Definition 1.1.

Although the computations are quite standard (see [3], [2]), the specificities of the paper are the following

- the support of the variables is unbounded;
- the error has to be measured using specific L_2 -norms;
- errors on the gradient are provided.

1 Definitions

Let us first introduce some notations

- Let $C_b^{k,l}$ be the set of continuously differentiable functions $\phi : (t, x) \in [0, T] \times \mathbb{R}^d$ with continuous and uniformly bounded derivatives w.r.t. t (resp. w.r.t. x) up to order k (resp. up to order l).
- C_p^k denotes the set of C^{k-1} functions whose k -th derivative is piecewise continuous.
- Constants $c_{i,j}(\cdot)$ and $C(d)$. For any function ϕ in $C_b^{i,j}$, $c_{i,j}(\phi)$ denotes $\sum_{k,l=0}^{i,j} |\partial_t^k \partial_x^l \phi|_\infty$. For $i = j = 0$, we set $c_0(\phi) := c_{0,0}(\phi)$. $C(d)$ denotes a constant depending only on d .
- Functions $K(T)$. $K(\cdot)$ denotes a generic function non decreasing in T which may depend on d, μ, β , on the coefficients b and σ (through $\sigma_0, \sigma_1, c_{1,3}(\sigma), c_{0,1}(\partial_t \sigma), c_{1,3}(b)$) and on other constants appearing in [1, Appendix A]. The parameter β is defined in [1, Section 2.1], μ is defined in [1, Section 3.2], σ_0 and σ_1 are defined in [1, Hypothesis 1].
- Functions $K_0(T)$. $K_0(T)$ are analogous to $K(T)$ except that they may also depend on the operator \mathcal{P} (through $c_1(K_t)$ and $c_2(K_x)$, defined in Section [1, Section 7]).

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Definition 1.1. We approximate a function $v(t, x)$ by

$$\mathcal{P}^k v(t, x) = \frac{r_n^k(t, x)}{f_n^k(t, x)} g(2^{d+1} T \lambda(B) f_n^k(t, x)), \quad (1.1)$$

where

- $r_n^k(t, x) = \frac{1}{nh_t h_x^d} \sum_{i=1}^n K_t\left(\frac{t-T_i^k}{h_t}\right) K_x\left(\frac{x-X_i^k}{h_x}\right) v(T_i^k, X_i^k)$;
- $f_n^k(t, x) = \frac{1}{nh_t h_x^d} \sum_{i=1}^n K_t\left(\frac{t-T_i^k}{h_t}\right) K_x\left(\frac{x-X_i^k}{h_x}\right)$;
- the points $(T_i^k, X_i^k)_{1 \leq i \leq n}$ are uniformly distributed on $[0, T] \times B$ where $B := B_\infty(0, a) = [-a, a]^d$, and \mathcal{A}_k denotes the set of points $(T_i^k, X_i^k)_{1 \leq i \leq n}$;
- $\lambda(B) = (2a)^d$;
- and g is such that

$$g(y) = \begin{cases} 0 & \text{if } y < 0, \\ 1 & \text{if } y > 1, \\ -y^4 + 2y^2 & \text{if } y \in [0, 1]; \end{cases} \quad (1.2)$$

- The kernel function K_t is defined on the compact support $[-1, 1]$, bounded, even, non-negative, C_p^2 and $\int_{\mathbb{R}} K_t(u) du = 1$;
- The kernel function K_x is defined on the compact support $[-1, 1]^d$, bounded, and such that $\forall y = (y_1, \dots, y_d) \in \mathbb{R}^d$, $K_x(y) = \prod_{j=1}^d K_x^j(y_j)$, where for $j = 1, \dots, d$ $K_x^j : \mathbb{R} \rightarrow \mathbb{R}$ is an even non-negative C_p^2 function and $\int_{\mathbb{R}} K_x^j(u) du = 1$;
- δ_n denotes $\frac{1}{nh_t h_x^d}$, and $T \lambda(B) \delta_n \ll 1$;
- $h_x \ll a$ and $h_t \ll \frac{T}{2}$. Since we study the convergence when h_t and h_x tend to 0, we assume in the following that $h_t \leq 1$ and $h_x \leq 1$.

Remark 1.2. We give some useful bounds for g and its first derivative. The function $G : x \mapsto \frac{g(x)}{x}$ is bounded by 2, g' is bounded by 2, $x \mapsto \frac{g'(x)}{x}$ is bounded by 4 and $x \mapsto \frac{g(x)}{x^2}$ is bounded by 2. Then, G' is bounded by 6.

Remark 1.3. This choice for the operator \mathcal{P}^k is not harmless. \mathcal{P}^k should be continuous and differentiable. That's why we multiply $\frac{r_n^k}{f_n^k}$ by a regularising function g at the point $2^{d+1} T \lambda(B) f_n^k$. Since the function $f_n^k(t, x)$ converges to $\frac{1}{T \lambda(B)}$ when n goes to infinity for $t \in]0, T[$ and $|x_i| < a$, $i = 1, \dots, d$, $g(2^{d+1} T \lambda(B) f_n^k(t, x))$ converges to 1 when n goes to ∞ . Hence, if $f_n^k \sim \frac{1}{T \lambda(B)}$, $\mathcal{P}^k v(t, x) = \frac{r_n^k(t, x)}{f_n^k(t, x)}$, which is a standard estimator. The function g has an impact on \mathcal{P}^k only when f_n^k is strictly positive and small (compared to $\frac{1}{T \lambda(B)}$).

We also introduce the space $H_{\beta, X}^{m, \mu}$:

Definition 1.4 (Space $H_{\beta,X}^{m,\mu}$). Let X denote the \mathbb{R}^d -valued process solution of

$$X_t = x + \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dW_s, \quad (1.3)$$

where W is a q -dimensional standard Brownian motion, $b : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}^d$, and $\sigma : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}^{d \times q}$. For any $m \leq 2, \beta > 0, \mu > 0$, let $H_{\beta,X}^{m,\mu}$ define the space of functions $v : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}$ such that

$$\|v\|_{H_{\beta,X}^{m,\mu}}^2 = \int_0^T e^{\beta s} \int_{\mathbb{R}^d} e^{-\mu|x|} \sum_{k \leq m} \mathbb{E} |\partial_x^k v(s, X_s^x)|^2 dx ds < \infty.$$

Definition 1.5 (Function ν_μ^t). For any $s, t \in [0, T]$ and any $x, y \in \mathbb{R}^d$ such that $t < s$ we define $\nu_\mu^t(s, y) := \int_{\mathbb{R}^d} e^{-\mu|x|} p(t, x; s, y) dx$, where μ is a positive constant and p is the transition density function of the process X defined by (1.3).

Remark 1.6. Using the definition of ν , we also get $\|v\|_{H_{\beta,X}^\mu}^2 = \int_0^T e^{\beta s} \int_{\mathbb{R}^d} dy \nu_\mu^0(s, y) |v(s, y)|^2$.

Hypothesis 1. We assume that the coefficients σ and b are Lipschitz and bounded measurable functions on $[0, T] \times \mathbb{R}^d$. We also assume that σ satisfies the ellipticity condition.

2 Main results

We aim at proving the following Propositions, which correspond to [1, Theorem 7.4].

Proposition 2.1. *Assume Hypothesis 1. We also assume that v is a $C^{1,2}([0, T] \times \mathbb{R}^d)$ function and v and $\partial_x v$ are bounded by $c_{0,1}(v)$ and v satisfies $\forall t, t' \in [0, T], \forall x \in \mathbb{R}^d, |\partial_x v(t, x) - \partial_x v(t', x)| \leq c_{1/2}(v) \sqrt{|t' - t|}$, where $c_{1/2}(v)$ is a positive constant. Then,*

$$\begin{aligned} \mathbb{E} \|\mathcal{P}^k v - v\|_{H_{\beta,X}^\mu}^2 + \mathbb{E} \|\partial_x(\mathcal{P}^k v) - \partial_x v\|_{H_{\beta,X}^\mu}^2 &\leq \epsilon_1(\mathcal{P}) (\mathbb{E} \|v\|_{H_{\beta,X}^{2,\mu}}^2 + \mathbb{E} \|\partial_t v\|_{H_{\beta,X}^\mu}^2) \\ &\quad + e_2(\mathcal{P}) (c_{1/2}^2(v) + c_{0,1}^2(v)), \end{aligned}$$

where $\epsilon_1(\mathcal{P}) = K_0(T)(h_t^2 + h_x^2 + \frac{T\lambda(B)\delta_n}{h_x^2})$, $e_2(\mathcal{P}) = K_0(T)(h_t + e^{-\mu a} \frac{a^{d-1}}{h_x} + e^{-\frac{\mu a}{\sqrt{d}}} + \frac{T\lambda(B)\delta_n}{h_x^2})$. Moreover, if v is a $C_b^{1,2}$ function, we get $\mathbb{E} \|\mathcal{P}^k v - v\|_{H_{\beta,X}^\mu}^2 + \mathbb{E} \|\partial_x(\mathcal{P}^k v) - \partial_x v\|_{H_{\beta,X}^\mu}^2 \leq (\epsilon_1(\mathcal{P}) + e_2(\mathcal{P})) (c_{1/2}^2(v) + c_{1,2}^2(v))$.

The proof of Proposition 2.1 is done in Sections 4 and 5. Section 4 (resp. Section 5) deals with the bound for $\mathbb{E} \|\mathcal{P}^k v - v\|_{H_{\beta,X}^\mu}^2$ (resp. $\mathbb{E} \|\partial_x(\mathcal{P}^k v) - \partial_x v\|_{H_{\beta,X}^\mu}^2$).

Proposition 2.2. *Under Hypothesis 1, for any random function v from $[0, T] \times \mathbb{R}^d$ to \mathbb{R} independent of \mathcal{A}_k , one has*

$$\mathbb{E} \|\mathcal{P}^k v\|_{H_{\beta,X}^\mu}^2 + \mathbb{E} \|\partial_x(\mathcal{P}^k v)\|_{H_{\beta,X}^\mu}^2 \leq c_4(\mathcal{P}) \mathbb{E} \|v\|_{H_{\beta,X}^\mu}^2, \text{ where } c_4(\mathcal{P}) = \frac{K_0(T)}{h_x^2}.$$

If $\mathbb{E}(v(t, x)) = 0$, one has $\mathbb{E} \|\mathcal{P}^k v\|_{H_{\beta,X}^\mu}^2 + \mathbb{E} \|\partial_x(\mathcal{P}^k v)\|_{H_{\beta,X}^\mu}^2 \leq \epsilon_4(\mathcal{P}) \mathbb{E} \|v\|_{H_{\beta,X}^\mu}^2$, where $\epsilon_4(\mathcal{P}) = K_0(T) \frac{T\lambda(B)\delta_n}{h_x^2}$.

The proof of Proposition 2.1 is done in Section 6.

Remark 2.3. For the sake of clearness, we omit the superscript k in the definition of r_n^k and f_n^k . From now on, r_n (resp. f_n) denotes r_n^k (resp. f_n^k).

3 Properties on f_n , r_n and other useful results

In this Section, we only recall some technical results on f_n and r_n proved in [4].

Lemma 3.1 (Lemma 12.13, [4]). *For all $(s, y) \in [0, T] \times \mathbb{R}^d$,*

$$\mathbb{E}[f_n(s, y)] = \frac{1}{T\lambda(B)} \int_{-1\sqrt{\frac{s}{h_t}}}^{1\wedge\frac{T-s}{h_t}} K_t(r) dr \prod_{j=1}^d \int_{-1\sqrt{\frac{-a-y_j}{h_x}}}^{1\wedge\frac{a-y_j}{h_x}} K_x^j(x_j) dx_j, \quad (3.1)$$

and $\mathbb{E}[f_n(s, y)] \leq \frac{1}{T\lambda(B)}$. Moreover, for $(s, y) \in [0, T] \times B$, $\mathbb{E}[f_n(s, y)] \geq \frac{1}{T\lambda(B)2^{d+1}}$, and for $(s, y) \in [h_t, T - h_t] \times B_\infty(0, a - h_x)$, $\mathbb{E}[f_n(s, y)] = \frac{1}{T\lambda(B)} = \bar{f}(s, y)$.

Proposition 3.2 (Proposition 12.20, [4]). *Assume $v : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}$ is a bounded function. Then, for all $(s, y) \in [0, T] \times \mathbb{R}^d$,*

$$\begin{aligned} (\mathbb{E}[r_n(s, y)])^2 &\leq \frac{c_0^2(v)}{(T\lambda(B))^2} \mathbf{1}_{\{y \in B_\infty(0, a+h_x)\}}, \\ \text{Var}(r_n(s, y)) &\leq 2^{d+1} \frac{c_0^2(K_t)c_0^2(K_x)c_0^2(v)\delta_n}{T\lambda(B)} \mathbf{1}_{\{y \in B_\infty(0, a+h_x)\}}. \end{aligned}$$

Using $T\lambda(B)\delta_n \ll 1$ yields $\mathbb{E}(r_n^2(s, y)) \leq 2^{d+2} \frac{c_0^2(K_t)c_0^2(K_x)c_0^2(v)}{(T\lambda(B))^2} \mathbf{1}_{\{y \in B_\infty(0, a+h_x)\}}$.

Assume $v : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}^+$ is a continuous function. Then,

$$\begin{aligned} \mathbb{E}(r_n(s, y))^2 &\leq \frac{2^{d+1}}{h_t h_x^d (T\lambda(B))^2} \int_0^T dr K_t^2\left(\frac{s-r}{h_t}\right) \int_B dz K_x^2\left(\frac{y-z}{h_x}\right) v^2(r, z), \\ \text{Var}(r_n(s, y)) &\leq \frac{1}{nh_t^2 h_x^{2d} T\lambda(B)} \int_0^T dr K_t^2\left(\frac{s-r}{h_t}\right) \int_B dz K_x^2\left(\frac{y-z}{h_x}\right) v^2(r, z). \end{aligned}$$

Using $T\lambda(B)\delta_n \ll 1$ yields

$$\mathbb{E}(r_n^2(s, y)) \leq \frac{2^{d+2}}{h_t h_x^d (T\lambda(B))^2} \int_0^T dr K_t^2\left(\frac{s-r}{h_t}\right) \int_B dz K_x^2\left(\frac{y-z}{h_x}\right) v^2(r, z).$$

Lemma 3.3 (Lemma 12.17, [4]). *For all $(s, y) \in [0, T] \times \mathbb{R}^d$, for all $i \in \{1, \dots, d\}$, the following assertion holds*

$$\mathbb{E}(\partial_{x_i} f_n(s, y))^2 \leq 2^{2d+3} \frac{c_0^2(K_t)c_{0,1}^2(K_x)}{h_x^2 (T\lambda(B))^2} \mathbf{1}_{\{y \in B_\infty(0, a+h_x)\}}.$$

Proposition 3.4 (Proposition 12.19, [4]). *Under Hypothesis 1, one has*

$$\int_0^T ds e^{\beta s} \int_B dy \nu^0(s, y) |\mathbb{E}(\partial_{x_i} f_n(s, y))|^2 \leq \frac{K_0(T)}{h_x (T\lambda(B))^2} e^{-\mu a} a^{d-1}.$$

Lemma 3.5 (Lemma 12.10, [4]). *Assume Hypothesis 1 and let f be a function from $[0, T] \times \mathbb{R}^d$ into \mathbb{R}^+ , g_t a positive bounded function with compact support in $[-1, 1]$ and g_x a positive bounded function with compact support in $[-1, 1]^d$. Then,*

$$\begin{aligned} \int_0^T ds e^{\beta s} \int_{\mathbb{R}^d} dy \nu^0(s, y) \int_0^T dr g_t\left(\frac{s-r}{h_t}\right) \int_{\mathbb{R}^d} dz g_x\left(\frac{y-z}{h_x}\right) f(r, z) \leq \\ K(T) c_0(g_t) c_0(g_x) h_t h_x^d \int_0^T dr e^{\beta r} \int_{\mathbb{R}^d} dz \nu^0(r, z) f(r, z). \end{aligned}$$

4 Proof of Proposition 2.1: term $\mathbb{E}\|\mathcal{P}^k v - v\|_{H_{\beta,X}^\mu}^2$

The study of $\mathbb{E}\|\mathcal{P}^k v - v\|_{H_{\beta,X}^\mu}^2$ will be done in two steps. To do so, we add and subtract

$$C_n(s, y) := \frac{r_n(s, y)}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}} \quad (4.1)$$

to the term $v - \mathcal{P}^k v$. C_n approximates well v inside the domain $[0, T] \times B$. We get $\mathbb{E}\|\mathcal{P}^k v - v\|_{H_{\beta,X}^\mu}^2 \leq 2\mathbb{E}\|\mathcal{P}^k v - C_n\|_{H_{\beta,X}^\mu}^2 + 2\mathbb{E}\|C_n - v\|_{H_{\beta,X}^\mu}^2$. The two following sections are devoted to the study of $\mathbb{E}\|C_n - v\|_{H_{\beta,X}^\mu}^2$ and $\mathbb{E}\|\mathcal{P}^k v - C_n\|_{H_{\beta,X}^\mu}^2$.

4.1 Study of $\mathbb{E}\|C_n - v\|_{H_{\beta,X}^\mu}^2$

Using the definition of C_n , we get

$$C_n(s, y) - v(s, y) = \frac{r_n(s, y) - v(s, y)\mathbb{E}[f_n(s, y)]}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}} - v(s, y) \mathbf{1}_{\{s \notin [0, T] \cup y \notin B\}}. \quad (4.2)$$

Then, we split $\mathbb{E}\|C_n - v\|_{H_{\beta,X}^\mu}^2$ in two terms, by using the bias-variance decomposition: $\mathbb{E}\|C_n - v\|_{H_{\beta,X}^\mu}^2 = \|\mathbb{E}(C_n - v)\|_{H_{\beta,X}^\mu}^2 + \|\text{Std}(C_n - v)\|_{H_{\beta,X}^\mu}^2$, where $\text{Std}(Y(s, y)) = \sqrt{\text{Var}(Y(s, y))}$.

4.1.1 Study of $\|\mathbb{E}(C_n - v)\|_{H_{\beta,X}^\mu}^2$

We have

$$\mathbb{E}(C_n - v)(s, y) = \frac{\mathbb{E}[r_n(s, y)] - v(s, y)\mathbb{E}[f_n(s, y)]}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}} - v(s, y) \mathbf{1}_{\{s \notin [0, T] \cup y \notin B\}}.$$

Since $\mathbb{E}[r_n(s, y)] = \frac{1}{T\lambda(B)h_t h_x^d} \int_B dz \int_0^T dr v(r, z) K_x\left(\frac{y-z}{h_x}\right) K_t\left(\frac{s-r}{h_t}\right)$, we obtain

$$\mathbb{E}[r_n(s, y)] - v(s, y)\mathbb{E}[f_n(s, y)] = \frac{1}{T\lambda(B)h_t h_x^d} \int_B dz \int_0^T dr K_x\left(\frac{y-z}{h_x}\right) K_t\left(\frac{s-r}{h_t}\right) (v(r, z) - v(s, y)).$$

We use the second property of Lemma 3.1 and the equality $v(r, z) - v(s, y) = v(r, z) - v(s, z) + v(s, z) - v(s, y)$ to bound $|\mathbb{E}(C_n - v)(s, y)|$ by $|A_1(s, y)| + |A_2(s, y)| + |A_3(s, y)|$, where

$$\begin{aligned} A_1(s, y) &:= \frac{2^{d+1}}{h_t h_x^d} \int_B dz \int_0^T dr K_x\left(\frac{y-z}{h_x}\right) K_t\left(\frac{s-r}{h_t}\right) (v(r, z) - v(s, z)), \\ A_2(s, y) &:= \frac{2^{d+1}}{h_t h_x^d} \int_B dz \int_0^T dr K_x\left(\frac{y-z}{h_x}\right) K_t\left(\frac{s-r}{h_t}\right) (v(s, z) - v(s, y)), \\ A_3(s, y) &:= v(s, y) \mathbf{1}_{\{s \notin [0, T] \cup y \notin B\}}. \end{aligned}$$

We analyze each term in the following three Lemmas.

Lemma 4.1. *Let us assume Hypothesis 1 and v is a function C^1 in time. Then,*

$$\|A_1(s, y)\|_{H_{\beta,X}^\mu}^2 \leq K_0(T) h_t^2 \|\partial_t v\|_{H_{\beta,X}^\mu}^2,$$

If $\partial_t v$ is bounded, we get $\|A_1(s, y)\|_{H_{\beta,X}^\mu}^2 \leq K_0(T) c_{1,0}^2(v) h_t^2$.

This Lemma ensues from [4, Lemma 12.36].

Lemma 4.2. *Let us assume Hypothesis 1 and v is a function C^1 in space. There exists a function $K_0(T)$ such that*

$$\|A_2(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)h_x^2\|\partial_x v\|_{H_{\beta, X}^\mu}^2.$$

In particular, if $\partial_x v$ is bounded, we get $\|A_2(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)c_{0,1}^2(v)h_x^2$.

Proof. The proof of this Lemma is the same as the one of Lemma 4.1, except that we split the difference $v(s, z) - v(s, y)$ as a sum of d terms: $v(s, z) - v(s, y) = \sum_{i=1}^d v(s, \bar{z}_i) - v(s, \bar{z}_{i-1})$, where $\bar{z}_i = (z_1, z_2, \dots, z_i, y_{i+1}, \dots, y_d)$, $\forall i \in \{1, \dots, d\}$, and $\bar{z}_0 = y$. For all $i \in \{1, \dots, d\}$, we get $v(s, \bar{z}_i) - v(s, \bar{z}_{i-1}) = \int_{y_i}^{z_i} dl \partial_{x_i} v(s, \bar{z}_i^l)$, where $\bar{z}_i^l = (z_1, \dots, z_{i-1}, l, y_{i+1}, \dots, y_d)$. ■

Lemma 4.3. *Assume Hypothesis 1 and v is bounded. Then, $\|A_3(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K(T)c_0^2(v)e^{-\frac{\mu a}{\sqrt{d}}}$.*

Proof. Since v is bounded, we get $\|A_3(s, y)\|_{H_{\beta, X}^\mu}^2 \leq c_0^2(v) \int_0^T dr e^{\beta r} \int_{B^c} dy \nu_\mu^0(r, y)$. To conclude, we use $\nu_\mu^0(r, y) \leq 2^d K e^{c_2 r} e^{-\mu|y|}$ (see the proof of [1, Proposition 3.8]). ■

Combining Lemmas 4.1, 4.2, 4.3 yields to the following Proposition.

Proposition 4.4. *Let us assume Hypothesis 1 and v is a bounded $C^{1,1}$ function. Then,*

$$\|\mathbb{E}(C_n - v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)(h_t^2\|\partial_t v\|_{H_{\beta, X}^\mu}^2 + h_x^2\|\partial_x v\|_{H_{\beta, X}^\mu}^2) + c_0^2(v)K(T)e^{-\frac{\mu a}{\sqrt{d}}}.$$

Moreover, if $\partial_t v$ and $\partial_x v$ are bounded, we get $\|\mathbb{E}(C_n - v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)c_{1,1}^2(v)(h_t^2 + h_x^2 + e^{-\frac{\mu a}{\sqrt{d}}})$.

4.1.2 Study of $\|\text{Std}(C_n - v)\|_{H_{\beta, X}^\mu}^2$

Let us study $\|\text{Std}(C_n - v)\|_{H_{\beta, X}^\mu}^2 = \int_0^T ds e^{\beta s} \int_{\mathbb{R}^d} dy \nu_\mu^0(s, y) \text{Var}(C_n - v)(s, y)$.

Proposition 4.5. *Let us assume Hypothesis 1. Then,*

$$\|\text{Std}(C_n - v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)T\lambda(B)\delta_n\|v\|_{H_{\beta, X}^\mu}^2.$$

If v is bounded, we get $\|\text{Std}(C_n - v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)c_0^2(v)T\lambda(B)\delta_n$.

Proof. Using (4.2) leads to $\|\text{Std}(C_n - v)\|_{H_{\beta, X}^\mu}^2 = \int_0^T ds e^{\beta s} \int_B dy \nu_\mu^0(s, y) \text{Var}(r_n(s, y)) \frac{1}{\mathbb{E}[f_n(s, y)]^2}$. We use Lemma 3.1 to get

$$\|\text{Std}(C_n - v)\|_{H_{\beta, X}^\mu}^2 \leq 2^{2d+2}(T\lambda(B))^2 \int_0^T ds e^{\beta s} \int_B dy \nu_\mu^0(s, y) \text{Var}(r_n(s, y)).$$

The end of the proof is similar to the one of [4, Proposition 12.34]. ■

4.1.3 Conclusion

We combine Propositions 4.4 and 4.5 to get the following result

Proposition 4.6. *Let us assume Hypothesis 1 and v is a bounded $C^{1,1}$ function. Then,*

$$\mathbb{E}\|C_n - v\|_{H_{\beta,X}^\mu}^2 \leq K_0(T)(T\lambda(B)\delta_n\|v\|_{H_{\beta,X}^\mu}^2 + h_t^2\|\partial_t v\|_{H_{\beta,X}^\mu}^2 + h_x^2\|\partial_x v\|_{H_{\beta,X}^\mu}^2) + c_0^2(v)K(T)e^{-\frac{\mu a}{\sqrt{d}}}.$$

Moreover, if $\partial_t v$ and $\partial_x v$ are bounded, we get $\|\mathbb{E}(C_n - v)\|_{H_{\beta,X}^\mu}^2 \leq K_0(T)c_{1,1}^2(v)(T\lambda(B)\delta_n + h_t^2 + h_x^2 + e^{-\frac{\mu a}{\sqrt{d}}})$.

4.2 Study of $\mathbb{E}\|\mathcal{P}^k v - C_n\|_{H_{\beta,X}^\mu}^2$

By using the definition of $\mathcal{P}^k v(s, y)$ and $C_n(s, y)$, we write

$$\mathcal{P}^k v(s, y) - C_n(s, y) = r_n(s, y) \left[\frac{1}{f_n(s, y)} g(2^{d+1}T\lambda(B)f_n(s, y)) - \frac{1}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}} \right].$$

If $y \notin B_\infty(0, a + h_x)$, $\mathcal{P}^k v(s, y) - C_n(s, y) = 0$. If $y \in B_\infty(0, a + h_x) \setminus B$, $\mathcal{P}^k v(s, y) - C_n(s, y) = \frac{r_n(s, y)}{f_n(s, y)} g(2^{d+1}T\lambda(B)f_n(s, y))$. Since g is bounded by 1 and $|r_n(s, y)| \leq f_n(s, y) \sup_{(s, y) \in [0, T] \times B_\infty(0, a + h_x) \setminus B} |v(s, y)|$, we get $|\mathcal{P}^k v(s, y) - C_n(s, y)| \leq c_0(v)$. If $y \in B$, $\mathcal{P}^k v(s, y) - C_n(s, y) = \frac{r_n(s, y)}{f_n(s, y)} [g(2^{d+1}T\lambda(B)f_n(s, y)) - \frac{f_n(s, y)}{\mathbb{E}[f_n(s, y)]}]$. Let us give two upper bounds for $\mathcal{P}^k v(s, y) - C_n(s, y)$ when $y \in B$.

Lemma 4.7. *For $y \in B$, the two following assertions hold*

$$|\mathcal{P}^k v(s, y) - C_n(s, y)| \leq 2^{d+3}T\lambda(B) \frac{r_n(s, y)}{f_n(s, y)} |f_n(s, y) - \mathbb{E}[f_n(s, y)]|,$$

$$|\mathcal{P}^k v(s, y) - C_n(s, y)| \leq 2^{d+3}(T\lambda(B))^2 |r_n(s, y)| |f_n(s, y) - \mathbb{E}[f_n(s, y)]|.$$

Proof. Let $\tilde{g}(x) := g(2^{d+1}T\lambda(B)x) - \frac{x}{\mathbb{E}[f_n(s, y)]}$. Then, we use the second property of Lemma 3.1 to get $\tilde{g}(\mathbb{E}[f_n(s, y)]) = 0$, and $\mathcal{P}^k v(s, y) - C_n(s, y) = \frac{r_n(s, y)}{f_n(s, y)} (\tilde{g}(f_n(s, y)) - \tilde{g}(\mathbb{E}[f_n(s, y)]))$. Moreover, Remark 1.2 leads to $|\tilde{g}(f_n(s, y)) - \tilde{g}(\mathbb{E}[f_n(s, y)])| \leq 2^{d+3}T\lambda(B) |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$. The first result follows. To get the second one, we introduce $\bar{g}(x) := \frac{g(2^{d+1}T\lambda(B)x)}{x}$. We have $\bar{g}(\mathbb{E}[f_n(s, y)]) = \frac{1}{\mathbb{E}[f_n(s, y)]}$ and $|\bar{g}(f_n(s, y)) - \bar{g}(\mathbb{E}[f_n(s, y)])| \leq 2^{2d+3}(T\lambda(B))^2 |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$. ■

Proposition 4.8. *Assume Hypothesis 1 and v is bounded. Then, $\forall \epsilon \geq 0$ such that $\epsilon^2 \leq (T\lambda(B))^{-2}$, one has*

$$\begin{aligned} \mathbb{E}\|\mathcal{P}^k v - C_n\|_{H_{\beta,X}^\mu}^2 &\leq K_0(T)\epsilon^2(T\lambda(B))^2\|v\|_{H_{\beta,X}^\mu}^2 \\ &\quad + K_0(T)c_0^2(v)(T\lambda(B))^2\left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)}\right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right). \end{aligned}$$

Proof. Using Lemma 4.7, we split $\mathcal{P}^k v(s, y) - C_n(s, y)$ in two terms, depending on the value of $|f_n(s, y) - \mathbb{E}[f_n(s, y)]|$ w.r.t. a constant ϵ . When $|f_n(s, y) - \mathbb{E}[f_n(s, y)]| \leq \epsilon$, we use the second inequality of Lemma 4.7, otherwise we use the first one. Since $r_n(s, y) \leq c_0(v)f_n(s, y)$, we use [4, Proposition 12.16] to get $\mathbb{E}|\mathcal{P}^k v(s, y) - C_n(s, y)|^2 \leq K(T)\epsilon^2(T\lambda(B))^4\mathbb{E}[r_n^2(s, y)] + K(T)c_0^2(v)\left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)}\right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right)$. We apply Proposition 3.2 and Lemma 3.5 to conclude. ■

4.3 Conclusion

To conclude, we combine Propositions 4.6 and 4.8 (with $\epsilon^2 = \frac{\delta_n}{T\lambda(B)}$). We obtain

Proposition 4.9. *We assume Hypothesis 1 and v is a bounded $C^{1,1}$ function. Then,*

$$\begin{aligned} \mathbb{E}\|\mathcal{P}^k v - v\|_{H_{\beta,X}^\mu}^2 &\leq K_0(T)(T\lambda(B)\delta_n\|v\|_{H_{\beta,X}^\mu}^2 \\ &\quad + h_t^2\|\partial_t v\|_{H_{\beta,X}^\mu}^2 + h_x^2\|\partial_x v\|_{H_{\beta,X}^\mu}^2) + c_0^2(v)K(T)(e^{-\frac{\mu a}{\sqrt{d}}} + T\lambda(B)\delta_n). \end{aligned}$$

Moreover, if $\partial_t v$ and $\partial_x v$ are bounded, we get $\|\mathbb{E}(\mathcal{P}^k v - v)\|_{H_{\beta,X}^\mu}^2 \leq K_0(T)c_{1,1}^2(v)(T\lambda(B)\delta_n + h_t^2 + h_x^2 + e^{-\frac{\mu a}{\sqrt{d}}})$.

5 Proof of Proposition 2.1: term $\mathbb{E}\|\partial_x(\mathcal{P}^k v) - \partial_x v\|_{H_{\beta,X}^\mu}^2$

We study $\mathbb{E}\|\partial_x(\mathcal{P}^k v) - \partial_x v\|_{H_{\beta,X}^\mu}^2$ componentwise, then we deal with $\mathbb{E}\|\partial_{x_i}(\mathcal{P}^k v) - \partial_{x_i} v\|_{H_{\beta,X}^\mu}^2$, for $1 \leq i \leq d$. The study of this term will be done in two steps. To do so, we add and subtract the term $\partial_{x_i} C_n(s, y)$ (see (4.1) for the definition of C_n) to $\partial_{x_i}(\mathcal{P}^k v)(s, y) - \partial_{x_i} v(s, y)$.

$$\partial_{x_i} C_n(s, y) = \left(\frac{\partial_{x_i} r_n(s, y)}{\mathbb{E}[f_n(s, y)]} - r_n(s, y) \frac{\mathbb{E}[\partial_{x_i} f_n(s, y)]}{(\mathbb{E}[f_n(s, y)])^2} \right) \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}} \quad (5.1)$$

We get $\mathbb{E}\|\partial_{x_i}(\mathcal{P}^k v) - \partial_{x_i} v\|_{H_{\beta,X}^\mu}^2 \leq 2\mathbb{E}\|\partial_{x_i}(\mathcal{P}^k v) - \partial_{x_i} C_n\|_{H_{\beta,X}^\mu}^2 + 2\mathbb{E}\|\partial_{x_i} C_n - \partial_{x_i} v\|_{H_{\beta,X}^\mu}^2$. The two following sections are devoted to the study of $\mathbb{E}\|\partial_{x_i} C_n - \partial_{x_i} v\|_{H_{\beta,X}^\mu}^2$ and $\mathbb{E}\|\partial_{x_i}(\mathcal{P}^k v) - \partial_{x_i} C_n\|_{H_{\beta,X}^\mu}^2$.

5.1 Study of $\mathbb{E}\|\partial_{x_i} C_n - \partial_{x_i} v\|_{H_{\beta,X}^\mu}^2$

Using the definition of $\partial_{x_i} C_n(s, y)$, we get

$$\begin{aligned} \partial_{x_i} C_n(s, y) - \partial_{x_i} v(s, y) &= -\partial_{x_i} v(s, y) \mathbf{1}_{\{s \notin [0, T] \cup y \notin B\}} \\ &\quad + \left(\frac{\partial_{x_i} r_n(s, y) - \partial_{x_i} v(s, y) \mathbb{E}[f_n(s, y)]}{\mathbb{E}[f_n(s, y)]} - r_n(s, y) \frac{\mathbb{E}[\partial_{x_i} f_n(s, y)]}{(\mathbb{E}[f_n(s, y)])^2} \right) \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}. \end{aligned} \quad (5.2)$$

Then, we split $\mathbb{E}\|\partial_{x_i} C_n - \partial_{x_i} v\|_{H_{\beta,X}^\mu}^2$ in two terms, by using the bias-variance decomposition: $\mathbb{E}\|\partial_{x_i} C_n - \partial_{x_i} v\|_{H_{\beta,X}^\mu}^2 = \|\mathbb{E}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta,X}^\mu}^2 + \|\text{Std}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta,X}^\mu}^2$.

5.1.1 Study of $\|\mathbb{E}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta,X}^\mu}^2$

By using (5.2), we split $\mathbb{E}(\partial_{x_i} C_n(s, y) - \partial_{x_i} v(s, y))$ in three terms :

$$\begin{aligned} B_1(s, y) &= \frac{\mathbb{E}[\partial_{x_i} r_n(s, y)] - \partial_{x_i} v(s, y) \mathbb{E}[f_n(s, y)]}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}, \\ B_2(s, y) &= -\mathbb{E}[r_n(s, y)] \frac{\mathbb{E}[\partial_{x_i} f_n(s, y)]}{(\mathbb{E}[f_n(s, y)])^2} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}, \\ B_3(s, y) &= -\partial_{x_i} v(s, y) \mathbf{1}_{\{s \notin [0, T] \cup y \notin B\}} \end{aligned}$$

such that $\mathbb{E}(\partial_{x_i} C_n(s, y) - \partial_{x_i} v(s, y)) = B_1(s, y) + B_2(s, y) + B_3(s, y)$.

We analyze each term in the three following Lemmas.

Lemma 5.1. *Let us assume Hypothesis 1. We also assume v is a bounded $C^{0,2}$ function which satisfies $\forall t, t' \in [0, T], \forall x \in \mathbb{R}^d, |\partial_x v(t, x) - \partial_x v(t', x)| \leq c_{1/2}(v) \sqrt{|t' - t|}$. Then,*

$$\|B_1(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T) h_x^2 \|\partial_x^2 v\|_{H_{\beta, X}^\mu}^2 + K_0(T) (c_{1/2}^2(v) h_t + c_0^2(v) e^{-\mu a} \frac{a^{d-1}}{h_x}).$$

If $\partial_x^2 v$ is bounded, we get $\|B_1(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T) (c_{0,2}^2(v) h_x^2 + c_{1/2}^2(v) h_t + c_0^2(v) e^{-\mu a} \frac{a^{d-1}}{h_x})$.

Proof. Let us recall $B_1(s, y) = \frac{\mathbb{E}[\partial_{x_i} r_n(s, y) - \partial_{x_i} v(s, y) \mathbb{E}[f_n(s, y)]]}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}$. We have $\mathbb{E}(\partial_{x_i} r_n(s, y)) = \frac{1}{h_t h_x^{d+1}} \frac{1}{T \lambda(B)} \int_0^T dr K_t \left(\frac{s-r}{h_t} \right) \int_B dz \partial_{x_i} K_x \left(\frac{y-z}{h_x} \right) v(r, z)$. We integrate by parts $\frac{1}{h_x} \int_{-a}^a dz_i (K_x^i)' \left(\frac{y_i - z_i}{h_x} \right) v(r, z)$ and we get $\frac{1}{h_x} \int_{-a}^a dz_i (K_x^i)' \left(\frac{y_i - z_i}{h_x} \right) v(r, z) = -K_x^i \left(\frac{y_i - a}{h_x} \right) v(r, z_{-a}^i) + K_x^i \left(\frac{y_i + a}{h_x} \right) v(r, z_{-a}^i) + \int_{-a}^a dz_i \partial_{x_i} v(r, z) K_x^i \left(\frac{y_i - z_i}{h_x} \right)$, where z_{-a}^i denotes the vector $(z_1, \dots, z_{i-1}, y, z_{i+1}, \dots, z_d)$. Then, $\mathbb{E}[\partial_{x_i} r_n(s, y) - \partial_{x_i} v(s, y) \mathbb{E}[f_n(s, y)]] = \frac{1}{T \lambda(B) h_t h_x^d} \int_0^T dr K_t \left(\frac{s-r}{h_t} \right) \int_B dz K_x \left(\frac{y-z}{h_x} \right) [\partial_{x_i} v(r, z) - \partial_{x_i} v(s, y)] + \frac{1}{T \lambda(B) h_t h_x^d} \int_0^T dr K_t \left(\frac{s-r}{h_t} \right) \int_{[-a, a]^{d-1}} dz^i \prod_{j=1, j \neq i}^d K_x^j \left(\frac{y_j - z_j}{h_x} \right) [-K_x^i \left(\frac{y_i - a}{h_x} \right) v(r, z_{-a}^i) + K_x^i \left(\frac{y_i + a}{h_x} \right) v(r, z_{-a}^i)]$. Combining this with the bound $\mathbb{E}[f_n(s, y)] \geq \frac{1}{2^{d+1} T \lambda(B)}$ (see Lemma 3.1) leads to the following upper bound for $B_1(s, y)$: $|B_1(s, y)| \leq B_{11}(s, y) + B_{12}(s, y) + B_{13}(s, y)$, where

$$\begin{aligned} B_{11}(s, y) &= \frac{2^{d+1}}{h_t h_x^d} \int_0^T dr K_t \left(\frac{s-r}{h_t} \right) \int_B dz K_x \left(\frac{y-z}{h_x} \right) [\partial_{x_i} v(r, z) - \partial_{x_i} v(s, z)] \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}, \\ B_{12}(s, y) &= \frac{2^{d+1}}{h_t h_x^d} \int_0^T dr K_t \left(\frac{s-r}{h_t} \right) \int_B dz K_x \left(\frac{y-z}{h_x} \right) [\partial_{x_i} v(s, z) - \partial_{x_i} v(s, y)] \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}, \\ B_{13}(s, y) &= \frac{2^{d+1}}{h_t h_x} c_0(v) c_0(K_x) \int_0^T dr K_t \left(\frac{s-r}{h_t} \right) (\mathbf{1}_{\{|y+a| \leq h_x\}} + \mathbf{1}_{\{|y-a| \leq h_x\}}) \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}. \end{aligned}$$

By using [4, Lemmas 12.53 and 12.54], we get $\|B_{11}(s, y)\|_{H_{\beta, X}^\mu}^2 \leq c_{1/2}^2(v) K(T) h_t$, $\|B_{12}(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T) h_x^2 \|\partial_x^2 v\|_{H_{\beta, X}^\mu}^2$. It remains to bound $\|B_{13}(s, y)\|_{H_{\beta, X}^\mu}^2$. We obtain $\|B_{13}(s, y)\|_{H_{\beta, X}^\mu}^2 \leq \frac{K_0(T) c_0^2(v)}{h_x^2} \int_0^T ds e^{\beta s} \int_{B \setminus B(0, a-h_x)} dy \nu_\mu^0(s, y)$. Since $\int_{B \setminus B(0, a-h_x)} dy \nu_\mu^0(s, y) \leq K(T) e^{-\mu(a-h_x)} a^{d-1} h_x$ (see [4, Equation (12.5), page 132]), we get $\|B_{13}(s, y)\|_{H_{\beta, X}^\mu}^2 \leq \frac{K_0(T) c_0^2(v)}{h_x} e^{-\mu a} a^{d-1}$. ■

Lemma 5.2. *Assume Hypothesis 1 and v is bounded. Then, $\|B_2(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T) c_0^2(v) e^{-\mu a} \frac{a^{d-1}}{h_x}$.*

Proof. Since v is bounded, we get $\mathbb{E}[r_n(s, y)] \leq c_0(v) \mathbb{E}[f_n(s, y)]$. Hence, $|B_2(s, y)| \leq c_0(v) \frac{\mathbb{E}[\partial_{x_i} f_n(s, y)]}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}$. To conclude, we apply Lemma 3.1 and Proposition 3.4. ■

Lemma 5.3. *Assume Hypothesis 1 and $\partial_x v$ is bounded. Then, $\|B_3(s, y)\|_{H_{\beta, X}^\mu}^2 \leq K(T)c_{0,1}^2(v)e^{-\frac{\mu a}{\sqrt{d}}}$.*

Proof. We refer to the proof of Lemma 4.3. ■

We combine Lemmas 5.1, 5.2 and 5.3 to get the following Proposition.

Proposition 5.4. *Assume Hypothesis 1 and v is a $C^{0,2} - C_b^{0,1}$ function which satisfies $\forall t, t' \in [0, T], \forall x \in \mathbb{R}^d, |\partial_x v(t, x) - \partial_x v(t', x)| \leq c_{1/2}(v)\sqrt{|t' - t|}$. Then,*

$$\|\mathbb{E}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)h_x^2 \|\partial_x^2 v\|_{H_{\beta, X}^\mu}^2 + K_0(T)(c_{1/2}^2(v)h_t + c_0^2(v)e^{-\mu a} \frac{a^{d-1}}{h_x} + c_{0,1}^2(v)e^{-\frac{\mu a}{\sqrt{d}}}).$$

Moreover, if $\partial_x^2 v$ is bounded, we get $\|\mathbb{E}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)(c_{0,2}^2(v) + c_{1/2}^2(v))(h_x^2 + h_t + e^{-\mu a} \frac{a^{d-1}}{h_x} + e^{-\frac{\mu a}{\sqrt{d}}})$.

5.1.2 Study of $\|\text{Std}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2$

Let us study $\|\text{Std}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 = \int_0^T ds e^{\beta s} \int_{\mathbb{R}^d} dy \nu_\mu^0(s, y) \text{Var}(\partial_{x_i} C_n - \partial_{x_i} v)(s, y)$.

Proposition 5.5. *Assume Hypothesis 1. It holds*

$$\|\text{Std}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T) \frac{T\lambda(B)\delta_n}{h_x^2} \|v\|_{H_{\beta, X}^\mu}^2.$$

If v is bounded, we get $\|\text{Std}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)c_0^2(v) \frac{T\lambda(B)\delta_n}{h_x^2}$.

Proof. We have $\|\text{Std}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 = \int_0^T ds e^{\beta s} \int_B dy \nu_\mu^0(s, y) \text{Var}(\partial_{x_i} C_n(s, y))$.

Using (5.1) leads to $\text{Var}(\partial_{x_i} C_n(s, y)) \leq$

$$2 \left(\frac{1}{(\mathbb{E}[f_n(s, y)])^2} \text{Var}(\partial_{x_i} r_n(s, y)) + \text{Var}(r_n(s, y)) \frac{(\mathbb{E}[\partial_{x_i} f_n(s, y)])^2}{(\mathbb{E}[f_n(s, y)])^4} \right) \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}}.$$

Then, we use [4, Proposition 12.51] and Lemma 3.1 to get $\int_0^T ds e^{\beta s} \int_B dy \nu_\mu^0(s, y) \frac{\text{Var}(\partial_{x_i} r_n(s, y))}{(\mathbb{E}[f_n(s, y)])^2} \leq K_0(T) \frac{T\lambda(B)\delta_n}{h_x^2} \|v\|_{H_{\beta, X}^\mu}^2$. It remains to bound

$\int_0^T ds e^{\beta s} \int_B dy \nu_\mu^0(s, y) \text{Var}(r_n(s, y)) \frac{(\mathbb{E}[\partial_{x_i} f_n(s, y)])^2}{(\mathbb{E}[f_n(s, y)])^4}$. To do it, we use Lemmas 3.1, 3.3 and the proof of Proposition 4.5. ■

5.1.3 Conclusion

We combine Propositions 5.4 and 5.5 to get the following result

Proposition 5.6. *Assume Hypothesis 1 and v is a $C^{1,2} - C_b^{0,1}$ function which satisfies $\forall t, t' \in [0, T], \forall x \in \mathbb{R}^d, |\partial_x v(t, x) - \partial_x v(t', x)| \leq c_{1/2}(v)\sqrt{|t' - t|}$. Then,*

$$\begin{aligned} \mathbb{E}\|\partial_{x_i} C_n - \partial_{x_i} v\|_{H_{\beta, X}^\mu}^2 &\leq K_0(T) \left(h_x^2 + \frac{T\lambda(B)\delta_n}{h_x^2} \right) \|v\|_{H_{\beta, X}^{\mu, 2}}^2 \\ &\quad + K_0(T) \left(c_{1/2}^2(v)h_t + c_0^2(v)e^{-\mu a} \frac{a^{d-1}}{h_x} + c_{0,1}^2(v)e^{-\frac{\mu a}{\sqrt{d}}} \right). \end{aligned}$$

Moreover, if $\partial_x^2 v$ is bounded, we get $\|\mathbb{E}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)(c_{0,2}^2(v) + c_{1/2}^2(v))(h_x^2 + \frac{T\lambda(B)\delta_n}{h_x^2} + h_t + e^{-\mu a} \frac{a^{d-1}}{h_x} + e^{-\frac{\mu a}{\sqrt{d}}})$.

5.2 Study of $\mathbb{E}\|\partial_{x_i}(\mathcal{P}^k v) - \partial_{x_i} C_n\|_{H_{\beta, X}^\mu}^2$

We have $\partial_{x_i}(\mathcal{P}^k v)(s, y) = \partial_{x_i} r_n(s, y) \frac{g(2^{d+1} T \lambda(B) f_n(s, y))}{f_n(s, y)} + 2^{2d+2} (T \lambda(B))^2 r_n(s, y) G'(2^{d+1} T \lambda(B) f_n(s, y)) \partial_{x_i} f_n(s, y)$, where G has been introduced in Remark 1.2. Using the definition of $\partial_{x_i} C_n$ (see (5.1)) yields

$$\begin{aligned} \partial_{x_i}(\mathcal{P}^k v)(s, y) - \partial_{x_i} C_n(s, y) &= \partial_{x_i} r_n(s, y) \left(\frac{g(2^{d+1} T \lambda(B) f_n(s, y))}{f_n(s, y)} - \frac{1}{\mathbb{E}[f_n(s, y)]} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}} \right) \\ &+ r_n(s, y) \left(2^{d+2} (T \lambda(B))^2 \partial_{x_i} f_n(s, y) G'(2^{d+1} T \lambda(B) f_n(s, y)) - \frac{\mathbb{E}[\partial_{x_i} f_n(s, y)]}{(\mathbb{E}[f_n(s, y)])^2} \mathbf{1}_{\{s \in [0, T]\}} \mathbf{1}_{\{y \in B\}} \right) \end{aligned} \quad (5.3)$$

Let us study $\partial_{x_i}(\mathcal{P}^k v)(s, y) - \partial_{x_i} C_n(s, y)$ w.r.t. the value of y . The first Lemma ensues from the Definition of f_n .

Lemma 5.7. *If $y \notin B_\infty(0, a + h_x)$, $\partial_{x_i}(\mathcal{P}^k v)(s, y) - \partial_{x_i} C_n(s, y) = 0$.*

Lemma 5.8. *If $y \in B_\infty(0, a + h_x) \setminus B$ and v is bounded, for all $i \in \{1, \dots, d\}$,*

$$\mathbb{E}|\partial_{x_i}(\mathcal{P}^k v)(s, y) - \partial_{x_i} C_n(s, y)|^2 \leq \frac{K_0(T) c_0^2(v)}{h_x^2}.$$

Proof. Let us introduce $\bar{f}_n^i(s, y) = \frac{1}{nh_t h_x^{d+1}} \sum_{i=1}^n K_t \left(\frac{s - T_i}{h_t} \right) |\partial_{x_i} K_x| \left(\frac{y - X_i}{h_x} \right)$. The indicators in (5.3) are null. Since $\frac{g(y)}{y}$ is bounded by 2 (see Remark 1.2 for the bounds for g and its first derivative), $\frac{|\partial_{x_i} r_n(s, y)|}{f_n(s, y)} g(2^{d+1} T \lambda(B) f_n(s, y)) \leq 2^{d+2} T \lambda(B) c_0(v) \bar{f}_n^i(s, y)$. It remains to bound the term containing G' . To do so, we write $G'(y) = \frac{g'(y)}{y} - \frac{g(y)}{y^2}$. Since $|G(y)| \leq 2$ and $|r_n(s, y)| \leq c_0(v) f_n(s, y)$, $|r_n(s, y)| \frac{g(2^{d+1} T \lambda(B) f_n(s, y))}{f_n^2(s, y)} |\partial_{x_i} f_n(s, y)| \leq 2^{d+2} T \lambda(B) c_0(v) |\partial_{x_i} f_n(s, y)|$. Since g' is bounded by 2, $2^{d+1} T \lambda(B) |r_n(s, y)| \frac{g'(2^{d+1} T \lambda(B) f_n(s, y))}{f_n(s, y)} |\partial_{x_i} f_n(s, y)|$ is bounded by $2^{d+2} T \lambda(B) c_0(v) |\partial_{x_i} f_n(s, y)|$. To conclude, we use $|\partial_{x_i} f_n(s, y)| \leq \bar{f}_n^i(s, y)$ and [4, Lemma 12.8], which states $\mathbb{E}(\bar{f}_n^i(s, y))^2 \leq \frac{K_0(T)}{h_x^2 (T \lambda(B))^2}$. ■

Lemma 5.9. *If $y \in B$, $\partial_{x_i}(\mathcal{P}^k v)(s, y) - \partial_{x_i} C_n(s, y) = A(s, y) + B(s, y) + C(s, y)$ where*

$$\begin{aligned} A(s, y) &= \partial_{x_i} r_n(s, y) \left(\frac{g(2^{d+1} T \lambda(B) f_n(s, y))}{f_n(s, y)} - \frac{1}{\mathbb{E}[f_n(s, y)]} \right), \\ B(s, y) &= 2^{2d+2} (T \lambda(B))^2 r_n(s, y) \partial_{x_i} f_n(s, y) [G'(2^{d+1} T \lambda(B) f_n(s, y)) - G'(2^{d+1} T \lambda(B) \mathbb{E}[f_n(s, y)])], \\ C(s, y) &= 2^{2d+2} (T \lambda(B))^2 r_n(s, y) G'(2^{d+1} T \lambda(B) \mathbb{E}[f_n(s, y)]) [\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]]. \end{aligned}$$

Proof. We add and subtract $2^{2d+2} (T \lambda(B))^2 r_n(s, y) \partial_{x_i} f_n(s, y) G'(2^{d+1} T \lambda(B) \mathbb{E}[f_n(s, y)])$ in (5.3) and we use $G'(2^{d+1} T \lambda(B) \mathbb{E}[f_n(s, y)]) = -\frac{1}{2^{2d+2} (T \lambda(B))^2 \mathbb{E}[f_n(s, y)]^2}$ (since $2^{d+1} T \lambda(B) \mathbb{E}[f_n(s, y)] \geq 1$). ■

5.2.1 Bound for $\mathbb{E}[A^2(s, y)]$

Lemma 5.10. *If v is bounded, $\forall \epsilon \geq 0$ such that $\epsilon^2 \leq (T\lambda(B))^{-2}$, we have*

$$\begin{aligned} \mathbb{E}[A^2(s, y)] &\leq K(T)(T\lambda(B))^4 \epsilon^2 \mathbb{E}[\partial_{x_i} r_n(s, y)]^2 \\ &+ K_0(T) c_0^2(v) \frac{(T\lambda(B))^2}{h_x^2} \left[\left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right) + \frac{\delta_n}{T\lambda(B)} \exp\left(-\frac{c}{T\lambda(B)\delta_n}\right) \right]. \end{aligned}$$

Proof. Studying $A(s, y)$ boils down to study $\mathcal{P}^k v - C_n$ where r_n is replaced by $\partial_{x_i} r_n$. First, the second inequality of Lemma 4.7 gives us

$$|A(s, y)| \leq 2^{d+3} (T\lambda(B))^2 |\partial_{x_i} r_n(s, y)| |f_n(s, y) - \mathbb{E}[f_n(s, y)]|,$$

and since $|\partial_{x_i} r_n(s, y)| \leq c_0(v) \bar{f}_n^i(s, y)$ ($\bar{f}_n^i(s, y)$ has been introduced in the proof of Lemma 5.8), we also have $|A(s, y)| \leq 2^{d+3} (T\lambda(B))^2 c_0(v) \bar{f}_n^i(s, y) |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$. As in the proof of Proposition 4.8, we split $A(s, y)$ in two terms, depending on the value of $|f_n(s, y) - \mathbb{E}[f_n(s, y)]|$ w.r.t. a constant ϵ_0 . When $|f_n(s, y) - \mathbb{E}[f_n(s, y)]| \leq \epsilon_0$, we use the first inequality, otherwise we use the second one. We get

$$\begin{aligned} |A(s, y)| &\leq 2^{d+3} (T\lambda(B))^2 \epsilon_0 |\partial_{x_i} r_n(s, y)| \\ &+ 2^{d+3} (T\lambda(B))^2 c_0(v) \bar{f}_n^i(s, y) |f_n(s, y) - \mathbb{E}[f_n(s, y)]| \mathbf{1}_{\{|f_n(s, y) - \mathbb{E}[f_n(s, y)]| \geq \epsilon_0\}}. \end{aligned}$$

We split again the second right hand term of the above inequality by introducing $\pm \mathbb{E}[\bar{f}_n^i(s, y)]$. We get

$$\begin{aligned} |A(s, y)| &\leq 2^{d+3} (T\lambda(B))^2 \epsilon_0 |\partial_{x_i} r_n(s, y)| \\ &+ 2^{d+3} (T\lambda(B))^2 c_0(v) |\bar{f}_n^i(s, y) - \mathbb{E}[\bar{f}_n^i(s, y)]| |f_n(s, y) - \mathbb{E}[f_n(s, y)]| \mathbf{1}_{\{|f_n(s, y) - \mathbb{E}[f_n(s, y)]| \geq \epsilon_0\}} \\ &+ 2^{d+3} (T\lambda(B)) c_0(v) \frac{K_0(T)}{h_x} |f_n(s, y) - \mathbb{E}[f_n(s, y)]| \mathbf{1}_{\{|f_n(s, y) - \mathbb{E}[f_n(s, y)]| \geq \epsilon_0\}}, \end{aligned}$$

where we have used $\mathbb{E}(\bar{f}_n^i(s, y))^2 \leq \frac{K_0(T)}{h_x^2 (T\lambda(B))^2}$. Then, we split the second term of the r.h.s. in two terms, depending on the value of $|\bar{f}_n^i(s, y) - \mathbb{E}[\bar{f}_n^i(s, y)]|$ w.r.t. a constant ϵ_1 . We obtain

$$\begin{aligned} |A(s, y)|^2 &\leq K(T)(T\lambda(B))^4 \epsilon_0^2 |\partial_{x_i} r_n(s, y)|^2 \\ &+ K(T)(T\lambda(B))^4 c_0^2(v) \bar{E}^2(s, y) E^2(s, y) \mathbf{1}_{\{E(s, y) \geq \epsilon_0\}} \mathbf{1}_{\{\bar{E}(s, y) \geq \epsilon_1\}} \\ &+ K_0(T)(T\lambda(B))^2 c_0^2(v) \left(\frac{1}{h_x^2} + (T\lambda(B))^2 \epsilon_1^2 \right) E^2(s, y) \mathbf{1}_{\{E(s, y) \geq \epsilon_0\}}. \end{aligned}$$

where $E(s, y) := |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$ and $\bar{E}(s, y) := |\bar{f}_n^i(s, y) - \mathbb{E}[\bar{f}_n^i(s, y)]|$. To conclude, it remains to apply [4, Propositions 12.16 and 12.18] (since $\bar{f}_n^i(s, y)$ is almost $\partial_{x_i} f_n$), Cauchy Schwarz inequality, to choose $\epsilon_1 = \frac{\epsilon_0}{h_x}$ and to use $\epsilon_0^2 \leq (T\lambda(B))^{-2}$. We get

$$\begin{aligned} \mathbb{E}[A^2(s, y)] &\leq K(T)(T\lambda(B))^4 \epsilon_0^2 \mathbb{E}[\partial_{x_i} r_n(s, y)]^2 \\ &+ K_0(T) c_0^2(v) \frac{(T\lambda(B))^2}{h_x^2} \left(\epsilon_0^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon_0^2 T\lambda(B)}{\delta_n}\right) \\ &+ K_0(T) c_0^2(v) \frac{(T\lambda(B))^4}{h_x^2} \left[\left(\epsilon_0^2 + \frac{\delta_n}{T\lambda(B)} \right)^2 \exp\left(-\frac{c\epsilon_0^2 T\lambda(B)}{\delta_n}\right) + \frac{\delta_n}{(T\lambda(B))^3} \exp\left(-\frac{c}{T\lambda(B)\delta_n}\right) \right]. \end{aligned}$$

Since $\epsilon_0^2 \leq (T\lambda(B))^{-2}$ and $T\lambda(B)\delta_n \ll 1$, we obtain $(T\lambda(B))^2(\epsilon_0^2 + \frac{\delta_n}{T\lambda(B)})^2 \leq \epsilon_0^2 + \frac{\delta_n}{T\lambda(B)}$, and the result follows. \blacksquare

5.2.2 Bound for $\mathbb{E}[B^2(s, y)]$

Lemma 5.11. *If v is bounded, $\forall \epsilon \geq 0$ such that $\epsilon^2 \leq (T\lambda(B))^{-2}$, we have*

$$\begin{aligned} \mathbb{E}[B^2(s, y)] &\leq C(d)(T\lambda(B))^4 \frac{\epsilon^2}{h_x^2} \mathbb{E}[r_n(s, y)]^2 \\ &+ K_0(T)c_0^2(v) \frac{(T\lambda(B))^2}{h_x^2} \left[\left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right) + \frac{\delta_n}{(T\lambda(B))} \exp\left(-\frac{c}{T\lambda(B)\delta_n}\right) \right]. \end{aligned}$$

Proof. First, we split $B(s, y)$ in two terms $B_1 + B_2$ by introducing $\pm \mathbb{E}[\partial_{x_i} f_n(s, y)]$. We get

$$\begin{aligned} B_1(s, y) &= 2^{2d+2} (T\lambda(B))^2 r_n(s, y) (\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]) \Delta G, \\ B_2(s, y) &= 2^{2d+2} (T\lambda(B))^2 r_n(s, y) \mathbb{E}[\partial_{x_i} f_n(s, y)] \Delta G, \end{aligned}$$

where $\Delta G := G'(2^{d+1}T\lambda(B)f_n(s, y)) - G'(2^{d+1}T\lambda(B)\mathbb{E}[f_n(s, y)])$.

Bound for B_2 . First, we use Lemma 3.3 to bound $\mathbb{E}[\partial_{x_i} f_n(s, y)]$: $\mathbb{E}[\partial_{x_i} f_n(s, y)] \leq \frac{K_0(T)}{T\lambda(B)h_x}$. Then, we give two bounds for B_2 . The first one uses that G' is a Lipschitz function on $[0, \infty[$. We get $G'(2^{d+1}T\lambda(B)f_n(s, y)) - G'(2^{d+1}T\lambda(B)\mathbb{E}[f_n(s, y)]) \leq C(d)T\lambda(B)|f_n(s, y) - \mathbb{E}[f_n(s, y)]|$. Thus, $|B_2(s, y)| \leq C(d) \frac{(T\lambda(B))^2}{h_x} r_n(s, y) |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$. The second bound relies on the inequality $r_n(s, y) \leq c_0(v)f_n(s, y)$ and the fact that the function $\tilde{g}(x) := xG'(2^{d+1}T\lambda(B)x) - xG'(2^{d+1}T\lambda(B)\mathbb{E}[f_n(s, y)])$ satisfies $\tilde{g}(\mathbb{E}[f_n(s, y)]) = 0$ and is a Lipschitz function. We get $|B_2(s, y)| \leq C(d)c_0(v) \frac{T\lambda(B)}{h_x} |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$. Once again, we split $B_2(s, y)$ in two terms, depending on the value of $|f_n(s, y) - \mathbb{E}[f_n(s, y)]|$ w.r.t. a constant ϵ . When $|f_n(s, y) - \mathbb{E}[f_n(s, y)]| \leq \epsilon$, we use the first inequality, otherwise we use the second one. By using [4, Proposition 12.16], we get

$$\mathbb{E}[B_2(s, y)]^2 \leq \epsilon^2 \frac{(T\lambda(B))^4}{h_x^2} \mathbb{E}[r_n(s, y)]^2 + K_0(T)c_0^2(v) \frac{(T\lambda(B))^2}{h_x^2} \left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right).$$

Bound for B_1 . As for B_2 , we give two bounds for B_1 : $|B_1(s, y)| \leq C(d)(T\lambda(B))^3 r_n(s, y) |\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]| |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$ and $|B_1(s, y)| \leq C(d)c_0(v)(T\lambda(B))^2 |\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]| |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$. Then, we split B_1 in four terms, depending on the value of $|f_n(s, y) - \mathbb{E}[f_n(s, y)]|$ w.r.t. a constant ϵ_0 and on the value of $|\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]|$ w.r.t. a constant ϵ_1 . We introduce $E'(s, y) := |\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]|$. Then, we get

$$\begin{aligned} |B_1(s, y)| &\leq |B_1(s, y)| \mathbf{1}_{\{E' \leq \epsilon_1\}} \mathbf{1}_{\{E \leq \epsilon_0\}} + |B_1(s, y)| \mathbf{1}_{\{E' \leq \epsilon_1\}} \mathbf{1}_{\{E > \epsilon_0\}} \\ &+ |B_1(s, y)| \mathbf{1}_{\{E' > \epsilon_1\}} \mathbf{1}_{\{E \leq \epsilon_0\}} + |B_1(s, y)| \mathbf{1}_{\{E' > \epsilon_1\}} \mathbf{1}_{\{E > \epsilon_0\}}. \end{aligned}$$

We bound the first term (resp. the three other terms) by using the first (resp. second) bound for B_1 . Applying Cauchy-Schwarz inequality, [4, Propositions 12.16 and 12.18] and choosing

$\epsilon_1 = \frac{\epsilon_0}{h_x}$ yield

$$\begin{aligned} \mathbb{E}|B_1(s, y)|^2 &\leq K(T)(T\lambda(B))^6 \frac{\epsilon_0^4}{h_x^2} \mathbb{E}[r_n(s, y)]^2 \\ &+ K(T)c_0^2(v) \frac{(T\lambda(B))^4 \epsilon_0^2}{h_x^2} \left(\epsilon_0^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon_0^2 T\lambda(B)}{\delta_n}\right) \\ &+ K(T)c_0^2(v) \frac{(T\lambda(B))^4}{h_x^2} \left[\left(\epsilon_0^2 + \frac{\delta_n}{T\lambda(B)} \right)^2 \exp\left(-\frac{c\epsilon_0^2 T\lambda(B)}{\delta_n}\right) + \frac{\delta_n}{(T\lambda(B))^3} \exp\left(-\frac{c}{T\lambda(B)\delta_n}\right) \right]. \end{aligned}$$

For $\epsilon_0^2 \leq (T\lambda(B))^{-2}$, we get $(T\lambda(B))^6 \frac{\epsilon_0^4}{h_x^2} \leq (T\lambda(B))^4 \frac{\epsilon_0^2}{h_x^2} \leq \frac{(T\lambda(B))^2}{h_x^2}$. Hence, the first two terms of the bound for $\mathbb{E}|B_1(s, y)|^2$ are smaller than the terms bounding $\mathbb{E}|B_2(s, y)|^2$. We end the proof as in Lemma 5.10. \blacksquare

5.2.3 Bound for $\mathbb{E}[C^2(s, y)]$

Lemma 5.12. *If v is bounded, $\forall \epsilon \geq 0$ such that $\epsilon^2 \leq (T\lambda(B))^{-2}$, we have*

$$\begin{aligned} \mathbb{E}[C^2(s, y)] &\leq K(T)(T\lambda(B))^4 \frac{\epsilon^2}{h_x^2} \mathbb{E}[r_n(s, y)]^2 \\ &+ K_0(T)c_0^2(v) \frac{(T\lambda(B))^2}{h_x^2} \left[\left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right) + \frac{\delta_n}{(T\lambda(B))} \exp\left(-\frac{c}{T\lambda(B)\delta_n}\right) \right]. \end{aligned}$$

Proof. We recall $C(s, y) = 2^{2d+2}(T\lambda(B))^2 r_n(s, y) G'(2^{d+1}T\lambda(B)\mathbb{E}[f_n(s, y)])[\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]]$. We use that G' is bounded and we split $C(s, y)$ in two terms depending on the value of $E' = |\partial_{x_i} f_n(s, y) - \mathbb{E}[\partial_{x_i} f_n(s, y)]|$ w.r.t. a constant ϵ_1 . We get

$$|C(s, y)|^2 \leq C(d)(T\lambda(B))^4 \epsilon_1^2 |r_n(s, y)|^2 + C(d)(T\lambda(B))^4 c_0^2(v) |f_n(s, y)|^2 (E')^2 \mathbf{1}_{\{E' > \epsilon_1\}},$$

where we have used $r_n(s, y) \leq c_0(v)f_n(s, y)$. Then, we split the second term of the r.h.s. of the above inequality by introducing $\pm \mathbb{E}[f_n(s, y)]$. Since $\mathbb{E}[f_n(s, y)] \leq \frac{1}{T\lambda(B)}$, we obtain

$$\begin{aligned} |C(s, y)|^2 &\leq K(T)(T\lambda(B))^4 \epsilon_1^2 |r_n(s, y)|^2 + K(T)(T\lambda(B))^2 c_0^2(v) (E')^2 \mathbf{1}_{\{E' > \epsilon_1\}} \\ &+ K(T)(T\lambda(B))^4 c_0^2(v) (E')^2 \mathbf{1}_{\{E' > \epsilon_1\}} |f_n(s, y) - \mathbb{E}[f_n(s, y)]|^2. \end{aligned}$$

Finally, we split the last term of the above inequality in two terms depending on the value of $E = |f_n(s, y) - \mathbb{E}[f_n(s, y)]|$ w.r.t. a constant ϵ_0 . We get

$$\begin{aligned} |C(s, y)|^2 &\leq K(T)(T\lambda(B))^4 \epsilon_1^2 |r_n(s, y)|^2 + C(d)(T\lambda(B))^4 \left(\frac{1}{(T\lambda(B))^2} + \epsilon_0^2 \right) c_0^2(v) (E')^2 \mathbf{1}_{\{E' > \epsilon_1\}} \\ &+ K(T)(T\lambda(B))^4 c_0^2(v) (E')^2 \mathbf{1}_{\{E' > \epsilon_1\}} E^2 \mathbf{1}_{\{E > \epsilon_0\}}. \end{aligned}$$

Combining Cauchy Schwarz inequality, [4, Propositions 12.16 and 12.18], choosing $\epsilon_1 = \frac{\epsilon_0}{h_x}$ and using $\epsilon_0 \leq (T\lambda(B))^{-1}$ and $T\lambda(B)\delta_n \ll 1$ lead to the result. \blacksquare

5.2.4 Conclusion

Combining Lemmas 5.10, 5.11 and 5.12 leads to the following Proposition.

Proposition 5.13. *If v is bounded, $\forall \epsilon \geq 0$ such that $\epsilon^2 \leq (T\lambda(B))^{-2}$ and $y \in B$, we have*

$$\begin{aligned} \mathbb{E}[|\partial_{x_i}(\mathcal{P}^k v)(s, y) - \partial_{x_i} C_n(s, y)|^2] &\leq C(d)(T\lambda(B))^4 \epsilon^2 \left(\mathbb{E}[\partial_{x_i} r_n(s, y)]^2 + \frac{1}{h_x^2} \mathbb{E}[r_n(s, y)]^2 \right) \\ &+ K_0(T) c_0^2(v) \frac{(T\lambda(B))^2}{h_x^2} \left[\left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right) + \frac{\delta_n}{(T\lambda(B))} \exp\left(-\frac{c}{T\lambda(B)\delta_n}\right) \right]. \end{aligned}$$

Combining Lemmas 5.7, 5.8, Proposition 5.13 and following the same proof as [4, Theorem 12.50] yields

Proposition 5.14. *Assume Hypothesis 1 and v is bounded. Then, $\forall \epsilon \geq 0$ such that $\epsilon^2 \leq (T\lambda(B))^{-2}$, we have*

$$\begin{aligned} \mathbb{E}\|\partial_{x_i}(\mathcal{P}^k v) - \partial_{x_i} C_n\|_{H_{\beta, X}^\mu}^2 &\leq K_0(T)(T\lambda(B))^2 \epsilon^2 (\|\partial_x v\|_{H_{\beta, X}^\mu}^2 + \frac{1}{h_x^2} \|v\|_{H_{\beta, X}^\mu}^2) + c_0^2(v) \frac{K_0(T)}{h_x} e^{-\mu a} a^{d-1} \\ &+ K_0(T) c_0^2(v) \frac{(T\lambda(B))^2}{h_x^2} \left[\left(\epsilon^2 + \frac{\delta_n}{T\lambda(B)} \right) \exp\left(-\frac{c\epsilon^2 T\lambda(B)}{\delta_n}\right) + \frac{\delta_n}{T\lambda(B)} \exp\left(-\frac{c}{T\lambda(B)\delta_n}\right) \right]. \end{aligned}$$

5.3 Conclusion

We combine Propositions 5.14 and 5.6 with $\epsilon^2 = \frac{\delta_n}{T\lambda(B)}$ to get the following result

Proposition 5.15. *Assume Hypothesis 1 and v is a $C^{1,2} - C_b^{0,1}$ function satisfying $\forall t, t' \in [0, T], \forall x \in \mathbb{R}^d, |\partial_x v(t, x) - \partial_x v(t', x)| \leq c_{1/2}(v) \sqrt{|t' - t|}$. Then,*

$$\begin{aligned} \mathbb{E}\|\partial_x(\mathcal{P}^k v) - \partial_x v\|_{H_{\beta, X}^\mu}^2 &\leq K_0(T) \left(h_x^2 + \frac{T\lambda(B)\delta_n}{h_x^2} \right) \|v\|_{H_{\beta, X}^{2, \mu}}^2 \\ &+ K_0(T) \left(c_{1/2}^2(v) h_t + c_0^2(v) e^{-\mu a} \frac{a^{d-1}}{h_x} + c_{0,1}^2(v) e^{-\frac{\mu a}{\sqrt{d}}} + c_0^2(v) \frac{T\lambda(B)\delta_n}{h_x^2} \right). \end{aligned}$$

Moreover, if $\partial_x^2 v$ is bounded, we get $\|\mathbb{E}(\partial_{x_i} C_n - \partial_{x_i} v)\|_{H_{\beta, X}^\mu}^2 \leq K_0(T)(c_{0,2}^2(v) + c_{1/2}^2(v))(h_x^2 + \frac{T\lambda(B)\delta_n}{h_x^2} + h_t + e^{-\mu a} \frac{a^{d-1}}{h_x} + e^{-\frac{\mu a}{\sqrt{d}}})$.

6 Proof of Proposition 2.2

6.1 Bound for $\mathbb{E}\|\mathcal{P}^k v\|_{H_{\beta, X}^\mu}^2$

From the definition of \mathcal{P}^k and since $\frac{g(x)}{x}$ is bounded by 2, we deduce $|\mathcal{P}^k v(s, y)|^2 \leq 2^{2d+3}(T\lambda(B))^2 |r_n|^2(s, y)$. Then, Proposition 3.2 gives

$$\begin{aligned} \mathbb{E}(|\mathcal{P}^k v(s, y)|^2) &\leq 2^{2d+3}(T\lambda(B))^2 \mathbb{E}(|r_n|^2(s, y)), \\ &\leq \frac{K_0(T)}{h_t h_x^d} \int_0^T dr K_t^2\left(\frac{s-r}{h_t}\right) \int_B dz K_x^2\left(\frac{y-z}{h_x}\right) \mathbb{E}(v^2(r, z)). \end{aligned}$$

Using the definition of $\|\cdot\|_{H_{\beta,X}^\mu}$ and Lemma 3.5 yields $\mathbb{E}\|\mathcal{P}^k v\|_{H_{\beta,X}^\mu}^2 \leq K_0(T)\mathbb{E}\|v\|_{H_{\beta,X}^\mu}^2$. If v is unbiased, $\mathbb{E}(|r_n|^2(s,y)) = \text{Var}(r_n(s,y))$. Proposition 3.2 gives

$$\begin{aligned} \mathbb{E}(|\mathcal{P}^k v(s,y)|^2) &\leq 2^{2d+3}(T\lambda(B))^2 \text{Var}(r_n(s,y)), \\ &\leq \frac{K_0(T)T\lambda(B)}{nh_t^2 h_x^{2d}} \int_0^T dr K_t^2\left(\frac{s-r}{h_t}\right) \int_B dz K_x^2\left(\frac{y-z}{h_x}\right) \mathbb{E}(v^2(r,z)), \end{aligned}$$

and we get $\mathbb{E}\|\mathcal{P}^k v\|_{H_{\beta,X}^\mu}^2 \leq K_0(T)T\lambda(B)\delta_n \mathbb{E}\|v\|_{H_{\beta,X}^\mu}^2$.

6.2 Bound for $\mathbb{E}\|\partial_x(\mathcal{P}^k v)(t,x)\|_{H_{\beta,X}^\mu}^2$

We have $\partial_{x_i} \mathcal{P}^k v(s,y) = 2^{d+1}T\lambda(B)\partial_{x_i} r_n(s,y)G(2^{d+1}T\lambda(B)f_n(s,y)) + (2^{d+1}T\lambda(B))^2 r_n(s,y)\partial_{x_i} f_n(s,y)G'(2^{d+1}T\lambda(B)f_n(s,y))$ where G has been introduced in Remark 1.2. Using the bounds for G and G' , we obtain $|\partial_{x_i} \mathcal{P}^k v(s,y)| \leq 2^{d+2}T\lambda(B)|\partial_{x_i} r_n(s,y)| + 6 * 2^{2d+2}(T\lambda(B))^2 |r_n(s,y)| |\partial_{x_i} f_n(s,y)|$, and

$$\mathbb{E}\|\partial_{x_i}(\mathcal{P}^k v)\|_{H_{\beta,X}^\mu}^2 \leq C(d)(T\lambda(B))^2 (\mathbb{E}\|\partial_{x_i} r_n\|_{H_{\beta,X}^\mu}^2 + (T\lambda(B))^2 \mathbb{E}\|(r_n \partial_{x_i} f_n)\|_{H_{\beta,X}^\mu}^2).$$

6.2.1 Bound for $(T\lambda(B))^2 \mathbb{E}\|\partial_{x_i} r_n\|_{H_{\beta,X}^\mu}^2$

We write $\mathbb{E}(|\partial_{x_i} r_n(s,y)|^2) = (\mathbb{E}(\partial_{x_i} r_n(s,y)))^2 + \text{Var}(\partial_{x_i} r_n(s,y))$. As in Proposition 3.2, we get $(\mathbb{E}(\partial_{x_i} r_n(s,y)))^2 \leq \frac{1}{h_t h_x^{d+2}} \frac{1}{(T\lambda(B))^2} \int_0^T dr K_t^2\left(\frac{s-r}{h_t}\right) \int_B dz (\partial_{x_i} K_x)^2\left(\frac{y-z}{h_x}\right) \mathbb{E}(v^2(r,z))$, $\text{Var}(\partial_{x_i} r_n(s,y)) \leq \frac{1}{nh_t h_x^{d+2} T\lambda(B)} \int_0^T dr K_t^2\left(\frac{s-r}{h_t}\right) \int_B dz (\partial_{x_i} K_x)^2\left(\frac{y-z}{h_x}\right) \mathbb{E}(v^2(r,z))$. Since we assume $T\lambda(B)\delta_n \ll 1$, Lemma 3.5 yields $(T\lambda(B))^2 \mathbb{E}\|\partial_{x_i} r_n\|_{H_{\beta,X}^\mu}^2 \leq \frac{K_0(T)}{h_x^2} \mathbb{E}\|v\|_{H_{\beta,X}^\mu}^2$. If v is unbiased, we get $(T\lambda(B))^2 \mathbb{E}\|\partial_{x_i} r_n\|_{H_{\beta,X}^\mu}^2 \leq K_0(T) \frac{T\lambda(B)\delta_n}{h_x^2} \mathbb{E}\|v\|_{H_{\beta,X}^\mu}^2$.

6.2.2 Bound for $(T\lambda(B))^4 \mathbb{E}\|r_n \partial_{x_i} f_n\|_{H_{\beta,X}^\mu}^2$

First, we develop the product $r_n^2(s,y)(\partial_{x_i} f_n)^2(s,y)$ by using the following formulae $(\partial_{x_i} f_n(s,y))^2 = \frac{1}{n^2 h_t^2 h_x^{2d+2}} \left(\sum_{j=1}^n K_t^2(j)(\partial_{x_i} K_x)^2(j) + \sum_{i,j=1, i \neq j}^n K_t(i)K_t(j)(\partial_{x_i} K_x)(i)(\partial_{x_i} K_x)(j) \right) := A + B$, $r_n^2(s,y) = \frac{1}{n^2 h_t^2 h_x^{2d}} \left(\sum_{k=1}^n K_t^2(k)K_x^2(k)v^2(k) + \sum_{k,l=1, k \neq l}^n K_t(k)K_t(l)K_x(k)K_x(l)v(k)v(l) \right) := C + D$, where $K_t(j) := K_t\left(\frac{s-T_j}{h_t}\right)$, $K_x(j) := K_x\left(\frac{y-X_j}{h_x}\right)$, $(\partial_{x_i} K_x)(j) := (\partial_{x_i} K_x)\left(\frac{y-X_j}{h_x}\right)$ and $v(k) := v(T_k, X_k)$. Developing $A \times C$ leads to

$$\begin{aligned} \mathbb{E}(A \times C) &= \frac{1}{n^4 h_t^4 h_x^{4d+2}} (n\mathbb{E}(K_t^4(1)(\partial_{x_i} K_x)^2(1)K_x^2(1)v^2(1)) \\ &\quad + n(n-1)\mathbb{E}(K_t^2(1)(\partial_{x_i} K_x)^2(1))\mathbb{E}(K_t^2(1)K_x^2(1)v^2(1))). \end{aligned}$$

Since $\mathbb{E}(K_t^2(1)(\partial_{x_i} K_x)^2(1))$ is bounded by $K_0(T) \frac{h_t h_x^d}{T\lambda(B)}$, we get $\mathbb{E}(A \times C) \leq \frac{\delta_n^3}{h_t h_x^{d+2}} \mathbb{E}(K_t^4(1)(\partial_{x_i} K_x)^2(1)K_x^2(1)v^2(1)) + \frac{\delta_n^2}{T\lambda(B)h_t h_x^{d+2}} \mathbb{E}(K_t^2(1)K_x^2(1)v^2(1))$. We write terms

of type $\mathbb{E}(g_t(1)g_x(1)v^2(1))$ as $\frac{1}{T\lambda(B)} \int_0^T dr g_t \left(\frac{s-r}{h_t} \right) \int_B dz g_x \left(\frac{y-z}{h_x} \right) \mathbb{E}(v^2(r, z))$, where g_t (resp g_x) represents a function depending on K_t (resp. on K_x and $\partial_x K_x$). Finally, by using the same procedure for the other terms, we obtain $\mathbb{E}((\partial_{x_i} f_n(s, y))^2 (r_n^2(s, y))) \leq \frac{K_0(T)}{(T\lambda(B))^4 h_t h_x^{d+2}} \int_0^T dr g_t \left(\frac{s-r}{h_t} \right) \int_B dz g_x \left(\frac{y-z}{h_x} \right) \mathbb{E}(v^2(r, z))$. Applying Lemma 3.5 yields $(T\lambda(B))^4 \mathbb{E} \|r_n \partial_{x_i} f_n\|_{H_{\beta, X}^\mu}^2 \leq \frac{K_0(T)}{h_x^2} \mathbb{E} \|v\|_{H_{\beta, X}^\mu}^2$.

If v is unbiased, terms like $(\mathbb{E}(K_t(1)K_x(1)v(1)))^2$ are null and this leads to $(T\lambda(B))^4 \mathbb{E} \|r_n \partial_{x_i} f_n\|_{H_{\beta, X}^\mu}^2 \leq \frac{K_0(T)T\lambda(B)\delta_n}{h_x^2} \mathbb{E} \|v\|_{H_{\beta, X}^\mu}^2$.

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