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# Improving Monte Carlo simulations by Dirichlet forms 

Nicolas Bouleau


#### Abstract

Equipping the probability space with a local Dirichlet form with square field operator $\Gamma$ and generator $A$ allows to improve Monte Carlo simulations of expectations and densities as soon as we are able to simulate a random variable $X$ together with $\Gamma[X]$ and $A[X]$. We give examples on the Wiener space, on the Poisson space and on the Monte Carlo space. When $X$ is real-valued we give an explicit formula yielding the density at the speed of the law of large numbers.


## Résumé

Nous montrons que, dans les situations où l'espace de probabilité est équipé d'une forme de Dirichlet locale avec carré du champ $\Gamma$ et générateur $A$, la possibilité de simuler une variable aléatoire $X$ ainsi que $\Gamma[X]$ et $A[X]$ permet d'accélérer le calcul de l'espérance de $X$ et de sa densité. Nous donnons des exemples dans les cas de l'espace de Wiener, de l'espace de Poisson et de l'espace de Monte Carlo. Lorsque $X$ est à valeurs réelles nous donnons une formule explicite permettant d'obtenir la densité à la vitesse de la loi des grands nombres. Pour citer cet article : N. Bouleau, C. R. Acad. Sci. Paris, Ser. I ... (2005).

## 1 Introduction

The efficiency of Dirichlet forms is known in order to obtain existence of densities under weak hypotheses (cf [3]). We show here that they are still usefull for the computation of such densities. Our framework is an error structure $(\Omega, \mathcal{A}, \mathbb{P}, \mathbb{D}, \Gamma)$, i.e. a probability space equipped with a local Dirichlet form $(\mathcal{E}, \mathbb{D})$ admitting a square field operator $\Gamma$ (cf $[2],[3])$. The associated $L^{2}$-generator is denoted $(A, \mathcal{D} A)$.

We consider a random variable $X \in \mathcal{D} A$ such that $X, \Gamma[X]$ and $A[X]$ are simulatable.
Example 1. Wiener space.
Let us consider a stochastic differential equation (sde) defined on the Wiener space equipped with the Ornstein-Uhlenbeck error structure (cf [2],[3])

$$
X_{t}=x_{0}+\int_{0}^{t} \sigma\left(X_{s}, s\right) d B_{s}+\int_{0}^{t} r\left(X_{s}, s\right) d s
$$

By the functional calculus for the operators $\Gamma$ and $A$, if the coefficients are smooth, the
triplet $\left(X_{t}, \Gamma\left[X_{t}\right], A\left[X_{t}\right]\right)$ is a diffusion, solution to the equation

$$
\begin{aligned}
\left(\begin{array}{l}
X_{t} \\
\Gamma\left[X_{t}\right] \\
A\left[X_{t}\right]
\end{array}\right)= & \left(\begin{array}{l}
x_{0} \\
0 \\
0
\end{array}\right)+\int_{0}^{t}\left[\begin{array}{ccc}
\sigma\left(X_{s}, s\right) & 0 & 0 \\
0 & 2 \sigma_{x}^{\prime}\left(X_{s}, s\right) & 0 \\
-\frac{1}{2} \sigma\left(X_{s}, s\right) & \frac{1}{2} \sigma_{x^{2}}^{\prime \prime}\left(X_{s}, s\right) & \sigma_{x}^{\prime}\left(X_{s}, s\right)
\end{array}\right]\left(\begin{array}{l}
1 \\
\Gamma\left[X_{s}\right] \\
A\left[X_{s}\right]
\end{array}\right) d B_{s} \\
& +\int_{0}^{t}\left[\begin{array}{ccc}
r\left(X_{s}, s\right) & 0 & 0 \\
\sigma^{2}\left(X_{s}, s\right) & 2 r_{x}^{\prime}\left(X_{s}, s\right)+\sigma_{x}^{\prime 2}\left(X_{s}, s\right) & 0 \\
0 & \frac{1}{2} r_{x^{2}}^{\prime \prime}\left(X_{s}, s\right) & r_{x}^{\prime}\left(X_{s}, s\right)
\end{array}\right]\left(\begin{array}{l}
1 \\
\Gamma\left[X_{s}\right] \\
A\left[X_{s}\right]
\end{array}\right) d s
\end{aligned}
$$

Denoting $Y_{t}$ the column vector $\left(X_{t}, \Gamma\left[X_{t}\right], A\left[X_{t}\right]\right)$ this equation writes $Y_{t}=Y_{0}+\int_{0}^{t} a\left(Y_{s}, s\right) d B_{s}+$ $\int_{0}^{t} b\left(Y_{s}, s\right) d s$ and applying the Euler scheme with mesh $\frac{1}{n}$ on $[0, T]: Y_{t}^{n}=Y_{0}+\int_{0}^{t} a\left(Y_{\frac{[n s]}{n}}^{n}, \frac{[n s]}{n}\right) d B_{s}+$ $\int_{0}^{t} b\left(Y_{\frac{[n s]}{n}}^{n}, \frac{[n s]}{n}\right) d s$. yields a process $Y_{t}^{n}=\left(X_{t}^{n},(\Gamma[X])_{t}^{n},(A[X])_{t}^{n}\right)^{t}$ for which it is easy to verify that $\Gamma\left[X_{t}^{n}\right]=(\Gamma[X])_{t}^{n}$ and $A\left[X_{t}^{n}\right]=(A[X])_{t}^{n}$.

By known results (cf [1] [4] [5]) in order to compute the density of $X_{T}$, we may approximate it by the solution $X_{T}^{n}$ of the Euler scheme. Thus, we have then to simulate $X_{T}^{n}$ in a situation where we are also able to simulate $\Gamma\left[X_{T}^{n}\right]$ and $A\left[X_{T}^{n}\right]$.

Example 2. Poisson space.
Let $\left(\mathbb{R}^{d}, \mathcal{B}\left(\mathbb{R}^{d}\right), \mu, \mathbf{d}, \gamma\right)$ be an error structure on $\mathbb{R}^{d},(a, \mathcal{D} a)$ its generator. Let $N$ be a Poisson point process defined on $(\Omega, \mathcal{A}, \mathbb{P})$ with state space $\mathbb{R}^{d}$ and intensity measure $\mu$. $(\Omega, \mathcal{A}, \mathbb{P})$ may be equipped with a so-called "white" error structure $(\Omega, \mathcal{A}, \mathbb{P}, \mathbb{D}, \Gamma)$ (cf [2]) with the following properties : if $h \in \mathcal{D} a$ then $N(h) \in \mathcal{D} A, \Gamma[N(h)]=N(\gamma[h])$ and $A[N(h)]=N(a[h])$.

In order to simulate $N(\xi)$ we have only to draw a finite (poissonian) number of i.i.d. random variables with law $\mu$ so that we are indeed in a situation where $N(h), \Gamma[N(h)]$, and $A[N(h)]$ are simulatable.

Example 3. Monte Carlo space.
Let $X=F\left(U_{0}, U_{1}, \ldots, U_{m}, \ldots ; V_{0}, V_{1}, \ldots, V_{n}, \ldots\right)$ be a random variable defined on the space
$\left([0,1]^{\mathbf{N}}, \mathcal{B}\left([0,1]^{\mathbf{N}}\right), d x^{\mathbf{N}}\right) \times\left([0,1]^{\mathbb{N}}, \mathcal{B}\left([0,1]^{\mathbf{N}}\right), d x^{\mathbf{N}}\right)$ where the $U_{i}$ are the coordinates of the first factor with respect to which $X$ is supposed to be regular, $V_{j}$ the ones of the second factor with respect to which $X$ is supposed to be irregular or discontinuous (rejection method, etc.).

Let us put on the $U_{i}$ the following error structure

$$
\left([0,1]^{\mathbb{N}}, \mathcal{B}\left([0,1]^{\mathbb{N}}\right), d x^{\mathbb{N}}, \mathbb{D}, \Gamma\right)=([0,1], \mathcal{B}([0,1]), d x, \mathbf{d}, \gamma)^{\mathbb{N}}
$$

where $(\mathbf{d}, \gamma)$ is the closure of the operator $\gamma[u](x)=x^{2}(1-x)^{2} u^{\prime 2}(x)$ for $u \in \mathcal{C}^{1}([0,1])$.
Then under natural regularity assumptions, we have $\Gamma[X]=\sum_{i=0}^{\infty} F_{i}^{\prime 2} U_{i}^{2}\left(1-U_{i}\right)^{2}$. and

$$
A[X]=\sum_{i=0}^{\infty}\left(\frac{1}{2} F_{i i}^{\prime \prime} U_{i}^{2}\left(1-U_{i}\right)^{2}+F_{i}^{\prime} U_{i}\left(1-U_{i}\right)\left(1-2 U_{i}\right)\right)
$$

so that $X, \Gamma[X]$ and $A[X]$ are simulatable.

## 2 Diminishing the bias

Let $(\Omega, \mathcal{A}, \mathbb{P}, \mathbb{D}, \Gamma)$ be an error structure. For $X \in(\mathcal{D} A)^{d}$, $\operatorname{var}[X]$ denotes the covariance matrix of $X, A[X]$ the column vector with components $\left.\left({\bar{A}\left[X_{1}\right.}\right], \ldots, A\left[X_{d}\right]\right), \underline{\Gamma}[X]$ is the matrix $\Gamma\left[X_{i}, X_{j}\right]$ and $\sqrt{\underline{\underline{\Gamma}}[X]}$ denotes the positive symmetric square root of $\underline{\underline{\Gamma}}[X]$.

We follow the idea that the random variable $X+\varepsilon A[X]+\sqrt{\varepsilon} \sqrt{\underline{\underline{\Gamma}}[X]} G$ where $G$ is an exogeneous independent reduced Gaussian variable, has almost the same law as $X$. Starting from the fundamental relation of the functional calculus on $A$, an integration by parts argument gives the following lemma.

Lemma 2.1 Let $X \in(\mathcal{D} A)^{d}$. we suppose that $X$ possesses a conditional density $\eta(x, \gamma, a)$ given $\underline{\underline{\Gamma}}[X]=\gamma$ et $A[X]=a$ such that $x \mapsto \eta(x, \gamma, a)$ be $\mathcal{C}^{2}$ with bounded derivatives. Then $\forall x \in \overline{\mathbb{R}}^{d}$

$$
\mathbb{E}\left[-(A[X])^{t} \nabla_{x} \eta(x, \underline{\underline{\Gamma}}[X], A[X])+\frac{1}{2} \operatorname{trace}\left(\underline{\underline{\Gamma}}[X] \cdot \operatorname{Hess}_{x} \eta\right)(x, \underline{\underline{\Gamma}}[X], A[X])\right]=0
$$

Theorem 2.2 Let $X$ be as in the preceding lemma, the conditional density $\eta(x, \gamma, a)$ being $\mathcal{C}^{3}$ bounded with bounded derivatives. When $\varepsilon \rightarrow 0$, the quantity

$$
\frac{1}{\varepsilon^{2}}(\mathbb{E}[g(x-X-\varepsilon A[X], \varepsilon \underline{=}[X])]-f(x))
$$

has a finite limit equal to

$$
\frac{1}{2} \mathbb{E}\left[(A[X])^{t}\left(\operatorname{Hess}_{x} \eta\right)(x, \underline{\underline{\Gamma}}[X], A[X]) A[X]-\sum_{i, j, k=1}^{d} A\left[X_{i}\right] \Gamma\left[X_{j}, X_{k}\right] \eta_{x_{i} x_{j} x_{k}}^{\prime \prime \prime}(x, \underline{\underline{\Gamma}}[X], A[X])\right]
$$

Proof. If we write $\mathbb{E}[g(x-X-\varepsilon A[X], \varepsilon \underline{\underline{\Gamma}}[X])]=\int \mu(d \gamma, d a) \int g(x-y-\varepsilon a, \varepsilon \gamma) \eta(y, \gamma, a) d y$ $=\int \mu(d \gamma, d a) \mathbb{E} \eta(x-\varepsilon a-\sqrt{\varepsilon} \sqrt{\gamma} G, \gamma, a)$ where $G$ is an $\mathbb{R}^{d}$-valued reduced Gaussian variable, and if we expand with respect to $\sqrt{\varepsilon}$ and take the expectation, terms in $\sqrt{\varepsilon}$ and $\varepsilon \sqrt{\varepsilon}$ vanish because $G$ and $G^{3}$ are centered and the term in $\varepsilon$ vanishes also thanks to the lemma. This gives the result.

About the variance, we obtain
Proposition 2.3 Let $X$ satisfying the assumptions of the lemma and such that $(\operatorname{det} \underline{\underline{\Gamma}}[X])^{-\frac{1}{2}} \in$ $L^{1}$, then
$\lim _{\varepsilon \rightarrow 0} \varepsilon^{d / 2} \mathbb{E} g^{2}(x-X-\varepsilon A[X], \varepsilon \underline{\underline{\Gamma}}[X])=\lim _{\varepsilon \rightarrow 0} \varepsilon^{d / 2} \operatorname{var} g(x-X-\varepsilon A[X], \varepsilon \underline{=}[X])=\mathbb{E}\left[\frac{\eta(x, \underline{\underline{\Gamma}}[X], A[X])}{(4 \pi)^{d / 2} \sqrt{\operatorname{det} \underline{\underline{\Gamma}}[X]}}\right]$.
The quantity $\mathbb{E} g(x-X-\varepsilon A[X], \varepsilon \underline{\underline{\hat{f}}}[X])$ is obtained by simulation with the law of large numbers, so that the approximation $\hat{f}$ of the density $f$ of $X$ is

$$
\hat{f}(x)=\frac{1}{N} \sum_{n=1}^{N} g\left(x-X_{n}-\varepsilon(A[X])_{n}, \varepsilon(\underline{\underline{\Gamma}}[X])_{n}\right)
$$

where the indices $n$ denote independent drawings. The preceding results show that, with respect to the usual kernel method, the speed, in the sense of the $L^{2}$-norm, is the same as if the dimension was divided by 2 .

## 3 Direct formulae

In the case where $X$ is real-valued, if in addition to $X, A[X], \Gamma[X]$ we are able to simulate $\Gamma\left[X, \frac{1}{X}\right]$, it is possible to obtain the dentity of $X$ at the speed of the law of large numbers thanks to the following formulae :

Theorem 3.1 a) If $X \in \mathcal{D} A$ with $\Gamma[X] \in \mathbb{D}$ and $\Gamma[X]>0$ a.s. then $X$ has a density $f$ which possesses an l.s.c. version $\tilde{f}$ given by

$$
\tilde{f}(x)=\lim _{\varepsilon \downarrow 0} \uparrow \frac{1}{2} \mathbb{E}\left(\operatorname{sign}(x-X)\left(\Gamma\left[X, \frac{1}{\varepsilon+\Gamma[X]}\right]+\frac{2 A[X]}{\varepsilon+\Gamma[X]}\right)\right) .
$$

b) If in addition $\frac{1}{\Gamma|x|} \in \mathbb{D}$, then $X$ has a density $f$ which is absolutely continuous and given by

$$
f(x)=\frac{1}{2} \mathbb{E}\left(\operatorname{sign}(x-X)\left(\Gamma\left[X, \frac{1}{\Gamma[X]}\right]+\frac{2 A[X]}{\Gamma[X]}\right)\right) .
$$

The proof is based on the relation

$$
\mathbb{E}\left[\varphi^{\prime \prime}(X) \frac{\Gamma[X]}{\varepsilon+\Gamma[X]}\right]=-\mathbb{E}\left[\varphi^{\prime}(X)\left(\Gamma\left[X, \frac{1}{\varepsilon+\Gamma[X]}\right]+\frac{2 A[X]}{\varepsilon+\Gamma[X]}\right)\right] .
$$

valid for any $\mathcal{C}^{2}$-function $\varphi$ with bounded derivatives which comes from the functional calculus using the general relation $\mathcal{E}[u, v]=-\langle A[u], v\rangle \forall u \in \mathcal{D} A \forall v \in \mathbb{D}$, and then applying it with $\varphi=\sqrt{\lambda^{2}+(y-x)^{2}}$ in order to get the monotone convergence result.

Under the hypotheses of theorem 3.1, as soon as $G \in \mathbb{D} \cap L^{\infty}$, there are similar formulae for conditional expectations $\mathbb{E}[G \mid X=x]$ :

$$
f(x) \mathbb{E}[G \mid X=x]=\frac{1}{2} \mathbb{E}\left(\operatorname{sign}(x-X)\left(\Gamma\left[X, \frac{G}{\Gamma[X]}\right]+\frac{2 G A[X]}{\Gamma[X]}\right)\right) .
$$

Let us finally remark that in these formulae, the factor on the right of $\operatorname{sign}(x-X)$ is centered and a variance optimisation may be performed thanks to an arbitrary deterministic function as done in [4] where direct formulae similar to those of section 3 are given in the case of the Wiener space involving Skorokhod integrals instead of Dirichlet forms.

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