

On the Construction of Quadrature Formulas for SDEs

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Introduction

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Computational task: constructive approximation of

- the distribution $\mu = P_X$ on the path space \mathcal{X} ,
- the marginal distribution $\mu = P_{X_1}$ on the state space \mathcal{X}

by probability measures

$$\hat{\mu} = \sum_{i=1}^n c_i \cdot \delta_{x_i}$$

with finite support $\{x_1, \dots, x_n\} \subset \mathcal{X}$.

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with finite support $\{x_1, \dots, x_n\} \subset \mathcal{X}$.

Note: $\hat{\mu}$ yields a quadrature formula

$$\int_{\mathcal{X}} f d\hat{\mu} = \sum_{i=1}^n c_i \cdot f(x_i) \quad \text{for} \quad \int_{\mathcal{X}} f d\mu.$$

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Challenges:

- distribution μ is given only implicitly by x_0 , a , b .
- $\dim(\mathcal{X}) = \infty$ for the path space \mathcal{X} .

OUTLINE

- I. Algorithms, Error and Cost
- II. Quadrature Formulas on the Path Space
- III. Quadrature Formulas on the State Space
- IV. Final Remarks

Joint project with

M. Scheutzow (Berlin)

S. Dereich, R. Schottstedt (Marburg),

F. Heidenreich, A. Neuenkirch, K. Ritter (Kaiserslautern),

T. M-G, L. Yaroslavtseva (Passau).

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I. Algorithms, Error and Cost

Class of scalar SDEs

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Put

$$\mathcal{M}(\mathcal{X}) = \left\{ \nu : \nu \text{ Borel prob. measure on } \mathcal{X}, \forall s \geq 1 : \int_{\mathcal{X}} \|x\|^s d\nu(x) < \infty \right\}$$

and consider a **metric** ρ on $\mathcal{M}(\mathcal{X})$

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Approximate $\mu: \mathcal{H} \rightarrow \mathcal{M}(\mathcal{X})$ with

$$\mu(x_0, a, b) = \begin{cases} P_X & \text{for a),} \\ P_{X_1} & \text{for b).} \end{cases}$$

Deterministic algorithms

$$\hat{\mu}: \mathcal{H} \rightarrow \{\nu \in \mathcal{M}(\mathcal{X}) : |\text{supp}(\nu)| < \infty\},$$

based on finitely many eval's of a, b, a', b', \dots

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Cost and Error

$$\text{cost}(\hat{\mu}) = \sup_{(x_0, a, b) \in \mathcal{H}} (\# \text{eval's of } a, b, a', b', \dots + \# \text{arithmetical operations})$$

$$e(\hat{\mu}) = \sup_{(x_0, a, b) \in \mathcal{H}} \rho(\mu(x_0, a, b), \hat{\mu}(x_0, a, b))$$

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Quantization numbers w.r.t. ρ . For $\nu \in \mathcal{M}(\mathcal{X})$

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Clearly,

$$e_N \geq \sup_{(x_0, a, b) \in \mathcal{H}} q_N(\mu(x_0, a, b)).$$

II. Quadrature Formulas on the Path Space

Class of SDEs: $(x_0, a, b) \in \mathcal{H} = [-L, L] \times H \times H$, where

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Metric: Wasserstein metric $\rho^{(s)}$ of order $s \geq 1$ on $\mathcal{M}(\mathcal{X})$

$$\rho^{(s)}(\nu, \hat{\nu}) = \inf_{\xi} \left(\int_{\mathcal{X} \times \mathcal{X}} \|x - y\|^s d\xi(x, y) \right)^{1/s}$$

with inf over all Borel prob. measures ξ on $\mathcal{X} \times \mathcal{X}$ with marginals $\nu, \hat{\nu}$.

Theorem (Dereich 2008). For every $(x_0, a, b) \in \mathcal{H}$

$$q_n(\mu(x_0, a, b)) \approx \kappa(x_0, a, b, \mathcal{X}, s) \cdot (\log n)^{-1/2}$$

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Remark

(i) Construction uses Brownian bridge quantization and yields $\hat{\mu}_n$ with

$$|\text{supp}(\hat{\mu}_n)| \leq n, \quad \text{cost}(\hat{\mu}_n) \leq c \cdot n, \quad e(\hat{\mu}_n) \leq c \cdot (\log n)^{-1/2}.$$

Moreover, if $\mathcal{X} = L_p([0, 1])$ and $s = p$ or if $\mathcal{X} = C([0, 1])$ then

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(ii) Alternative approaches to constructive quantization

- ODE-based, using rough paths theory,
see *Luschgy, Pagès (2006)*, *Pagès, Sellami (2010)*,
- using series expansions for X , see *Luschgy, Pagès (2008)*.

Sketch of Construction for $p = s = 2$.

Idea: Approximate $X = X(x_0, a, b)$ by $\widehat{X} = \widehat{X}^1 + \widehat{X}^2$, where

$\widehat{X}^1 =$ piecewise linear interpolation of Milstein scheme $\widehat{X}_{t_0}, \dots, \widehat{X}_{t_m}$ at times $t_\ell = \ell/m$, *(coarse level)*

$\widehat{X}_t^2 = \sum_{\ell=1}^m b(\widehat{X}_{t_{\ell-1}}) \cdot B_t^{(\ell)} \cdot 1_{[t_{\ell-1}, t_\ell]}(t)$ *(local refinement)*

with Brownian bridges

$$B_t^{(\ell)} = W_t - W_{t_{\ell-1}} - (t - t_{\ell-1}) \cdot m \cdot (W_{t_\ell} - W_{t_{\ell-1}}), \quad t \in [t_{\ell-1}, t_\ell].$$

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Note: $(\widehat{X}_{t_0}, \dots, \widehat{X}_{t_m}), B^{(1)}, \dots, B^{(m)}$ are independent.

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Construct approximations

$$\widehat{\mu}^1 = \sum_{i=1}^{M_1} w_i \cdot \delta_{\mathbf{x}_i} \quad \text{of } P_{(\widehat{X}_{t_0}, \dots, \widehat{X}_{t_m})},$$

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with $\mathbf{x}_i \in \mathbb{R}^{m+1}$ and functions $f_{i,j} \in L_2([0, 1])$.

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with $\mathbf{x}_i \in \mathbb{R}^{m+1}$ and functions $f_{i,j} \in L_2([0, 1])$. Approximate $\mu(x_0, a, b) = P_X$ by

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Ingredients

- Quantization of $N(0, 1)$: $\nu_n \in \mathcal{M}(\mathbb{R})$ with $|\text{supp}(\nu_n)| = n$ and

$$\rho^{(2)}(N(0, 1), \nu_n) \leq c \cdot n^{-1}.$$

- Quantization of Brown. bridge B : $Q_n \in \mathcal{M}(L_2([0, 1]))$ with $|\text{supp}(Q_n)| = n$ and

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Construction: parameters $m, n, N \in \mathbb{N}$

- Quantization of Milstein scheme: note that

$$\widehat{X}_{t_\ell} = g(\widehat{X}_{t_{\ell-1}}, m^{-1/2} \cdot Z_\ell),$$

where Z_1, \dots, Z_m i.i.d. $\sim N(0, 1)$. Employ m times ν_n .

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Adjust parameters, e.g., $m = n = (\log N)^\alpha$ with $\alpha \in (1/2, 1)$.

Example: square-root diffusion

$$dX_t = \alpha(\kappa - X_t) dt + \beta\sqrt{X_t} dW_t.$$

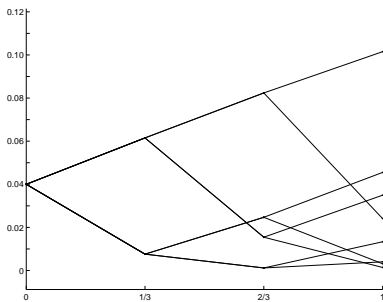
with $\alpha = 1.0$, $\kappa = 0.02$, $\beta = 0.2$, $x_0 = 0.04$.

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Coarse level via quantization of Milstein scheme with step-size $1/3$:
8 polygons with uniform weight $1/8$.



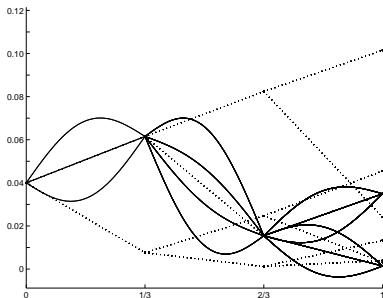
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Local refinement via quantization of Brownian bridges based on Karhunen-Loève expansion with basis functions

$$g_k(t) = \sqrt{2} \cdot \sin(k\pi \cdot t), \quad k \in \mathbb{N}.$$



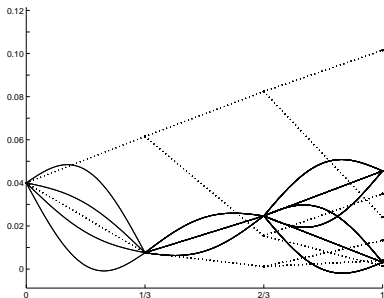
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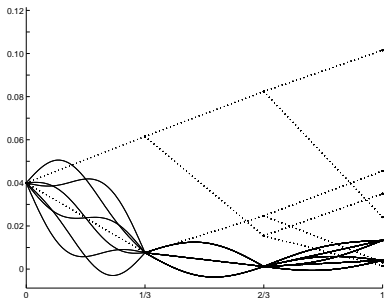
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III. Quadrature Formulas on the State Space

Class of SDEs: $(x_0, a, b) \in \mathcal{H} = [-L, L] \times H \times H^\varepsilon$, where

$$H = \{h \in C^4(\mathbb{R}): |h(0)|, |h^{(j)}| \leq K, j = 1, \dots, 4\},$$

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with $L, K, \varepsilon \geq 0$.

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Metric: for $\nu, \hat{\nu} \in \mathcal{M}(\mathbb{R})$

$$\rho_F(\nu, \hat{\nu}) = \sup_{f \in F} \left| \int f d\nu - \int f d\hat{\nu} \right|$$

where

$$F = \{f \in C^4(\mathbb{R}) : |f^{(j)}(z)| \leq M \cdot (1 + |z|^\beta), j = 1, \dots, 4\}$$

with $M, \beta \geq 0$.

Theorem (M-G, Ritter, Yaroslavtseva 2011). For every $\delta > 0$

$$e_N \leq \begin{cases} c \cdot N^{-2/3+\delta} & \text{if } \varepsilon > 0, \\ c \cdot N^{-1/2+\delta} & \text{if } \varepsilon = 0 \end{cases}$$

with $c = c(\delta, \varepsilon, \mathcal{H}, F)$.

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- Weighted integration on \mathbb{R}^d : *Wasilkowski, Woźniakowski (2000, 2001)*.
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- Nonlinear integration problems for SDEs: *Petras, Ritter (2006)*.
For a semi-metric $\rho_{\{f\}}$ with fixed f , fixed x_0 , $b = 1$, varying $a \in H_{r,d}$,

$$e_N \geq c \cdot N^{-r/d}.$$

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Remark. Related results and alternative approaches

- Quadrature on the Wiener space: *Kusuoka (2001, 2004)*, *Lyons, Victoir (2004)*, *Ninomiya, Victoir (2008)*, *Litterer, Lyons (2010)*, ...
- Finite difference methods via Feynman-Kac representation

Sketch of Construction for $\varepsilon = 1$.

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Leads to **Markov chain** $(Y_k^{x_0})_{k \in \mathbb{N}_0}$ with

- state space $S = G \cup \{x_0\}$, where

$$G = \{i \cdot m^{-1/2} : i = -\lceil m^{1/2+\delta} \rceil, \dots, \lceil m^{1/2+\delta} \rceil\},$$

- initial value x_0 ,
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Approximation

$$\hat{\mu}(x_0, a, b) = \mathbb{P}_{Y_m^{x_0}} = \sum_{z \in S} p_{x_0, z}^{(m)} \cdot \delta_z.$$

Fix $y \in S$. Euler step

$$X^E = \underbrace{y + a(y) \cdot m^{-1}}_e + b(y) \cdot m^{-1/2} \cdot V, \quad V \sim N(0, 1).$$

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$$|\mathbb{E}(X^E - e)^j - \mathbb{E}(Y_1^y - e)^j| \leq c \cdot (1 + |y|^c) \cdot m^{-2}$$

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Approach, essentially,

$$\begin{aligned} \text{gridpoints: } & \lfloor e \rfloor_G, \lfloor e \rfloor_G \pm \lceil |b(y)| \rceil \cdot m^{-1/2}, \\ & \lceil e \rceil_G, \lceil e \rceil_G \pm \lceil |b(y)| \rceil \cdot m^{-1/2} \end{aligned}$$

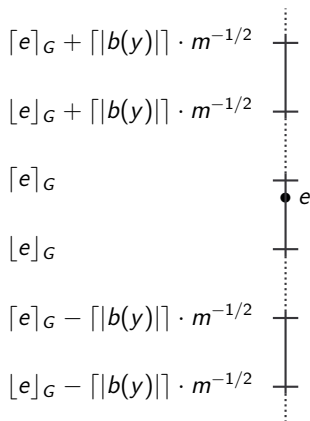
weights: solve

$$\mathbb{E}(X^E - e)^j = \mathbb{E}(Y_1^y - e)^j, \quad j = 1, 2, 3.$$

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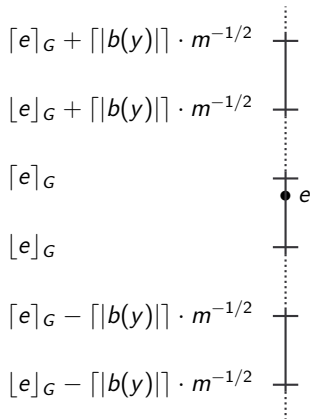
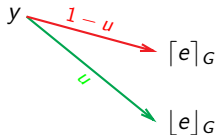
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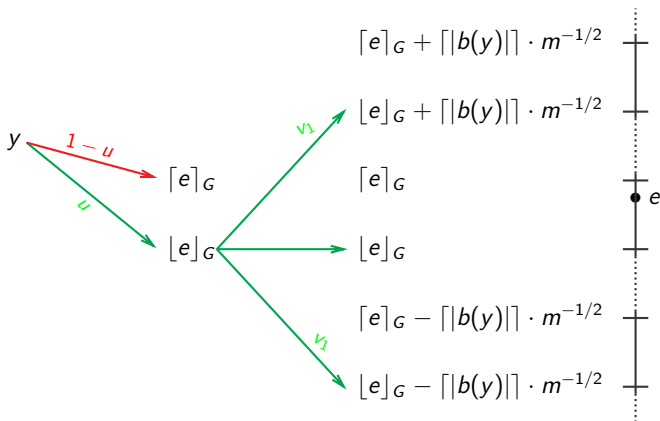


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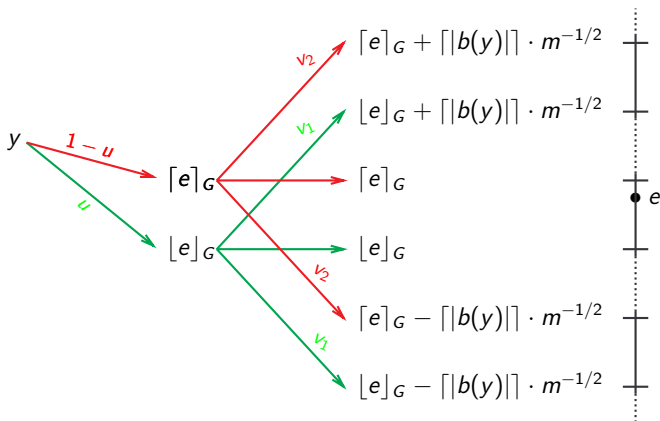


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Cost and Error

Recall

$$\hat{\mu}(x_0, a, b) = \sum_{z \in S} p_{x_0, z}^{(m)} \cdot \delta_z.$$

We have

| | eval's of a, b | arithm. op. |
|---|-------------------------------|-------------------------------|
| support points, S | | $\leq c \cdot m^{1/2+\delta}$ |
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Hence,

$$\text{cost}(\hat{\mu}) \leq c \cdot m^{3/2+\delta}.$$

Furthermore,

$$e(\hat{\mu}) \leq c \cdot m^{-1}.$$

IV. Final Remarks

- path space:
 d -dim. systems of SDEs need quantization of Lévy-areas
- state space:
gap between lower bound $N^{-r/d}$ and upper bound $N^{-(r-2)/(d+2)}$
- better results via approximation by general measures?
- what can be achieved with randomized algorithms?