

# On an extension of an algorithm of higher-order weak approximation to SDEs

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## Background:

- ▶ A new higher-order weak approximation scheme based on [Kusuoka '01] and [Lyons and Victoir '04]

## Objective:

- ▶ Construction of Concrete higher-order weak approximation algorithms that are:
  - ▶ Versatile, (applicable to a broad class of SDEs)
  - ▶ Easy to use, (Blackbox algorithm)

## Current status:

- ▶ Two kinds of schemes of order 2 (say [Alg 1 \[Victoir & N '08\]](#) and [Alg 2 \[Ninomiya & N '09\]](#)) Both work in practice.
- ▶ General extrapolation method for [Alg 1](#) [Oshima, Teichmann and Veluscek '09]  
Enables arbitraly order weak approximation

## This talk is on:

- ▶ Construction of concrete [Alg 2](#) algorithm of [order > 2](#).
- ▶ The state is under construction.

## References 1/2:

- ▶ Kusuoka, S.: “*Approximation of Expectation of Diffusion Process and Mathematical Finance.*” In: T. Sunada (ed.) Advanced Studies in Pure Mathematics, Proceedings of Final Taniguchi Symposium, Nara 1998, vol. 31, pp. 147–165 (2001)
- ▶ Kusuoka, S.: “*Approximation of Expectation of Diffusion Processes based on Lie Algebra and Malliavin Calculus.*” Advances in Mathematical Economics **6**, 69–83 (2004)
- ▶ Lyons, T., Victoir, N.: “*Cubature on Wiener Space.*” Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences **460**, 169–198 (2004)

## References 2/2:

- ▶ N. and Victoir, N.: “*Weak Approximation of Stochastic Differential Equations and Application to Derivative Pricing.*” Applied Mathematical Finance **15**, 107–121 (2008)
- ▶ Ninomiya, M. and N.: “*A new weak approximation scheme of stochastic differential equations by using the Runge–Kutta method*” Finance and Stochastics **13**, 415–443 (2009)
- ▶ Oshima, K., Teichmann, J. and Veluscek, D.: “*A new extrapolation method for weak approximation schemes with applications*” Preprint: arXiv:0911.4380v1 [math.PR] (2009)

## The Problem :

Numerical calculation of  $E[f(X(T, x))]$ , where

$$X(t, x) = x + \sum_{j=0}^d \int_0^t V_j(X(s, x)) \circ dB^j(s)$$

$$V_j \in C_b^\infty(\mathbb{R}^N; \mathbb{R}^N)$$

$$B(t) = (B^0(t), B^1(t), \dots, B^d(t)),$$

$$B^0(t) = t, \quad (B^1(t), \dots, B^d(t)) : d\text{-dim Std. BM},$$

(1)

$\circ dB^j(s)$  : Stratonovich integral.

## Two approaches:

### PDE method

$$\frac{\partial u}{\partial t}(t, x) = Lu, \quad u(0, x) = f(x).$$

where  $L = V_0 + (1/2) \sum_{i=1}^d V_i^2$ .

### Probabilistic method — “Simulation”

Step 1. Discretize  $X(t, x)$  and obtain  $X^n(t, x)$ .

$$n = \#\{\text{partitions of } [0, T]\}$$

Euler–Maruyama, Higher order (Milstein, Kusuoka,...)

Step 2. Integrate  $f(X^n(T, x))$  over  $D(n)$ -dimensional domain  $[0, 1]^{D(n)}$  by MC, QMC, etc.

$D(n)$  depends on the discretization scheme

**Step. 2** of the simulation is the numerical integration:

$$E[f(X^n(T, x))] = \int_{[0,1)^{D(n)}} F(a_1, \dots, a_{D(n)}) da_1 \cdots da_{D(n)}$$

Calc. RHS by using **MC or QMC**.

## MC and QMC

$$W : \text{r. v.}/(\Omega, \mathcal{F}, P), \quad M \in \mathbb{Z}_{>0}$$

$$\text{MC}(W, M) := \frac{1}{M} \sum_{k=1}^M W_k, \quad \text{where } \{W_i\}_{i=1}^M : \text{iid s. t. } W_1 \sim W$$

$$\text{QMC}(W, M) := \frac{1}{M} \sum_{k=1}^M W(\omega_k), \quad \{\omega_i\}_{i=1}^\infty : \text{deterministic sequence (LDS)}$$

$$\text{MC}(W, M) : \quad \text{r. v.}$$

$$\text{QMC}(W, M) \in \mathbb{R}.$$

## Two types of approximation errors in simulation:

### 1. Discritization error

$$\left| E[f(X(T, x))] - E[f(X^n(T, x))] \right|$$

### 2. Integration error

$$\left| MC(f(X^n(T, x)), M)(\omega) - E[f(X^n(T, x))] \right|$$

or

$$\left| QMC(f(X^n(T, x)), M) - E[f(X^n(T, x))] \right|$$

## Integration error and MC

By CLT,

$$\text{MC}(f(X^n(T, x)), M) \sim N\left(E[f(X^n(T, x))], \frac{\text{Var}[f(X^n(T, x))]}{M}\right).$$

When we proceed simulation

$$\text{Var}[f(X(T, x))] \approx \text{Var}[f(X^n(T, x))]$$

### Remark 1

As long as we use MC, the number of sample points  $M$  needed to attain the given accuracy is independent of  $n$  and discretizing algorithm (Euler–Maruyama or Kusuoka etc.).

## Integration error and QMC

There exist sequences which satisfy

$$\exists C_{f,n} > 0 \forall M \in \mathbb{Z}_{>0}$$

$$|QMC(f(X^n(T, x)), M) - E[f(X^n(T, x))]| \leq C_{f,D(n)} \frac{(\log M)^{D(n)}}{M}.$$

### Remark 2

In contrast to the MC case, the number of sample points  $M$  needed by the QMC to attain the given accuracy **depends** heavily on **the dimension of integration  $D(n)$** . Smaller the dimension, smaller number of samples are needed.

$$D(n) = \begin{cases} n \times d & \text{Euler–Maruyama,} \\ n \times (d + 1) & \text{N. & Victoir,} \\ 2n \times d & \text{Ninomiya, & N.} \end{cases}$$

## Order 1: Euler–Maruyama scheme

$$X^{(\text{EM}),n}(0, x) = x,$$

$$X^{(\text{EM}),n}\left(\frac{k+1}{n}, x\right) = X^{(\text{EM}),n}\left(\frac{k}{n}, x\right) + \sqrt{\frac{T}{n}} \sum_{i=0}^d \tilde{V}_i\left(X^{(\text{EM}),n}\left(\frac{k}{n}, x\right)\right) Z_{k+1}^i,$$

where,

$$\forall j Z_j^k = \begin{cases} \sqrt{T/n}, & \text{if } k = 0, \\ \text{iid. r. v. } \sim N(0, 1), & \text{if } k \in \{1, \dots, d\}, \end{cases}$$

$$\tilde{V}_k^i(y) = \begin{cases} V_0^i(y) + \frac{1}{2} \sum_j V_j V_j^i(y) & \text{if } k = 0, \\ V_k^i & \text{if } k \in \{1, \dots, d\}. \end{cases}$$

## Approx. Error of Euler–Maruyama scheme

$$\begin{aligned} \left| E[f(X(T, x))] - E\left[f\left(X^{(\text{EM}), n}(T, x)\right)\right] \right| &= O(n^{-1}) \\ &= O(\Delta t) \end{aligned}$$

when  $f$  : bdd.& measurable and  $\{V_i\}_{i=0}^d$  : Unif. Hörmander Cond. [Bally & Talay '96][Kohatsu-Higa '00]

Euler–Maruyama scheme is an order 1 scheme.

## Intuitive explanation of the scheme (1/3)

$$(P_t^X f)(x) := E[f(X(t, x))], \quad f \in C_b^\infty(\mathbb{R}^N)$$

$$L := V_0 + \frac{1}{2} \sum_{j=1}^d V_j^2.$$

## Intuitive explanation of the scheme (2/3)

Applying Ito formula repeatedly, we obtain

$$\begin{aligned} E[f(X(t, x))] &= (P_t^X f)(x) = f(x) + \int_0^t (P_{s_1}^X L f)(x) ds_1 \\ &= f(x) + \int_0^t \left\{ (Lf)(x) + \int_0^{s_1} (P_{s_2}^X L^2 f)(x) ds_2 \right\} ds_1 \\ &\vdots \\ &= \sum_{i=0}^n \left( \frac{(tL)^i}{i!} f \right)(x) + \frac{1}{n!} \int_0^t (t-s)^n (P_s^X L^{n+1} f)(x) ds. \end{aligned}$$

## Intuitive explanation of the scheme(3/3)

Observation:  $\sum_{i=0}^n \left( \frac{(tL)^i}{i!} f \right)(x)$  gives a  $n$ th order approx. of  $E[f(X(t, x))]$ .

Slogan: Construct a random variable  $\Xi$  s. t.

$$E[\Xi] = \sum_{i=0}^n \left( \frac{(tL)^i}{i!} f \right)(x).$$

## Non-commutative algebra (1)

$A := \{v_0, \dots, v_d\}$  : alphabet

$A^* := \left( \cup_{k=1}^{\infty} A^k \right) \cup \{1\}$  : free monoid on  $A$

For  $w = w_1 \cdots w_k \in A^*$ , ( $w_i \in A$ )

$|w| := k$ ,  $\|w\| := |w| + \text{card}(\{1 \leq i \leq |w| ; w_i = v_0\})$ ,

$A_m^* := \{w \in A^* \mid \|w\| = m\}$ ,

$A_{\leq m}^* := \{w \in A^* \mid \|w\| \leq m\}$ .

*Concatenation product:*

For  $u = u_1 \cdots u_k$ ,  $v = v_1 \cdots v_l \in A^*$ ,

$$uv := u_1 \cdots u_k v_1 \cdots v_l.$$

## Non-commutative algebra (2)

$\mathbb{R}\langle\langle A \rangle\rangle := \left\{ \sum_{w \in A^*} a_w w \mid a_w \in \mathbb{R} \right\}$  :  $\mathbb{R}$ -algebra of formal series with basis  $A^*$ ,

$\mathbb{R}\langle A \rangle := \left\{ \sum_{w \in A^*} a_w w \in \mathbb{R}\langle\langle A \rangle\rangle \mid \exists k \in \mathbb{N} \text{ s.t. } a_w = 0 \text{ if } |w| \geq k \right\}$

: free  $\mathbb{R}$ -algebra with basis  $A^*$ ,

$(P, w) := a_w, \text{ for } P = \sum_{w \in A^*} a_w w \in \mathbb{R}\langle\langle A \rangle\rangle,$

$(PQ, w) := \sum_{\substack{uv=w \\ u,v \in A^*}} (P, u)(Q, v), \text{ for } P, Q \in \mathbb{R}\langle\langle A \rangle\rangle, w \in A^*.$

## Non-commutative algebra (3)

- ▶ Projection, Truncation:

$$j_m(P) := \sum_{\|w\| \leq m} (P, w)w$$

$$P|_k := \sum_{|w|=k} (P, w)w$$

- ▶ Homogeneous component:

$$\mathbb{R}\langle A \rangle_m := \{ P \in \mathbb{R}\langle A \rangle \mid (P, w) = 0 \text{ if } \|w\| \neq m \}$$

## Free Lie algebra:

$[P, Q] := PQ - QP$  for  $P, Q \in \mathbb{R}\langle\langle A \rangle\rangle$ ,

$$\mathcal{J}_A := \left\{ K_{\text{sub } \mathbb{R}\text{-module}} \mid A \subset K, [x, y] \in K^{\vee} \forall x, y \in K \right\}$$

$$\mathcal{L}_{\mathbb{R}}(A) := \bigcap_{K \in \mathcal{J}_A} K : \mathbb{R}\text{-coefficients free Lie algebra on } A$$

$$\mathcal{L}_{\mathbb{R}}((A)) := \left\{ P \in \mathbb{R}\langle\langle A \rangle\rangle \mid \text{s.t. } P|_k \in \mathcal{L}_{\mathbb{R}}(A), \forall k \in \mathbb{N} \right\}.$$

## Logarithm and exponential:

For  $P \in \mathbb{R}\langle\langle A \rangle\rangle$  s.t.  $(P, 1) = 0$

$$\exp(P) := 1 + \sum_{k=1}^{\infty} \frac{P^k}{k!}.$$

For  $Q \in \mathbb{R}\langle\langle A \rangle\rangle$  s.t.  $(Q, 1) = 1$

$$\log(Q) := \sum_{k=1}^{\infty} \frac{(-1)^{k-1}(Q - 1)^k}{k}.$$

$$\log(\exp(P)) = P \quad \text{and} \quad \exp(\log(Q)) = Q.$$

## Hausdorff product:

For  $z_1, z_2 \in \mathcal{L}_{\mathbb{R}}((A))$ ,

$$z_1 \text{Hz} z_2 := \log(\exp(z_1) \exp(z_2)).$$

- ▶  $(z_1 \text{Hz} z_2) \text{Hz} z_3 = \log(\exp(z_1) \exp(z_2) \exp(z_3)) = z_1 \text{H} (z_2 \text{Hz} z_3)$   
 $=: z_1 \text{Hz} z_2 \text{Hz} z_3$
- ▶  $z_2, z_1 \in \mathcal{L}_{\mathbb{R}} \implies z_2 \text{Hz} z_1 \in \mathcal{L}_{\mathbb{R}}((A))$   
 $\therefore \text{the Baker–Campbell–Hausdorff–Dynkin formula.}$

## $\mathcal{L}_{\mathbb{R}}(A)$ and $\mathbb{R}\langle A \rangle$

Element of  $\mathcal{L}_{\mathbb{R}}$   $\iff$  Vector field generated by  $V_0, \dots, V_d$

Elements of  $\mathbb{R}\langle A \rangle$   $\iff$  Differential operator generated by  $V_0, \dots, V_d$

## Resurgence and rescaling

- ▶ Resurgence operator  $\Phi$ :

$$\Phi(1) := \text{id}, \quad \Phi(v_{i_1} \cdots v_{i_n}) := V_{i_1} \cdots V_{i_n}$$

- ▶ Rescaling operator: For  $s > 0$ ,  $\Psi_s : \mathbb{R}\langle\langle A \rangle\rangle \rightarrow \mathbb{R}\langle\langle A \rangle\rangle$  is defined as:

$$\Psi_s \left( \sum_{m=0}^{\infty} P_m \right) = \sum_{m=0}^{\infty} s^{m/2} P_m \quad \text{where } P_m \in \mathbb{R}\langle A \rangle_m.$$

Example:

$$\Phi \left( \Psi_s \left( v_0 + \frac{1}{2}[v_1, v_2] \right) \right) = sV_0 + \frac{s}{2} [V_1, V_2]$$

## Notation: $\exp(V)(x)$

For a smooth vector field  $V$ , (i.e.  $V \in C_b^\infty(\mathbb{R}^N; \mathbb{R}^N)$ )

$$\exp(V)(x) := y(1)$$

where  $y(t)$  is a solution to the ODE:

$$y(0) = x, \quad \frac{dy(t)}{dt} = V(y(t))$$

## Order $m$ Integration scheme: $\mathcal{IS}(m)$

$$g \in \mathcal{IS}(m) \stackrel{\text{def}}{\iff} \begin{cases} g : C_b^\infty(\mathbb{R}^N; \mathbb{R}^N) \longrightarrow (\mathbb{R}^N \rightarrow \mathbb{R}^N), \\ \exists C_m > 0 \quad \text{s.t. } \forall W \in C_b^\infty(\mathbb{R}^N; \mathbb{R}^N) \\ \sup_{x \in \mathbb{R}^N} |g(W)(x) - \exp(W)(x)| \leq C_m (\|W\|_{C^{m+1}})^{m+1} \end{cases}$$

- ▶  $\mathcal{IS}(m) \doteq$  “Set of order  $m$  ODE solver”
- ▶ We need to integrate, for example:

$$sV_0 + \frac{\sqrt{s}}{2}(V_1 + \cdots + V_d).$$

Not necessarily  $s$ -linear.

## $\mathcal{R}\langle\langle A \rangle\rangle$ , $\mathcal{L}_{\mathbb{R}}((A))$ -valued random variables

- ▶ Topology:  $\mathcal{R}\langle\langle A \rangle\rangle \approx \mathcal{R}^\infty$  – Direct product topology
- ▶  $\mathcal{R}\langle\langle A \rangle\rangle$ -valued and  $\mathcal{L}_{\mathbb{R}}((A))$ -valued probability theory can be considered.  
(Ito formula, etc.)

## Approximation theorem (1/2)

$m \geq 1, M \geq 2,$

$Z_1, \dots, Z_M$ :  $\mathcal{L}_{\mathbb{R}}((A))$ -valued random variables s. t.

$$Z_i = j_m Z_i \quad \text{for } i = 1, \dots, M,$$

$$E [\|j_m Z_i\|_2] < \infty \quad \text{for } i = 1, \dots, M,$$

$$E \left[ \exp \left( a \sum_{j=1}^M \left\| \Phi(\Psi_s(Z_j)) \right\|_{C^{m+1}} \right) \right] < \infty \quad \text{for any } a > 0.$$

## Approximation theorem (2/2)

$\implies$

$\forall p \in [1, \infty), \forall g_1, \dots, \forall g_M \in \mathcal{IS}(m), \exists C_{m,M} > 0$  s. t.

$$\left\| \sup_{x \in \mathbb{R}^N} |g_1(\Phi(\Psi_s(Z_1))) \circ \cdots \circ g_M(\Phi(\Psi_s(Z_M)))(x) - \exp(\Phi(\Psi_s(j_m(Z_M \text{H} \cdots \text{H} Z_1))))(x)| \right\|_{L^p} \leq C_{m,M} S^{(m+1)/2}$$

for  $\forall s \in (0, 1]$  where  $C_{m,M}$  depends only on  $m$  and  $M$ .

$f \circ g(x) := f(g(x))$

## Cor. to the Approximation theorem

“ $Q_{(s)}$  gives  $(m - 1)/2$ -order weak approximation.”

Let  $Q_{(s)}$  for  $s \in (0, 1]$  be

$$(Q_{(s)}f)(x) := E[f(g(\Phi(\Psi_s(Z_1))) \circ \cdots \circ g(\Phi(\Psi_s(Z_M)))(x))],$$

where  $f \in C_b^\infty(\mathbb{R}^N; \mathbb{R})$  and  $g \in \mathcal{IS}(m)$  then  $\exists C > 0$ ,

$$\|P_s f - Q_{(s)} f\|_\infty \leq C s^{(m+1)/2} \|\text{grad}(f)\|_\infty$$

$$P_s(f) := E[f(X(t, x))]$$

**(Remark:** When  $\{V_0, \dots, V_d\}$  finitely generated.)

## Algorithm 1 [Victoir–N.(2004)]

$(\Lambda_i, Z_i)_{i \in \{1, \dots, n\}}$  :  $2n$  indep. r. v.,

$$\forall i P(\Lambda_i = \pm 1) = \frac{1}{2}, Z_i \sim N(0, I_d).$$

$\{X_k^{(\text{Alg.1}),n}\}_{k=0,\dots,n}$  : a family of r. v. defined as:

$$X_0^{(\text{Alg.1}),n} := x,$$

$$X_{(k+1)/n}^{(\text{Alg.1}),n} :=$$

$$\begin{cases} \exp\left(\frac{V_0}{2n}\right) \exp\left(\frac{Z_k^1 V_1}{\sqrt{n}}\right) \cdots \exp\left(\frac{Z_k^d V_d}{\sqrt{n}}\right) \exp\left(\frac{V_0}{2n}\right) X_k^{(\text{Alg.1}),n} & \text{if } \Lambda_k = +1, \\ \exp\left(\frac{V_0}{2n}\right) \exp\left(\frac{Z_k^d V_d}{\sqrt{n}}\right) \cdots \exp\left(\frac{Z_k^1 V_1}{\sqrt{n}}\right) \exp\left(\frac{V_0}{2n}\right) X_k^{(\text{Alg.1}),n} & \text{if } \Lambda_k = -1. \end{cases}$$

## Extrapolations of Algorithm 1

- ▶ To an arbitrary order [Oshima, Teichmann and Veluscek '09]
- ▶ To the 6th order [Fujiwara '06]

## General framework of Algorithm 2 (1)

- ▶ Remind the Slogan
- ▶ Find the  $\Xi$  written as:

$$\Xi = Z_1 \text{H} Z_2 \text{H} \cdots \text{H} Z_M$$

$$Z_j = c_j v_0 + \sum_{i=1}^d S_j^i v_i, \quad j \in \{1, \dots, M\}$$

where

$$c_j \in \mathbb{R} \text{ s.t. } c_1 + \cdots + c_M = 1$$

$$E[S_j^i S_{j'}^{i'}] = R_{jj'} \delta_{ii'}$$

$$S_j^i \sim N(0, R_{jj}) \quad (i \in \{1, \dots, d\}, j \in \{1, \dots, M\})$$

## General framework of Algorithm 2 (2)

The slogan is equivalent to:

$$E[j_m(\exp(Z_1) \cdots \exp(Z_M))] = j_m \left( \exp \left( v_0 + \frac{1}{2} \sum_{i=1}^d v_i^2 \right) \right) \quad (2)$$

The problem:

Find real numbers  $\{c_j\}_{j=1}^M$ ,  $\{R_{ij}\}_{1 \leq i \leq j \leq M}$  that satisfy (2).

$$\#\text{unknown vars} = \frac{1}{2}M(M+3)$$

## Main tools (Theorem 1):

### For the LHS of (2)

If  $n^w(i)$  is odd for some  $i \in \{1, \dots, d\}$ , then  $C(w) = 0$ .

If  $n^w(i)$  is even for every  $i \in \{1, \dots, d\}$ , then

$$C(w) =$$

$$\begin{aligned}
 & \sum_{\vec{k}=(k_1, \dots, k_M) \in \mathcal{K}_t(M)} \frac{1}{k_1! \cdots k_M!} \prod_{j=1}^M (c_j)^{N^w(0, j, \vec{k})} \\
 & \times \prod_{p=1}^d \left( \sum_{\substack{\{d_{ij}\}_{1 \leq i \leq j \leq M} \in \\ e(N^w(p, 1, \vec{k}), \dots, N^w(p, M, \vec{k}))}} 2^{-\sum_{i=1}^M d_{ii}} \frac{\prod_{j=1}^M (N^w(p, j, \vec{k})!) }{\prod_{1 \leq i \leq j \leq M} (d_{ij}!)} \prod_{1 \leq i \leq j \leq M} R_{ij}^{d_{ij}} \right) \tag{3}
 \end{aligned}$$

## Main tools (Theorem 2):

### For the RHS of (2)

Let  $A^0 = \{v_0, v_1 v_1, v_2 v_2, \dots, v_d v_d\} \subset A^*$ . Then

$$\exp\left(v_0 + \frac{1}{2} \sum_{i=1}^d v_i^2\right) = \sum_{\substack{w=w_1 \cdots w_l \\ w_1, \dots, w_l \in A^0}} \frac{1}{2^{|w|-l} l!} w,$$

that is,

$$C(w) = \begin{cases} \frac{1}{2^{|w|-l} l!} & \text{if } w \in A^0 \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

## Algebraic relations between $\{c_j\}_{j=1}^M$ , $\{R_{ij}\}_{1 \leq i \leq j \leq M}$

Using following 3 results, the algebraic relations are obtained.

## An example of Algorithm 2 [Ninomiya–N. (2009)]

When  $(m, M) = (5, 2)$ ,

$$c_1 = \frac{\mp \sqrt{2(2u - 1)}}{2}, \quad c_2 = 1 \pm \frac{\sqrt{2(2u - 1)}}{2}$$

$$R_{22} = 1 + u \pm \sqrt{2(2u - 1)}, \quad R_{12} = -u \mp \frac{\sqrt{2(2u - 1)}}{2}$$

$$R_{11} = u \quad \text{for some } u \geq 1/2.$$

Becomes 1-dimensional ideal.

## Partial results (1):

The case  $m \geq 6$

- ▶  $(m, M) = (7, 2)$ : ideal becomes trivial  
(i.e.  $= \mathbb{C}[c_1, c_2, R_{11}, R_{12}, R_{13}]$ )
- ▶  $(m, M, d) = (7, 3, 1)$ : ideal becomes trivial.

## Partial results (2):

The case  $(m, M, d) = (7, 3, 2)$  and  $v_0$  free:

The algebraic relation:

$$\begin{aligned} & 14R_{22} + 24R_{13} - 13, \quad 4R_{33} + 14R_{22} + 4R_{11} - 15, \quad 36R_{33}^2 - 60R_{22} + 25, \\ & -72R_{22}R_{33} + 68R_{33} + 24R_{23} + 22R_{22} - 17, \\ & -288R_{23}R_{33} - 8R_{33} + 264R_{23} - 46R_{22} + 77, \\ & 12R_{23} - 22R_{22} + 12R_{12} + 23, \quad 8R_{33} + 216R_{22}R_{23} - 156R_{23} + 34R_{22} - 27, \\ & -22R_{33} - 324R_{23}^2 - 192R_{23} + 46R_{22} - 57, \\ & 144R_{33}^2 - 64R_{33} + 168R_{23} + 46R_{22} + 7 \end{aligned}$$

Unfortunately, the solution is:

$$R_{33} = \frac{5 \pm \sqrt{-11}}{12} \notin \mathbb{R}$$

## Partial results (3):

The case  $(m, M, d) = (7, 4, 3)$  and  $v_0$  free:

Over 1-month symbolical calculation cannot find the answer.....

We have some more results (Theorem 3):  $A^* = \bigcup_{i=0}^{\infty} A^i$ ,  
 $\pitchfork: A^* \otimes A^* \rightarrow A^*$ : Shuffle product.  
( $A^*, \pitchfork$ ) becomes an algebra (shuffle algebra).

$C(\cdot)$

$$C : (A^*, \pitchfork) \longrightarrow \mathbb{R}[c_j, R_{ij}, (1 \leq i \leq j \leq M)]$$

is ring homomorphism.

**Cor.**

$$C((0)^{n_0} \pitchfork (11) \pitchfork \cdots \pitchfork (\ell\ell)) = C(0)^{n_0} C(11)^\ell$$

Def: shuffle product.

$A = \{v_1, \dots, v_d\}$  : alphabet

$$A^* = \bigcup_{i=0}^{\infty} A^i,$$

$$\{I_1 \sqcup \dots \sqcup I_p = \{1, \dots, n\}$$

$$\{u_i \in A^*, |u_i| = \# I_i \quad (i=1, \dots, p)$$

$$A^* \ni (I_1, I_2, \dots, I_p) = w \iff \underset{\text{def}}{\underset{\substack{\downarrow \\ \text{def}}}{w|_{I_i} = u_i}} \quad 1 \leq i \leq p.$$

[where fn  $w = a_1 \dots a_n$ ,  $I = \{i_1 < \dots < i_k\} \subset \{1, \dots, n\}$ ]

$$w|_I := a_{i_1} a_{i_2} \dots a_{i_k}$$

$$I(u_1, \dots, u_p) := \left\{ \{I_i\}_{i=1}^p \mid \bigsqcup_{i=1}^p I_i = \{1, \dots, n\}, \# I_i = u_i \right\}.$$

Then the shuffle product of  $u_1, \dots, u_p$ :

$$u_1 \pitchfork u_2 \pitchfork \dots \pitchfork u_p := \sum_{\substack{\{I_i\}_{i=1}^p \\ \in I(u_1, \dots, u_p)}} (I_1 \dots I_p)$$

Ex.  $(12) \pitchfork (13) = (1213) + (1123) + (1132) + (1123) + (1132) + (1312)$   
 $= (1213) + 2(1123) + 2(1132) + (1312)$

# Some remarks

- ①  $V(m, M, d) := \{(c_1, \dots, c_m, R_{11}, R_{12}, \dots, R_{1m}) \mid (2) \text{ holds}\}$
- $V(m, M, d) \supset V(m+2, M, d)$
  - $V(m, M, d) \supset V(m, M, d+1)$  hold.
  - $V(m, M, d) \supset V(m, M+1, d)$
  - $V(m, M, d) = (m, M, \frac{m-1}{2})$  for  $d \geq \frac{m-1}{2}$

What we know

$(m, M, d)$	# unknown vars	# relations	ideal
$(5, 2, 2)$	5	10	1-dim
$(6, 2, *)$	5	68	trivial (even when $d=2$ )
$(6, 3, 1)$	9	20	when $C_1 - C_3 = 0 \Rightarrow$ trivial o/w $\Rightarrow$ unknown
$(6, 3, 2)$	9	53	0-dim when $V_2$ -free
$(6, 3, 3)$	9	68	but $\notin \mathbb{R}$
$(6, 4, 2)$	14	53	?
$(6, 4, 3)$		68	
		15	

## An example of Algorithm 2 [Ninomiya–N. (2005)]

$$\left( Z_{i,k}^j \right)_{\substack{i \in \{1, \dots, d\}, j \in \{1, 2\}, \\ k \in \{0, \dots, n-1\}}}$$

$$\begin{pmatrix} Z_{i,k}^1 \\ Z_{i,k}^2 \end{pmatrix} = \begin{pmatrix} 1/2 & 1/\sqrt{2} \\ 1/2 & -1/\sqrt{2} \end{pmatrix} \begin{pmatrix} \eta_{i,k}^1 \\ \eta_{i,k}^2 \end{pmatrix}, \quad \text{where } \eta_{i,k}^j \stackrel{\text{i.i.d.}}{\sim} N(0, 1).$$

$\{X_k^{(\text{Alg.2}),n}\}_{k=0,\dots,n}$  : a family of r. v. defined as:

$$X_0^{(\text{Alg.2}),n} := x,$$

$$X_{(k+1)/n}^{(\text{Alg.2}),n} :=$$

$$\exp\left(\frac{1}{2n} V_0 + \sum_{i=1}^d \frac{Z_{i,k}^1}{\sqrt{n}} V_i\right) \exp\left(\frac{1}{2n} V_0 + \sum_{i=1}^d \frac{Z_{i,k}^M}{\sqrt{n}} V_i\right) X_{k/n}^{(\text{Alg.2}),n}$$

## Theorem

Both  $X^{(\text{Alg.1}),n}$  and  $X^{(\text{Alg.2}),n}$  are of order 2.

## Recent result by Kusuoka

If  $Q_{(s)}$  is constructed by  $X^{(\text{Alg.1}),n}$  or  $X^{(\text{Alg.2}),n}$  then  $\exists C > 0$  s.t.

$$(P_s f)(x) - (Q_{(s)} f)(x) = Cs^{(m+1)/2} + O(s^{(m+3)/2})$$

## D(n)

D(n) : dimension of integration domain

$$D(n) = \begin{cases} n \times d & \text{Euler–Maruyama,} \\ n \times (d + 1) & \text{Algorithm 1} \\ n \times 2 \times d & \text{Algorithm 2} \end{cases}$$

## How to calc. $\exp(Z_i)(x)$ ?

- ▶ Lucky case: We can get exact form of  $\exp(Z_i)(x)$ . Often the case with Algorithm 1.
- ▶ Otherwise: Forced to proceed with numerical approximation.

Good news:

### Theorem [Ninomiya–N.]

Classical order  $m$  Runge–Kutta methods belongs to  $IS(m)$

## MC or QMC with Algorithms 1 and 2

- ▶  $W$ : “a set of ODEs”-valued r. v. by Algorithm 1 or 2
- ▶ MC or QMC:
  - ▶ Draw a set of ODEs “ $W(\omega)$ ” from  $W$  and obtain (something like)  $\exp(W(\omega))(x)$  numerically
  - ▶ Iterate the step above and calculate the average:

$$\frac{1}{M} \sum_{i=1}^M \exp(W(\omega_i))(x)$$

## Advantages of the approach

- ▶ Free from symbolical calculation.
  - ▶ Calc. in group is easy.
    - ▶ Numerical ODE solver works (by the 2nd th'm)
  - ▶ Calc. in algebra is difficult.
    - ▶ Huge symbolical calc.
    - ▶ Simultaneous distributions of multiple integrations of BMs are not known. (except for the 2nd order.)
- ▶ Universal (applicable to non-commutative  $\{V_i\}_{i=0}^d$ )  
Naïve “Ito-Taylor expansion with the Runge–Kutta” suffers from the non-commutativity.

## Numerical Example:

### Pricing of Asian option under the Heston model:

Heston model:

$$Y_1(t, x) = x_1 + \int_0^t \mu Y_1(s, x) ds + \int_0^t Y_1(s, x) \sqrt{Y_2(s, x)} dW^1(s),$$

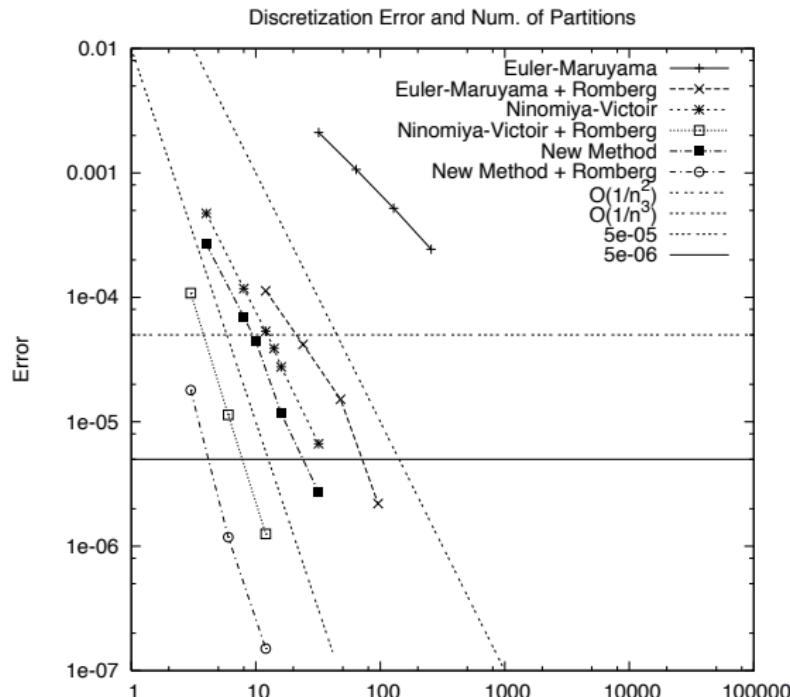
$$Y_2(t, x) = x_2 + \int_0^t \alpha (\theta - Y_2(s, x)) ds + \int_0^t \beta \sqrt{Y_2(s, x)} dW^2(s),$$

$$\langle W^1, W^2 \rangle_t = \rho t$$

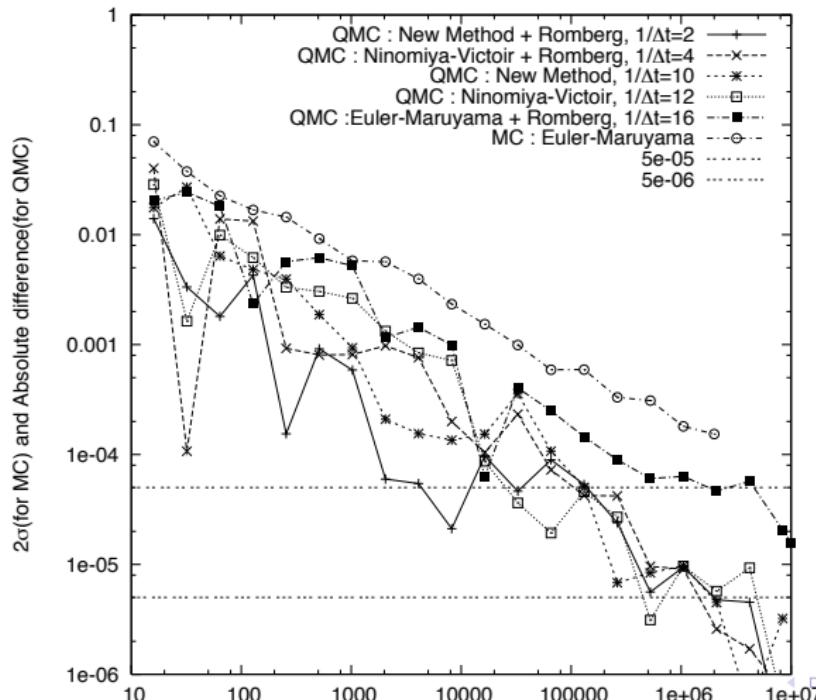
Asian Option:

$$Y_3(t, x) = \int_0^t Y_1(s, x) ds, \quad \text{Payoff} = \max\left(\frac{Y_3(T, x)}{T} - K, 0\right).$$

## Discretization Error



## Convergencence Error from quasi-Monte Carlo and Monte Carlo



## Overall performance comparison:

#Partition, #Dim, #Sample, and CPU time required for  $10^{-4}$  accuracy.

Method	#Partition	#Dim	#Sample	CPU time (sec)
E-M + MC	2000	4000	$10^8$	$1.72 \times 10^5$
E-M + Extrpltn + QMC	$16 + 8$	48	$5 \times 10^6$	$1.27 \times 10^2$
N-V + QMC	12	36	$2 \times 10^5$	3.24
N-V + Extrpltn + QMC	$4 + 2$	18	$2 \times 10^5$	1.76
KNN + QMC	10	40	$2 \times 10^5$	3.4
KNN + Extrpltn + QMC	$2 + 1$	12	$2 \times 10^5$	1.2

## Recent developments:

- ▶ Existence of the asymptotic expansion of the errors of Algorithms 1 and 2 [Kusuoka]
- ▶ Order 6 algorithm [Fujiwara]
- ▶ SPDE case [Teichmann]

Both approaches are necessary because:

- ▶ PDE approach works only when
  - ▶  $L$  is elliptic,
  - ▶ dimension is small.
- ▶ Simulation is the last resort but (people believe) very time consuming.

This presentation focuses on “Simulation.”