

# Discretization of SDEs

Then  $Z_t$  is a-dim cadlag semimart. with

$Z_0 = 0$ .  $F: \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^{d \times d}$  is Lip. i.e.:

$$|F(t, x) - F(t, y)| \leq L_t |x - y|. \quad \forall x, y \in \mathbb{R}^d.$$

Then:  $X_t = X_0 + \int_0^t F(s, X_{s-}) dZ_s$  admits  
a unique sol.  $X_t$  is semimart.

Prop: For  $F \in C^2(\mathbb{R}^d \times \mathbb{R}^d)$ ,  $X \mapsto F(t, X)$

and  $X \mapsto DF(t, X) F(t, X)$  are Lip.

for  $\forall t \in \mathbb{R}^d$ ,  $\forall 1 \leq i \leq d$ . Where

$$F_i(t, x) = (F(t, x)_i^j)_{j=1}^d.$$

result also works for Stratonovich

$$\text{case: } X_t = X_0 + \int_0^t F(s, X_{s-}) \circ dZ_s$$

(1) Euler method.

$$\text{Consider } dX_t = V_0(X_t) dt + \sum_1^k V_i(X_t) dB_t^i, \quad \text{st.}$$

$V_i$ 's are uniform Lip. and linearly bounded.

So its sol.  $X_t$  exists uniquely.

Set grid  $D = \{0 = t_0 < t_1 < \dots < t_N = T\}$ .  $|D| =$

$$\max | \Delta t_k |. \quad \Delta t_k = t_k - t_{k-1}. \quad L_t = \sup \{ L_i \mid t_i \leq t \}.$$

Def: For approx:  $\bar{X}^D$  for  $X$ .

i)  $\bar{X}^D \rightarrow X$  strongly if  $\lim_{|D| \rightarrow 0} \mathbb{E} |X_T - \bar{X}_T^D| = 0$

AND it has strong order  $\gamma$  if

$$\mathbb{E} |X_T - \bar{X}_T^D| \leq C |D|^\gamma. (|D| \rightarrow 0)$$

ii) For class  $\mathcal{G}$  of func.  $f: \mathbb{R}^n \rightarrow \mathbb{R}$ .

$\bar{X}^D \rightarrow X$  weakly w.r.t  $\mathcal{G}$  if  $\forall f \in \mathcal{G}$

$$\lim_{|D| \rightarrow 0} \mathbb{E} (f(\bar{X}_T^D)) = \mathbb{E} (f(X_T)).$$

$Z_t$  has weak order  $\gamma > 0$  if  $\forall f$

$$\in \mathcal{G}. |\mathbb{E} (f(\bar{X}_T^D)) - \mathbb{E} (f(X_T))| \leq C |D|^\gamma.$$

Remark: For  $\mathcal{G} = \text{Lip.}$ : Strong  $\Rightarrow$  weak.

① Euler - Maruyama method:

Note for ODE  $x'(t) = V(x(t)), x(0) = x_0.$

$$X(t_i) = X(t_{i-1}) + X'(t_{i-1}) \Delta t_i + O(\Delta t_i^2)$$

$$= X(t_{i-1}) + V(X(t_{i-1})) \Delta t_i + O(\Delta t_i^2)$$

$$\text{Soe } \bar{X}_{t_i} = V(\bar{X}_{t_{i-1}}) \Delta t_i + \bar{X}_{t_{i-1}}. \bar{X}_{t_0} = X_0.$$

$$\text{So } |X(t) - \bar{X}_{t_N}| \leq \sum_i^N O(\Delta t_i^2) \leq T O(|D|).$$

As for SDE:

$$\text{Set } \bar{X}_{t_i} = \bar{X}_{t_{i-1}} + U_i(\bar{X}_{t_{i-1}}) \Delta t_i + \sum_j^d V_j(\bar{X}_{t_{i-1}}) \Delta B_{t_i}^j,$$

extend it to whole path by interpolation:

$$\bar{X}_t = \bar{X}_{\lfloor t \rfloor} + U(\bar{X}_{\lfloor t \rfloor})(t - \lfloor t \rfloor) + \sum_j^d V_j(\bar{X}_{\lfloor t \rfloor})(B_t^j - B_{\lfloor t \rfloor}^j)$$

Remark: Now the scheme may not also

have order one, since  $B_t \sim \sqrt{t}$

Thm: Under  $X(0) = X$ , Approx.  $\bar{X}_t$  satisfies:

$$\mathbb{E} \left[ \sup_{0 \leq t \leq T} |X_t - \bar{X}_t| \right] \leq C |D|^{1/2}.$$

Remark: So it has strong order  $1/2$ .

Pf: Denote  $B_t^0 = t$  and recall:

$$\mathbb{E} \left[ \sup_{0 \leq t \leq T} |X_t| \right] \leq C(1 + |X|^2).$$

Next estimate  $\mathcal{L}_t = \mathbb{E} \left[ \sup_{0 \leq s \leq t} |X_s - \bar{X}_s|^2 \right]$

$$X_s - \bar{X}_s = \sum_0^n \int_0^s (V_i(X_u) - V_i(\bar{X}_{\lfloor u \rfloor})) \Delta B_u^i.$$

$$= \sum_0^n \left( \int_0^s (V_i(X_u) - V_i(X_{\lfloor u \rfloor})) + (V_i(X_{\lfloor u \rfloor}) - V_i(\bar{X}_{\lfloor u \rfloor})) \right) \Delta B_u^i$$

$$\text{So: } \mathcal{L}_t \leq \sum_0^n \mathbb{E} \left[ \sup_{0 \leq s \leq t} \left| \int_0^s V_i(X_u) - V_i(X_{\lfloor u \rfloor}) \Delta B_u^i \right|^2 \right] + \mathbb{E} \left[ \sup_{0 \leq s \leq t} \left| \int_0^s V_i(X_{\lfloor u \rfloor}) - V_i(\bar{X}_{\lfloor u \rfloor}) \Delta B_u^i \right|^2 \right]$$

$$=: \sum_0^n \mathcal{L}_t^i + \mathcal{L}'_t.$$

$$\mathcal{L}_t^i =: \sum_0^n \mathcal{L}_t^i + \mathcal{L}'_t.$$

Using Doob's inequality and Hölder inequality:

$$L_t^0 \leq K^2 T \int_0^t e_{i,s} ds. \quad L_t^i \leq t K^2 \int_0^t e_{i,s} ds. \quad 1 \leq i \leq d.$$

where  $K$  is common Lipschitz const. of  $V_i$ :

$$C_t^0 \stackrel{\text{Hölder}}{\leq} K^2 T \int_0^t \mathbb{E} \left[ \left( \sum_0^u \int_{L_{u_j}}^u V_i(x_s) \mathbb{1}_{|B_s^i|^2} \right) ds \right] du$$

$$\leq K^2 T (d+1) \int_0^t \sum_0^u \mathbb{E} \left[ \int_{L_{u_j}}^u V_i(x_s) \mathbb{1}_{|B_s^i|^2} ds \right] du$$

$$\stackrel{\text{Hölder}}{\leq} C K^2 \int_0^t (u - L_{u_j}) \left( \int_{L_{u_j}}^u \mathbb{E} [1 + |x_s|^2] ds \right) +$$

$$+ \int_{L_{u_j}}^u \mathbb{E} [1 + |x_s|^2] ds \Big) du$$

$$\leq C (1 + X^2) \int_0^t (u - L_{u_j})^2 + \mathbb{1}_{L_{u_j}} du.$$

$$\leq T C (1 + X^2) (|D| + d) |D|.$$

With Doob's inequality we also have:

$$L_t^i \leq C (1 + |x_t|^2) |D|. \quad 1 \leq i \leq d.$$

$$S_t := L_t \leq C |D| + C \int_0^t e_{i,s} ds.$$

Apply Brownian's inequality:  $L_t \leq C |D|$ .

Apply Hölder again to get the result

Remark: It can be used to prove the

uniqueness and existence of SDE:

With first we also have:

$$\mathbb{E} \left( \sup_{0 \leq t \leq T} |\bar{X}_t^D|^2 \right) \leq C (1 + |x|^2).$$

1) Uniqueness is obvious.

$$2) \text{ Note: } \mathbb{E} \left( \sup_{0 \leq t \leq T} |\bar{X}_t^D - \bar{X}_t^{D'}|^2 \right) \leq C |D - D'|.$$

3) Set  $\tilde{X} = \lim \bar{X}^D$ . prove  $\tilde{X}$  also satisfies the SDE since  $\bar{X}^D$  satisfies it.

Next, we consider the weak convergence of the Euler method.

Prop: Weak approxi. of SDE can be used as a numerical method to solve the linear parabolic PDE:

Since  $u(t, x) = \mathbb{E}(f(X_T) | X_t = x)$  solve the Kolmogorov backward eq.:

$$\begin{cases} \partial_t u / \partial t = -L u & \text{where } L = \tilde{V}_0 + \frac{1}{2} \sum_i V_i^2 \\ u(T, x) = f(x) & \tilde{V}_0 = V_0 - \frac{1}{2} \sum D V_i \cdot V_i \end{cases}$$

and  $V g(x) = \nabla g(x) \cdot V(x)$ .

Thm. If  $V_i$ 's are  $C^\alpha$ -b.v.d.  $g = C^\alpha \cap \mathcal{E} f$  is

poly. growth. Let  $\{h_i = \Delta t_i = \tau/n, \forall i\}$ . Then:

$$\begin{aligned} \mathcal{E}(T, h, f) &= \mathbb{E}(f(\bar{X}_T^0) - f(X_T)) \\ &= h \int_0^T \mathbb{E}(\psi_1(s, X_s)) ds + h^2 \mathcal{E}_2(T, f) + O(h^3) \end{aligned}$$

where  $\psi_1$  is given by

$$\begin{aligned} \psi_1(t, x) &= \frac{1}{2} \sum_{i,j=1}^n V^i(x) V^j(x) \partial_{(i,j)} u(t, x) + \frac{1}{2} \sum_{i,j,k=1}^n V^i(x) a_k^j(x) \partial_{(i,j,k)} u(t, x) + \\ &+ \frac{1}{8} \sum_{i,j,k,l=1}^n a_j^i(x) a_l^k(x) \partial_{(i,j,k,l)} u(t, x) + \frac{1}{2} \frac{\partial^2}{\partial t^2} u(t, x) + \\ &+ \sum_{i=1}^n V^i(x) \frac{\partial}{\partial t} V^i(x) \partial_i u(t, x) + \frac{1}{2} \sum_{i,j=1}^d a_j^i(x) \frac{\partial}{\partial t} a_j^i(x) \partial_{(i,j)} u(t, x), \end{aligned}$$

where  $\partial_I = \frac{\partial^{|I|}}{\partial x^{i_1} \dots \partial x^{i_k}}$  for a multi-index  $I = (i_1, \dots, i_k)$  and  $a_j^i(x) = \sum_{k=1}^d V_k^i(x) V_k^j(x)$ ,  $1 \leq i, j \leq n$ .

Lemma. Under cond. above. Sol.  $u(t, x)$  of PDE above is smooth and all its derivatives are poly-growth.

Pf: By Fubini. Then.

Lemma. Under cond. above. We have:

$$\mathbb{E}(u(t, \bar{X}_{i,1}, \bar{X}_{i,2}, \dots, \bar{X}_{i,i}) \mid \bar{X}_i = x) = u(t, x) + h^2 \psi_1(t, x) + O(h^3)$$

Pf: WLOG. let  $i=0$ .

Apply Taylor expansion on  $u(h-x+\Delta x)$  on  $h$  and  $\Delta x$ :

$$u(h, x + \Delta x) = u(0, x) + h \partial_t u(0, x) + \frac{1}{2} h^2 \partial_{tt} u(0, x) + h \sum \Delta x^i \partial_{tt} u(0, x) +$$

$$h^2 \sum \Delta x^i \partial_{tt} u(0, x) +$$

$$\frac{1}{2} h \sum_{i,j} \Delta x^i \Delta x^j \partial_t \partial_{(i,j)} \mu(t, x) + \sum_k^d \sum_{i=1}^n \Delta x^{i,i} \dots \Delta x^{i,i} \partial_{(i, \dots, i)} \mu(t, x) + O(h \Delta x^3) + O(\Delta x^4)$$

Insert  $\Delta X = A \bar{X} = V_0(x) h + \sum_1^k V_i(x) \Delta B_k^i$  and take expectation on both sides.

Combine with  $\Delta B_k^i \sim \sqrt{h}$  and eq.:

$$\partial_t \mu(t, x) = -L \mu(t, x).$$

Pf. Note  $e^{(T, h, f)} = \mathbb{E}(\mu(t, \bar{X}_n^0) - \mu(t, x))$

$$= \sum_0^{n-1} \mathbb{E}(\mu(t_{i+1}, \bar{X}_{i+1}) - \mu(t_i, \bar{X}_i))$$

$$= \sum_0^{n-1} h^2 \mathbb{E}(\psi_i(t_i, \bar{X}_i)) + O(h^3)$$

$$\leq C h^2 n + \mu O(h^3) = O(h + O(h^2))$$

Since by Lind. :  $|\mathbb{E}(\psi_i(t_i, x))| \leq C$ .

Also :  $|h \sum_0^{n-1} \mathbb{E}(\psi_i(t_i, \bar{X}_i)) - \int_0^T \mathbb{E}(\psi_i(t, x_t))|$

$$\leq h \sum_i |\mathbb{E}(\psi_i(t_i, \bar{X}_i)) - \psi_i(t_i, x_{t_i})| +$$

$$|h \sum_i \mathbb{E}(\psi_i(t_i, x_{t_i})) - \int_0^T \mathbb{E}(\psi_i(t, x_t))|$$

$$:= A + B.$$

$B = O(h)$ . Besides,  $\psi_i \in C^1 \Rightarrow \psi_i \in \mathcal{G}$ . So :

$$|\mathbb{E}(\psi_i(t_i, \bar{X}_i)) - \psi_i(t_i, x_{t_i})| = O(h).$$

Remark: Note we only use scaling prop.  
of BM rather other gaussian prop.  
So we can use general Lévy  
process  $Y_t \sim \sqrt{t}$ .

Thm. If  $f, V_i$ 's  $\in C^k$  and has poly.-bad  
deriv. Then: it has weak order  $k$ .

Thm. If  $V_i$ 's  $\in C^\infty$  satisfies Hörmander's  
cond. and their deriv's are bad.

Then:  $\forall f$  has measur. it has weak  
order  $\infty$ .

Remark: It's a trading on regularity  
between  $f$  and  $V_i$ 's.

Sometimes the Euler scheme  
can still work in a.s. smooth case

② Euler - Monte-Carlo method:

Note we can approxi.  $\mathbb{E}(f(X_{T_n}))$  by  $\mathbb{E}(f(\bar{X}_{T_n}))$ . So next step we want to  
approximate the integral  $\mathbb{E}(f(\bar{X}_{T_n}))$ .

Prob: Assume the SDE is driven by a-dim Lévy process.  $\Rightarrow \bar{X}_N$  is func. of  $(\Delta z^i)_{1 \leq i \leq d, 1 \leq n \leq N}$ . So  $\mathbb{E}(f(\bar{X}_N))$  is integral on  $\mathbb{R}^{dN}$ , which still cause dim. problem if  $N$  large.

$$\begin{aligned} \Rightarrow \text{Error} &= \left| \mathbb{E}(f(X_T)) - \mathbb{E}(f(\bar{X}_N)) \right| \\ &\leq \left| \mathbb{E}(f(X_T)) - \mathbb{E}(f(\bar{X}_N)) \right| + \\ &\quad \left| \mathbb{E}(f(\bar{X}_N)) - \mathbb{E}(f(\bar{X}_N^{(i)})) \right| \\ &\stackrel{\Delta}{=} \text{error}_{\text{discret}}(N) + \text{error}_{\text{int}}(M). \end{aligned}$$

It left us two para.  $m, N$  to choose:

$$\text{error}_{\text{discret}}(N) \leq C_D N^{-p}, \quad p \in \left[ \frac{1}{2}, 1 \right).$$

$$\text{error}_{\text{int}}(M) \leq C_I M^{-z}, \quad z \in \left[ \frac{1}{2}, 1 - \varepsilon \right).$$

Note the computational work will be proportional to  $mN$

So we want to optimize:

$$\min \{ mN \mid C_I m^{-z} + C_D N^{-p} \leq \varepsilon \}$$

$$\text{Lagrangian } F(m, N, \lambda) = mN + \lambda (C_I m^{-z} + C_D N^{-p} - \varepsilon)$$

$$\text{let } \frac{\partial F}{\partial N} = \frac{\partial F}{\partial m} = 0 \Rightarrow m \approx N^{p/z}.$$

$$\Rightarrow m \approx \varepsilon^{-1/2}, \quad N \approx \varepsilon^{-1/p}, \quad mN \approx \varepsilon^{-c/p + 1/2}$$

Problem description	$p$	$q$	$M(N)$	$k$
Euler (Lipschitz) + MC	1/2	1/2	$N$	4
Euler (Lipschitz) + QMC	1/2	$1-\delta$	$N^{1/2+\delta}$	$3+\delta$
Euler (regular) + MC	1	1/2	$N^2$	3
Order $p$ + MC	$p$	1/2	$N^{2p}$	$2+1/p$

$k = 1/p + 1/2$  is complexity of EML.

Key: Note higher order method can't improve the cost significantly if combined with a low order scheme.

Next, consider Lévy noise case:

$$dX_t = \sum_i V_i(X_{t-}) dZ_t^i$$

For the Euler scheme, we can replace

$B_{t_i, t_{i+1}}$  by  $Z_{t_i, t_{i+1}}$  directly. If we can

sample increments of  $Z_t$ . Then:

Thm. If  $(V_i), f \in C_B^+$ . Then its Euler

scheme  $\rightarrow$  sol. of SDE weakly.

Moreover, if Lévy measure  $\nu$  of  $Z_t$  has bad moments up to  $\delta$ . then, it has weak rate one.

RMF: i) The rate is smaller than  
BM case (even no such rate)

ii) In the proof:  $Z_t$  is approxi.  
by  $Z_t^m$  (exclude the jumps  $> m$ )  
so the error estimate will  
be on  $|D|$  and  $m$ . And if  
 $V$  admits high order moments,  
then this step can be avoided.

But generally, given Lévy-c.a.  $(\Sigma, V)$ . We  
don't know its list. so can't sample  
it. We can still approxi. incre.  $A Z_t$  by  
compound Poi-Process  $\Delta Z_t^\varepsilon$ .

Thm. If i) SDE sol.  $X_t$  and i.i.d. r.v.'s  
 $(\xi_i^h)$ ; satisfy:  $\forall g \in C_b^q$ .  $\exists K_h$  const. of  $h$   
 $|\mathbb{E}(g \circ \xi_i^h) - \mathbb{E}(g \circ Z_h)| \leq K_h \|g\|_{C^q}$ .  
ii)  $(V_i) \in C_b^q$ .  $Z$  has finite moments  
up to order eight.  
Then Euler scheme for partition  $D$

$$= \sum_{k=0}^N (f^k) : \bar{X}_0 = X_0, \bar{X}_{n+1} = \bar{X}_n + \sum_i^N v_i(\bar{X}_n) f_{n+1}^k$$

Satisfies:  $\forall f \in C_b^k$ .

$$|\mathbb{E}(f(X_T)) - \mathbb{E}(f(\bar{X}_n))| \leq C \max_k |v_k| \|f\|_{C_b^k}$$

Prop: i) Note if we can simulate  $Z$ ,

then we can choose  $u_n = 0$ .

ii) To obtain approxi.  $f_i^h$  of  $Z$ , we

can choose  $f_i^h = Z_{(i-1)h, ih}^\varepsilon$ . So  $u_n$

will also depend on  $\varepsilon$ .

Lemma.  $\exists \lambda_\varepsilon := \nu\{\tau \leq \varepsilon\} \leq C/\varepsilon^\gamma$ .

$\exists \gamma \in [0, 2]$ .  $\forall \varepsilon \leq 1$ . Then:

$$u_n = \varepsilon^{3-\gamma}$$

Note by integrability cond. in  $\nu$

of  $Z_t$ , it always satisfies for

$\gamma = 2$ . So to get  $u_n \sim h$ :

we let  $\varepsilon \sim h^{1/(3-\gamma)}$ .

(2) Advanced methods:

① Multilevel MC simulation:

Next, we consider a simulation of schemes with different time grids, i.e. set  $h_1 > \dots > h_L$  time increments. Sol.  $X_t$  will be approx. by  $\bar{X}^{(h_k)}$ . And  $\mathbb{E}(f(X_t))$  will base on samples of  $(\bar{X}^{(h_k)})_k$ .

Remark: i) The discret. error is given by the finest discretization  $\bar{X}^{(h_1)}$ . And the computational cost will be average of the works w.r.t different  $h_k$ .  
ii) The idea of MMC is based on the variance reduction. Note  $\bar{X}^{(h_k)}$  and  $\bar{X}^{(h_{k+1})}$  should be close. So:  $\text{Cov}(f(\bar{X}^{(h_k)}), f(\bar{X}^{(h_{k+1})}))$  will be high.

Steps:

- i) Use MC simulation to compute  $\mathbb{E}(f(\bar{X}^{(h_1)}))$
- ii) Use variance reduction to compute  $\mathbb{E}(f(\bar{X}^{(h_2)}))$  based on  $f(\bar{X}^{(h_1)})$ .

ii) Repeat it on  $(f(\bar{X}^{(k+1)}), f(\bar{X}^{(k+1)}))$ .

Remark: We can use Brownian bridge since the BM on finer grid can be based on the coarse one.

Fix  $N \in \mathbb{N}$ .  $N > 1$ .  $h_n := N^{-\alpha} T$ .  $L = 0, \dots, L$ . Let

$P_n := f(\bar{X}^{(n)})$ .  $I_n := \max_{i=1, \dots, m_n} (P_n^{(i)} - P_{n-1}^{(i)})$  and

assume  $I_n$ 's are independent.

Thm. If  $\exists$  const's  $\alpha \geq \frac{1}{2}$ ,  $C_1, C_2, \beta > 0$  satisfy

$$\mathbb{E}(f(X_T) - P_n) \leq C_1 h_n^\alpha, \quad \text{Var}(I_n) \leq C_2 h_n^\beta / m_n$$

Then:  $\exists L \in \mathbb{N}$  and  $(m_i)_0^L$  s.t. the

multilevel estimate  $I = \sum_0^L I_n$  satisfy:

$$\left( \mathbb{E} \left[ (I - \mathbb{E}(f(X_T)))^2 \right] \right)^{\frac{1}{2}} \leq \varepsilon.$$

And computational cost  $C$  satisfies:

$$C \leq \begin{cases} C_3 \varepsilon^{-2} & \beta > 1 \\ C_3 \varepsilon^{-2} (\log \varepsilon)^2 & \beta = 1 \\ C_3 \varepsilon^{-2 - (1-\beta)/\alpha} & 0 < \beta < 1 \end{cases}$$

Remark:  $\mathbb{E}(I) = \sum \mathbb{E}(I_n)$

$$= \sum \mathbb{E}(P_n) - \mathbb{E}(P_{n-1}) = \mathbb{E}(P_L)$$

which explains the error comes from the finest term

Cor. Given Euler method of rank order one and strong order  $1/2$ . Choose  $L = \log \varepsilon^{-1} / \log N + O(1)$  ( $\varepsilon \rightarrow 0$ ) and  $m_\varepsilon \propto \varepsilon^{-2(L+1)}$

h.e. Then: for error  $O(\varepsilon)$  of  $I$ , its comp. cost =  $O(\varepsilon^{-2} (\log \varepsilon)^2)$

Proof: Choose  $\alpha = \beta = 1$  than above. We can obtain this cor.

Pf: 1) Set  $L := \lceil \frac{\log \lfloor \sqrt{2} \lfloor \varepsilon^{-1} \rfloor \rfloor}{\log N} \rceil$

$\Rightarrow C_{i,k} \in \lfloor \varepsilon / \sqrt{2} m, \varepsilon / \sqrt{2} \rfloor$ .

$\int_0: \mathbb{E} (I) - \mathbb{E} (f(x_{T+1})) \stackrel{\leq}{\sim} \varepsilon^2 / 2$ .

Choose  $m_\varepsilon := \lceil 2 \varepsilon^{-2(L+1)} \lfloor \varepsilon / \sqrt{2} \rfloor \rceil$

$\text{Var}(I) = \sum \text{Var}(I_k)$

$\leq C_2 \sum h_k / m_\varepsilon \leq \varepsilon^2 / 2$ .

$\int_0: \text{MSE}(I) = \text{Var}(I) +$

$(\mathbb{E}(I) - \mathbb{E}(f(x_{T+1})))^2 \leq \varepsilon^2$

2)  $L+1 \leq \lceil \log \varepsilon^{-1} \rceil$ .  $m_\varepsilon \leq 2 \varepsilon^{-2(L+1)} \lfloor \varepsilon / \sqrt{2} \rfloor + 1$

$$\Rightarrow \text{Cost} \leq C \sum_0^L M_n / h_n \leq \sum_{i=0}^L (2 \varepsilon^{-2} (L+1)) (C_2 + h_i^{-1})$$

$$\leq 2 \varepsilon^{-2} (L+1)^2 C_2 + \sum h_i^{-1}$$

$$\sum h_i^{-1} = h_L^{-1} \sum N^{-i} = h_L^{-1} \frac{N^{-L+1} - 1}{N^{-1} - 1}$$

$$< h_L^{-1} N / N-1 \leq N^2 \int_2 C_1 \varepsilon^{-1} / (N-1)$$

$$\text{So: Cost} \leq C \varepsilon^{-2} (\log \varepsilon^{-1})^2.$$

Key: Set  $L = \lceil \log ( \int_2 C_1 T^\alpha \varepsilon^{-1} ) \rceil / \alpha$

$$M_n = \lceil 2 \varepsilon^{-2} (L+1) C_2 h_n^\beta \rceil$$

We can prove general (α, β).

## ② Stochastic Taylor schemes:

Note in deterministic case, high order Taylor expansion can lead to high order scheme while in stochastic case, due to BM behave differently with BV, we can try to obtain it by Ito's.

Assume:  $dX_t = \sum_0^L V_i(X_t) \circ dB_t^i$  (Stratonovich)

By Ito's:  $f(X_t) = f(X_0) + \sum_0^L \int_0^t V_i f(X_s) \circ dB_s^i$

Apply it on  $x \mapsto V_i f(x)$ , we have:

$$V_i f(x_s) = V_i f(x_0) + \sum_{j=0}^k \int_0^s V_j V_i f(x_u) \circ dB_u^j, \quad \forall i.$$

insert back on  $f(x_t) = f(x_0) + \square$ :

$$f(x_t) = f(x_0) + \sum_0^k V_i f(x_0) \int_0^t \circ dB_t^i + \sum_{ij}^k \int_0^t \int_0^s V_j V_i f(x_u) \circ dB_u^j \circ dB_s^i$$

$\Rightarrow$  We can get high order expansion by iteration. For order of expansion:

Note  $B_t^0 = t \sim t$ ,  $B_t^i \sim \sqrt{t} B_t^i$ ,  $\forall i > 0$ .

$$\int_0^t B_t^{\mathbb{I}} \stackrel{A}{=} \int_{0 \leq t_1 \leq \dots \leq t_k \leq t} \circ dB_{t_1}^{i_1} \dots \circ dB_{t_k}^{i_k} \sim t^{k \deg(\mathbb{I})/2} B_t^{\mathbb{I}}.$$

where  $\mathbb{I} = (i_1, \dots, i_k) \in \{0, \dots, k\}^k$  and  $\deg(\mathbb{I}) = k + \#\{1 \leq j \leq k \mid i_j = 0\}$ .

Thm. If  $f, (V_i) \in C_B^{m+1}$ ,  $X_0 = X \in \mathbb{R}^n$ . Then:

$$f(X_t) = f(X) + \sum_{\substack{\mathbb{I} \in \{0, \dots, k\}^k, k \leq m \\ \deg(\mathbb{I}) \leq m}} V_{i_1} \dots V_{i_k} f(X) B_t^{\mathbb{I}} + R_m^{t, f, X}$$

$\forall t, \forall t < 1,$

$$\sup_x \mathbb{E} \left( |R_m^{t, f, X}|^2 \right)^{\frac{1}{2}} \leq C t^{\frac{m+1}{2}} \sup_{m \leq \deg(\mathbb{I}) \leq m+2} \|V_{i_1} \dots V_{i_k} f\|_{\infty}$$

Pf: Expand  $f(x_t)$  up to order  $m$  and transf. back to Itô's integral to get the estimate.

Remark: For  $Z_t^0$  case,  $\mu X_t = \int_0^t V_i(x_t) \mu B_t^i$ .

Let  $\tilde{V}_0 f(x) = V f(x) + \frac{1}{2} \sum_1^k V_i(x)^T V f(x) V_i(x)$

where  $V f$  is Hessian matrix of  $f$ .

Remark:  $\tilde{V}_0$  isn't vector field! ( $2^{nd}$ -order)

$\Rightarrow f(x_t) = f(x_0) + \int_0^t \sum_1^k \tilde{V}_i f(x_s) \mu B_s^i$  where

$\tilde{V}_i = V_i$ ,  $i=1, 2, \dots, k$ .

Def:  $\mathcal{D} A_m = \{I = (i_1, \dots, i_k) \in \{0, \dots, k\}^k \mid 1 \leq k \leq m, k \notin I, \# \{j \mid i_j = 0\} = \frac{m+1}{2}\}$ .

Remark:  $A_m^*$  contains one term with order  $= \frac{m+1}{2} \cdot 2 = m+1$ .

ii)  $V_I = V_{i_1} \dots V_{i_k}$  for  $I = (i_1, \dots, i_k) \in \{0, \dots, k\}^k$

Remark: By theorem above:

$$\begin{aligned} f(x_t) &= f(x) + \sum_{I \in \mathcal{D} A_m} V_I f(x) B_t^I + R_m^{t, f, x} \\ &= f(x) + \sum_{I \in \mathcal{D} A_m} \tilde{V}_I f(x) \tilde{B}_t^I + \tilde{R}_m^{t, f, x} \end{aligned}$$

(where  $\tilde{B}_t^I = \int_0^t \mu B_{t_1}^{i_1} \dots \mu B_{t_k}^{i_k}$ )

Def: String stochastic Taylor scheme of order  $m$  for  $Z_t^0$ -SDE is:  $\bar{X}_0 = X_0$  and

$$\bar{X}_{j+1} = \bar{X}_j + \sum_{I \in A_m^+} \tilde{V}^I(x) \Delta \tilde{B}_j^I \quad \text{where } \Delta \tilde{B}_j^I := \int_{t_j \leq s_1, \dots, s_k \leq t_{j+1}} \lambda_{B_{s_1}^{i_1}} \dots \lambda_{B_{s_k}^{i_k}}, \quad I = (i_1, \dots, i_k).$$

Thm. If  $\forall I \in A_m, \tilde{V}^I \in C^m$ . Then the strong stochastic Taylor scheme  $\rightarrow X_T$  sol. of  $Z_{t_0}^{\tilde{V}}\text{-SDE}$  with strong order  $m/2$ .

Proof: Euler scheme is strong Taylor scheme with  $m=1$ .

Def: Weak stochastic Taylor scheme of order  $m$  for  $Z_{t_0}^{\tilde{V}}\text{-SDE}$  is:  $\bar{X}_0 = X_0$  and

$$\bar{X}_{j+1} = \bar{X}_j + \sum_{\substack{I \in U_{\Sigma_0, \dots, \Sigma_k} \\ |I| \leq m}} \tilde{V}^I(x) \Delta \tilde{B}_j^I$$

Thm.  $(V_i) \in C^{2(m+1)}$ . Then for  $g = \{f \in C, \text{ its pari. is poly. ker}\}$ , the weak Taylor scheme have weak order  $m$ .

Proof: i) Euler scheme is weak Taylor scheme with  $m=1$  as well.

ii) We can also refine the weak Stratonovich Taylor scheme:

$$\bar{X}_{j+1} = \bar{X}_j + \sum_{I \in \mathcal{A}_m} V^I(\bar{X}_j) \Delta B_j^I$$

it has weak order  $(m-1)/2$  for  $g$  if  $f, (V_i)$  regular enough.

eg. (Milstein scheme)

It's a scheme with weak order one and strong order two, given by:

$$\bar{X}_{j+1} = \bar{X}_j + V(\bar{X}_j) \Delta t_j + \sum_{i=1}^d V_i(\bar{X}_j) \Delta B_j^i + \sum_{(i_1, i_2) \in \{1, \dots, d\}^2} V^{(i_1, i_2)}(\bar{X}_j) \Delta \bar{B}_j^{(i_1, i_2)}.$$

Here,  $V^{(i_1, i_2)}(x) = DV_{i_2}(x) \cdot V_{i_1}(x)$  and

$$\Delta \bar{B}_j^{(i_1, i_2)} = \int_{t_j}^{t_{j+1}} B_s^{i_1} dB_s^{i_2}.$$

Remark: i) For  $i_1 = i_2 = i \Rightarrow \Delta \bar{B}_j^{(i, i)} = (\Delta B_j^i)^2 - \Delta t_j$   
 For  $i_1 \neq i_2$ , there is no explicit formula for the increments.

ii) For  $[V_{i_1}, V_{i_2}] = 0$ . Note:

$$B_t^{i_1} B_t^{i_2} = \int B_s^{i_1} dB_s^{i_2} + \int B_s^{i_2} dB_s^{i_1} + [B^{i_1}, B^{i_2}]_t$$

$\Rightarrow$  We can just calculate:

$$B_t^{i_1} B_t^{i_2} - [B^{i_1}, B^{i_2}]_t.$$

Next, we consider the sampling of  $B^z$ :

eg. (Milstein scheme in 2-dim)

We need to sample  $(B_t, D_t, A_t)$ .

$A_t$  is Lévy's area of  $B'$ .  $B^2$

Remark: There exists explicit formula  
for ch.f. of  $(B', B^2, A)$ . But  
no way to obtain its density.  
So Accept-reject method do  
not work.

We can use def of Itô's integral  
in Riemann's sum to approxi.:

$$B_t^i \approx \sum_1^N A B_k^i, \quad i=1,2. \quad D = (t/N), \quad \tilde{\phantom{x}}$$

$$A_t \approx \sum_1^{\tilde{N}} B_{t_{j-1}}^i \Delta B_j^i - B_{t_{j-1}}^2 \Delta B_j^i$$

Remark: Itô's has a competitive algo.

and we can consider mo-  
ment matching (up to two)