

# On weak approximation of stochastic differential equations with discontinuous drift coefficient

(joint work with A. Kohatsu-Higa and A. Lejay)

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# Introduction 1 (Problem)

- In this talk we consider the following  $d$ -dimensional SDE:

$$dX_t = \mathbf{b}(t, \mathbf{X}_t)dt + \sigma(t, X_t)dW_t. \quad (1)$$

where  $b(t, x)$ ,  $\sigma(t, x)$  are suitable functions and  $W_t$  is a Brownian motion.

- We would like to consider a **weak convergence rate of (1) with a discontinuous drift coefficient  $b(t, x)$** .
- For simplicity, we split the interval  $[0, T]$  equally in  $n$  subintervals and let the length of each time subinterval  $\Delta t$  be equal to  $\frac{T}{n}$ .
- We say that an approximation process  $\bar{X}_T$  weakly converges to  $X_T$  with order  $\gamma$  if

$$\left| E[f(X_T)] - E[f(\bar{X}_T)] \right| \leq C\Delta t^\gamma.$$

holds for every  $f$  in a certain class.



## Introduction 2 (Previous studies: continuous coeff.)

- When we use the Euler-Maruyama approximation as the approximation process  $\bar{X}_T$ , then the following result has been known.
- For  $\alpha \in (0, 1) \cup (1, 2) \cup (2, 3)$ , let  $H_T^{(\alpha)}$  be the Hölder space on  $[0, T] \times \mathbb{R}^d$  and  $H^{(\alpha)}$  be also the Hölder space on  $\mathbb{R}^d$ .
- If  $b, \sigma\sigma^* \in H_T^{(\alpha)}$  and  $f \in H^{(2+\alpha)}$  for some  $\alpha \in (0, 1) \cup (1, 2) \cup (2, 3)$ , there exists some positive constant  $K$  such that

$$\left| E[f(X_T)] - E[f(\bar{X}_T)] \right| \leq \frac{K}{n^{E(\alpha)}},$$

where

$$E(\alpha) = \begin{cases} \frac{\alpha}{2}, & \alpha \in (0, 1), & \leftarrow 0 \sim \frac{1}{2} \\ \frac{1}{3-\alpha}, & \alpha \in (1, 2), & \leftarrow \frac{1}{2} \sim 1 \\ 1, & \alpha \in (2, 3). \end{cases}$$

- For more details, see Mikulevicius and Platen [5] or a book of Kloeden and Platen [3].

## Introduction 3 (Previous studies: **dis**continuous coeff.)

- In this talk, we are interested in a discontinuous drift coefficient  $b(t, x)$ .
- Some results of weak convergence of SDE with discontinuous (drift and **diffusion**) coefficient and the Euler-Maruyama approximation:
  - ▶ Chan, Stramer (1998) [1]:

$$dX(t) = b(X(t))dt + \sigma(X(t))dW(t).$$

If  $b, \sigma$  are **piecewise continuous** and locally bounded, then the Euler-Maruyama approximation weakly converges. **Note that they do not mention about the rate.**

- ▶ Yan (2002) [9]:

$$dX(t) = b(t, X(t))dt + \sigma(t, X(t))dW(t).$$

If  $b, \sigma$  have that the set of all discontinuous points has measure 0 and linear growth, then the Euler-Maruyama approximation weakly converges. **Note that they do not mention about the rate, neither.**

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# Settings and Assumptions 1 (Original SDE)

- Let a fixed  $T > 0$ .
- $\sigma(t, x) : d \times d$ -symmetric matrix value **uniformly continuous function** on  $[0, T] \times \mathbb{R}^d$ , and there exist some positive constants  $\Lambda \geq \lambda > 0$  such that for all  $(t, x) \in [0, T] \times \mathbb{R}^d$  and  $\xi \in \mathbb{R}^d$ ,

$$\lambda|\xi|^2 \leq \xi^* a(t, x)\xi \leq \Lambda|\xi|^2,$$

where set  $a(t, x) = \sigma\sigma^*(t, x)$ .

- $b(t, x) : d$ -dimensional **measurable function** on  $[0, T] \times \mathbb{R}^d$ , and for all  $(t, x) \in [0, T] \times \mathbb{R}^d$ ,  $|b(t, x)| \leq \Lambda$  holds.
- Then the SDE (1) has a weak solution.
- $C_{SI}(\mathbb{R}^d)$  : a class of all **continuous function**  $f$  such that for all  $k > 0$ ,

$$\lim_{|x| \rightarrow \infty} |f(x)|e^{-k|x|^2} = 0.$$

## Settings and Assumptions 2 (Approximation)

- Let  $\varepsilon > 0$ .
- $b_\varepsilon(t, x)$  :  $d$ -dimensional measurable function on  $[0, T] \times \mathbb{R}^d$ , and for all  $(t, x) \in [0, T] \times \mathbb{R}^d$ ,  $|b(t, x)| \leq \Lambda$  holds.  
 $\implies$  Later we assume Hölder continuity or smoothness as necessary.
- Then we consider the following SDE:

$$dX_t^\varepsilon = x + \int_0^t b_\varepsilon(s, X_s^\varepsilon) ds + \int_0^t \sigma(s, X_s^\varepsilon) dB_s.$$

The drift coefficient  $b(t, x)$  is replaced by  $b_\varepsilon(t, x)$ .

- We consider the Euler-Maruyama approximation of  $X_t^\varepsilon$  with  $\Delta t = \frac{T}{n}$  :

$$\bar{X}_t^\varepsilon = x + \int_0^t b_\varepsilon(\phi(s), \bar{X}_{\phi(s)}^\varepsilon) ds + \int_0^t \sigma(\phi(s), \bar{X}_{\phi(s)}^\varepsilon) dB_s,$$

where  $\phi(s) = \sup\{t \leq s | t = \frac{k}{n} \text{ for } k \in \mathbb{N}\}$ .

# Theorem 1

## Theorem

We assume that for  $\gamma, \beta, \delta > 0$ , the following two inequalities hold:

- (i). for  $\gamma > 0$ ,  $\left| E[f(X_T)] - E[f(X_T^\varepsilon)] \right| = O(\varepsilon^\gamma)$ ,
- (ii). and for  $\beta, \delta > 0$ ,  $\left| E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] \right| = O\left(\frac{1}{\varepsilon^\beta n^\delta}\right)$ .

Then for  $\varepsilon = O(n^{-\frac{\delta}{\gamma+\beta}})$ , the following holds :

$$\left| E[f(X_T)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq O\left(n^{-\frac{\delta\gamma}{\gamma+\beta}}\right).$$

Remark:

- Note that  $\bar{X}_T^\varepsilon$  is **NOT** the direct Euler-Maruyama approximation of  $X_T$ .
- When  $\varepsilon = n^{-\frac{\delta}{\gamma+\beta}}$ , the following holds :

$$\frac{1}{\varepsilon^\beta n^\delta} = n^{-\frac{\delta\gamma}{\gamma+\beta}} \xrightarrow{n \rightarrow \infty} 0.$$

## Proposition 1 (About assumption (i))

On the assumption (i) in Theorem:

### Proposition

For some  $\alpha, p > 2$  such that  $\frac{1}{\alpha} + \frac{1}{p} < \frac{1}{2}$ , and all  $f \in C_{SI}(\mathbb{R}^d)$ , we have

$$\left| E[f(X_T)] - E[f(X_T^\varepsilon)] \right| \leq C(\alpha, p, T) A_T(\varepsilon) \sqrt{\text{Var}(f(X_T))},$$

where set

$$C(\alpha, p, T) = T^{\frac{1}{2} - \frac{1}{p}} \exp \left( T \Lambda \lambda^{-1} \left( \alpha - \frac{1}{2} + \left( 1 - \frac{2}{\alpha} \right) \frac{\alpha(\frac{1}{2} + \frac{1}{p}) - 1}{\alpha(\frac{1}{2} - \frac{1}{p}) - 1} \right) \right),$$

$$A_T(\varepsilon) = E \left[ \int_0^T |b_\varepsilon(s, Y_s) - b(s, Y_s)|^p ds \right]^{\frac{1}{p}},$$

where  $Y_t$  is a weak solution of  $Y_t = x + \int_0^t \sigma(s, Y_s) dW_s$ .

## Remark 1 (About $A_T(\varepsilon)$ )

### Remark

- If the transition density function  $p(t, x, y)$  of  $Y_t$  has a Gaussian upper estimation, then for every  $1 < r, q \leq \infty$  such that  $\frac{d}{2r} + \frac{1}{q} < 1$ , we have

$$A_T(\varepsilon) \leq C_3 \left\{ \int_0^T \left( \int_{\mathbb{R}^d} |b(s, y) - b_\varepsilon(s, y)|^{pq} dy \right)^{\frac{r}{q}} ds \right\}^{\frac{1}{rp}}.$$

A rate of convergence depends on a kind of  $L^p$ -error between  $b$  and  $b_\varepsilon$ . When  $a = \sigma\sigma^* \in H^{\frac{\alpha}{2}, \alpha}([0, T] \times \mathbb{R}^d)$  ( $\alpha > 0$ ) holds, it has a Gaussian upper estimation.

- Even if it does NOT have a Gaussian upper estimation, from bounded and uniformly elliptic assumptions, we have the following when  $b(t, x) = b(x)$ ,

$$A_T(\varepsilon) \leq C(\lambda, \Lambda) e^T \|b - b_\varepsilon\|_{L^p}.$$



## Proposition 2 (About assumption (ii))

On the assumption (ii) in Theorem:

- When we adopt a **Hölder continuous function** as  $b_\varepsilon$ , we can use the following result (which was mentioned before). For example, a broken line approximation is in this case.

### Proposition

(Mikulevicius and Platen [5]) If  $b_\varepsilon, \sigma\sigma^* \in H_T^{(\alpha)}$  and  $f \in H^{(2+\alpha)}$  for some  $\alpha \in (0, 1) \cup (1, 2) \cup (2, 3)$ , there exists some positive constant  $K$  such that

$$\left| E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq \frac{K}{n^{E(\alpha)}},$$

where

$$E(\alpha) = \begin{cases} \frac{\alpha}{2}, & \alpha \in (0, 1), & \leftarrow 0 \sim \frac{1}{2} \\ \frac{1}{3-\alpha}, & \alpha \in (1, 2), & \leftarrow \frac{1}{2} \sim 1 \\ 1, & \alpha \in (2, 3). \end{cases}$$

- Note that the constant  $K$  **linearly** depends on  $\|b_\varepsilon\|_{H^\alpha}$ .

## Proposition 3 (About assumption (ii))

- When  $b$  is quite complicate and we use a mollifier (**smooth approximation**) as  $b_\varepsilon$ , then

### Proposition

Let  $f \in C^3(\mathbb{R}^d) \cap C_{SI}(\mathbb{R}^d)$  and  $b_\varepsilon, \sigma \in C_b^{1,3}([0, T] \times \mathbb{R}^d)$ . Then we have

$$\left| E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq \frac{C}{n} \|b_\varepsilon\|_{3,\infty},$$

where  $C$  is a positive constant and  $\|b_\varepsilon\|_{3,\infty}$  is defined as follows:

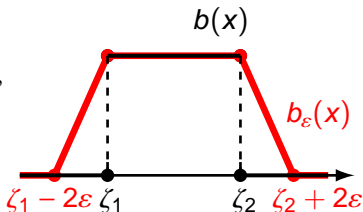
$$\|b_\varepsilon\|_{3,\infty} = \sum_{j=0}^3 \|b_\varepsilon^{(j)}\|_\infty.$$

## Example (Indicator function)

### Remark

- Set  $d = 1$ ,  $b(t, x) = \mathbf{1}_{[\zeta_1, \zeta_2]}(x)$  ( $\zeta_1 < \zeta_2$ ) and

$$b_\varepsilon(x) = \begin{cases} \frac{1}{2\varepsilon}x - \frac{\zeta_1 - 2\varepsilon}{2\varepsilon}, & [\zeta_1 - 2\varepsilon, \zeta_1), \\ -\frac{1}{2\varepsilon}x + \frac{\zeta_2 + 2\varepsilon}{2\varepsilon}, & (\zeta_2, \zeta_2 + 2\varepsilon], \\ 1, & [\zeta_1, \zeta_2], \\ 0, & \text{Otherwise.} \end{cases}$$



(broken line approximation)

- Assumption (i): For  $p > 2$ , we have

$$\left\{ \int_{-\infty}^{\infty} |b_\varepsilon(x) - b(x)|^p dx \right\}^{\frac{1}{p}} = O(\varepsilon^{\frac{1}{p}}).$$

- Assumption (ii): The rate of the divergence is  $\|b_\varepsilon\|_{H^\alpha} = O(\varepsilon^{-1})$ .
- An optimal rate of  $\varepsilon$  is  $\varepsilon = O(n^{-\frac{p}{2(1+p)}})$ .

## Settings and Assumptions 3 (Constant diffusion coeff.)

- Now we assume that  $\sigma(t, x)$  is a constant matrix (Here unit-matrix) and  $b(t, x) = b(x)$  is time-homogeneous.

That is, we consider the following SDE:

$$X_t = x + \int_0^t b(X_s) ds + B_t.$$

- $X_t^\varepsilon$ : The solution of SDE with an approximated drift  $b_\varepsilon(x)$ .
- $\bar{X}_t^\varepsilon$ : The Euler-Maruyama approximation of  $X_t^\varepsilon$ .
- The Euler-Maruyama approximation of  $X_t$ :

$$\bar{X}_t = x + \int_0^t b(\bar{X}_{\phi(s)}) ds + B_t.$$

- Until the previous slide, we consider about weak approximation between  $X_t$  and  $\bar{X}_t^\varepsilon$  which is **NOT** the direct Euler-Maruyama approximation of  $X_t$ . Now as the approximation  $\bar{X}_t$  of  $X_t$ , **we consider the direct Euler-Maruyama approximation of  $X_t$ .**

# Lemmas

## Lemma

For  $p > 2 \vee d$ , there exists some positive constant  $C_1(p, \Lambda, T)$  such that

$$\left| E[f(X_T)] - E[f(X_T^\varepsilon)] \right| \leq C_1(p, \Lambda, T) \sqrt{\text{Var}(f(x + B_T))} \|\mathbf{b} - \mathbf{b}_\varepsilon\|_{L^p}.$$

## Lemma

For  $p > 2$ , there exists some positive constant  $C_2(p, \Lambda, T)$  such that

$$\left| E[f(\bar{X}_T)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq C_2(p, \Lambda, T) \sqrt{\text{Var}(f(x + B_T))} \|\mathbf{b} - \mathbf{b}_\varepsilon\|_{L^p}.$$

- The both lemmas are similar results to Proposition 1.
- We use a happy property of the Euler-Maruyama approximation in the case of the constant diffusion coefficient:  $\sum_{i=1}^n (B_{i\Delta t} - B_{(i-1)\Delta t}) = B_T$ .

## Proposition 4

### Proposition

(Theorem 1 in Mackevičius [4]) Let  $b_\varepsilon$  be a bounded and Lipschitz continuous function with constant  $\text{Lip}(b_\varepsilon)$  and  $f$  be in  $C_p^3(\mathbb{R}^d)$ . Then there exists some positive constant  $C(T, \Lambda, f)$  such that

$$\left| E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq \frac{C(T, \Lambda, f)}{n} \text{Lip}(b_\varepsilon).$$

- In the paper of Mackevičius [4], the boundedness of  $b_\varepsilon$  is not assumed.

Notations:

- For a set  $G$  in  $\mathbb{R}^d$ , we define  $G(\varepsilon) = \{x \in \mathbb{R}^d \mid d(x, G) \leq \varepsilon\}$ , where  $d(x, G) = \inf_{y \in G} |x - y|$  is the distance between  $x$  and  $G$ .

By summing up the above results, we have the following theorem.

## Theorem 2

### Theorem

Let  $b$  be a bounded measurable function on  $\mathbb{R}^d$  which is Lipschitz except on a set  $G$  such that the Lebesgue measure  $\text{meas}(G(\varepsilon)) = O(\varepsilon^d)$ . Then for any  $f \in C_p^3(\mathbb{R}^d)$  and  $p > d \vee 2$ , we have

$$\left| E[f(X_T)] - E[f(\bar{X}_T)] \right| = O\left(n^{-\frac{d}{p+d}}\right).$$

### Remark

- An optimal size of  $\varepsilon$  is  $\varepsilon = O\left(n^{-\frac{p}{d+p}}\right)$ , where we assume  $\text{Lip}(b_\varepsilon) = O(\varepsilon^{-1})$  and  $\|b - b_\varepsilon\|_{L^p} = O(\varepsilon^{\frac{d}{p}})$ .
- From the theorem, we find that if  $p \rightarrow 2$  and  $d = 1$ , the rate of the weak convergence is **order**  $\frac{1}{3}$ . Note that for  $\alpha \in (0, 1)$  (Hölder continuous case), the result in Kloeden and Platen [3] is the **order**  $\frac{1}{2}$ . (where in their case,  $\sigma$  is also  $\alpha$ -Hölder continuous.)

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# Numerical Experiments 1

- We consider the following SDE ( $d = 1$ ):

$$X_t = x + \int_0^t b(X_s) ds + B_t, \quad \text{where } b(x) = \begin{cases} \theta_1, & x \leq 0, \\ \theta_0, & x > 0. \end{cases}$$

- From Karatzas and Shreve [2], we have a representation of the transition density function of  $X_t$ .
- If  $\theta_1 = -\theta_0 > 0$  and  $x = 0$ , the distribution of  $X_t$  is symmetric. And if  $f$  is an odd function, we have  $E[f(X_t)] = 0$ .
- As  $b_\varepsilon$ , we use

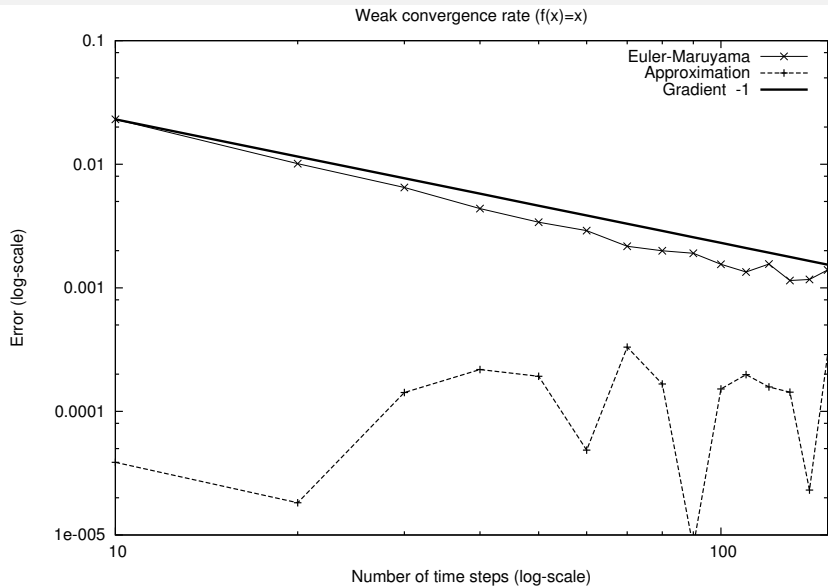
$$b_\varepsilon(x) = \begin{cases} \theta_1, & x \leq -\varepsilon, \\ \frac{\theta_0 - \theta_1}{2\varepsilon} x + \frac{\theta_0 + \theta_1}{2}, & -\varepsilon < x \leq \varepsilon, \\ \theta_0, & x > \varepsilon. \end{cases}$$

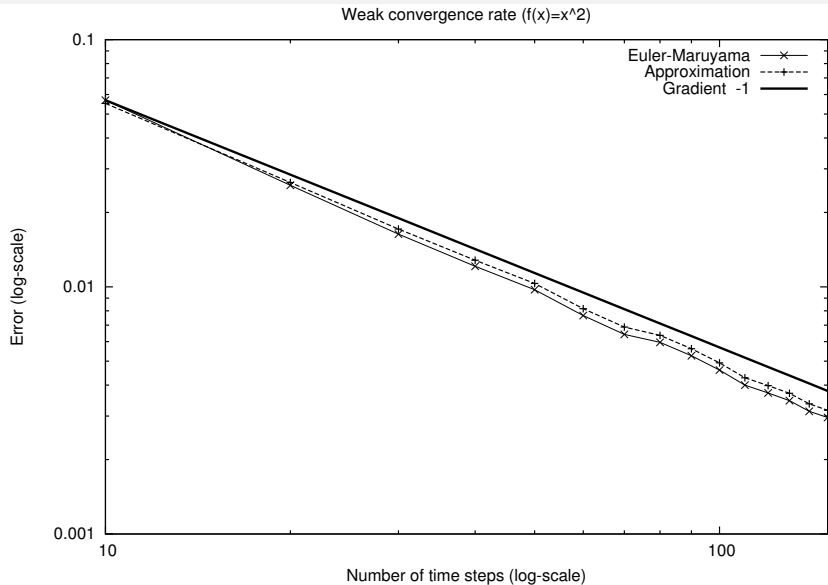
- Here we adopt  $\varepsilon = n^{-\frac{2}{3}}$  from the previous slide.

## Numerical Experiments 2

- We consider two types of errors:
  - ▶  $|E[f(X_T)] - E[f(\bar{X}_T)]|$ : thin line in all graphs below.
  - ▶  $|E[f(X_T)] - E[f(\bar{X}_T^\varepsilon)]|$ : dotted line in all graphs below.
- Let  $T = 1$ ,  $\theta_1 = -\theta_0 = 1$  and  $X_0 = 0$ .
- We use  $10^7$  times Monte-Carlo simulations to  $E[f(\bar{X}_1)]$  and  $E[f(\bar{X}_1^\varepsilon)]$  each time step  $n$ .
- First Example:  $f(x) = x$ .
  - ▶ True value:  $E[f(X_1)] = 0$  from the odd function  $f$  and the initial value  $X_0 = 0$ .
- Second Example:  $f(x) = x^2$ .
  - ▶ True value:  $E[f(X_1)] = 0.333369$  which is analytically obtained.
- Third Example:  $f(x) = \mathbf{1}(x > 0) - \mathbf{1}(x \leq 0)$ . (This is outside of our theorem.)
  - ▶ True value:  $E[f(X_1)] = 0$  from the odd function  $f$  a.e. and the initial value  $X_0 = 0$ .

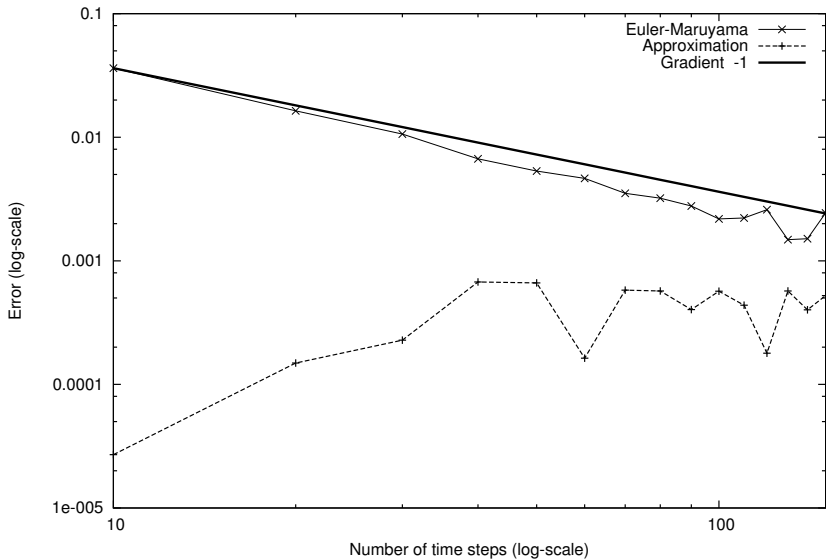
# Numerical Experiments 3: $f(x) = x$



Numerical Experiments 4:  $f(x) = x^2$ 

# Numerical Experiments 5: $f(x) = \mathbf{1}(x > 0) - \mathbf{1}(x \leq 0)$

Weak convergence rate ( $f(x)=\text{indicator}$ )



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# Proposition 1

On the assumption **(i)** in Theorem:

## Proposition

For some  $\alpha, p > 2$  such that  $\frac{1}{\alpha} + \frac{1}{p} < \frac{1}{2}$ , and all  $f \in C_{SI}(\mathbb{R}^d)$ , we have

$$\left| E[f(X_T)] - E[f(X_T^\varepsilon)] \right| \leq C(\alpha, p, T) A_T(\varepsilon) \sqrt{\text{Var}(f(X_T))},$$

where set

$$C(\alpha, p, T) = T^{\frac{1}{2} - \frac{1}{p}} \exp \left( T \Lambda \lambda^{-1} \left( \alpha - \frac{1}{2} + \left( 1 - \frac{2}{\alpha} \right) \frac{\alpha(\frac{1}{2} + \frac{1}{p}) - 1}{\alpha(\frac{1}{2} - \frac{1}{p}) - 1} \right) \right),$$

$$A_T(\varepsilon) = E \left[ \int_0^T |b_\varepsilon(s, Y_s) - b(s, Y_s)|^p ds \right]^{\frac{1}{p}},$$

where  $Y_t$  is a weak solution of  $Y_t = x + \int_0^t \sigma(s, Y_s) dW_s$ .

# Proof of Proposition 1 (1)

- We define  $Z_t$  as

$$Z_t = \exp\left(\int_0^t \gamma(s, X_s) dB_s - \frac{1}{2} \int_0^t \gamma\gamma^*(s, X_s) ds\right),$$

where set  $\gamma(s, x) = (b^\varepsilon(s, x) - b(s, x))^* \sigma^{-1}(s, x)$ .

## Lemma

Set  $\hat{\gamma} = \sup_{s \in [0, T], x \in \mathbb{R}^d} |\gamma(s, x)|$ . For  $\alpha > 1$ , we have

$$E\left[Z_T^\alpha\right]^{\frac{1}{\alpha}} \leq \exp\left(\left(\alpha - \frac{1}{2}\right) \hat{\gamma}^2 T\right). \quad (2)$$

Proof. Set  $M_t = \int_0^t \gamma(s, X_s) dB_s$ . From the Schwarz inequality,

$$E\left[Z_T^\alpha\right] \leq E\left[\exp\left(2\alpha M_T - \frac{4\alpha^2}{2} \langle M \rangle_T\right)\right]^{\frac{1}{2}} E\left[\exp\left((2\alpha^2 - \alpha) \langle M \rangle_T\right)\right]^{\frac{1}{2}}.$$

We obtain the consequence from the exponential martingale and

$$\langle M \rangle_T \leq \hat{\gamma}^2 T. \quad \square$$



## Proof of Proposition 1 (2)

- Set  $L = \sum_{i,j=1}^d \frac{1}{2} a_{i,j} \frac{\partial^2}{\partial x_i \partial x_j} + \sum_{i=1}^d b_i \frac{\partial}{\partial x_i}$ .
- We consider the following Cauchy problem:

$$\begin{cases} \frac{\partial u(t, x)}{\partial t} + Lu(t, x) = 0, & \text{on } [0, T) \times \mathbb{R}^d, \\ u(T, x) = f(x), & \text{on } \mathbb{R}^d. \end{cases}$$

### Lemma

(Lemma 1 and Corollary, Veretennikov [8]) We have the following representation and estimation by using the solution  $u$ :

- (i).  $f(X_T) = u(0, X_0) + \int_0^T \nabla u(s, X_s) \sigma(s, X_s) dB_s,$
- (ii).  $E \left[ \int_0^T |\nabla u(s, X_s)|^2 ds \right] \leq \text{Var}(f(X_T)).$

- About existence and uniqueness, see Theorem 3 and 3' in [8].

## Proof of Proposition 1 (3)

- From Girsanov theorem,  $E[f(X_T^\varepsilon)] = E[Z_T f(X_T)]$ .
- $Z_t$  follows to  $Z_t = 1 + \int_0^t Z_s \gamma(s, X_s) dB_s$ .
- From the previous Lemma (i) and martingale property of  $Z_t$ ,

$$\begin{aligned}
 |\Delta| &= \left| E[f(X_T^\varepsilon)] - E[f(X_T)] \right| = \left| E[(Z_T - 1) f(X_T)] \right| \\
 &= \left| E \left[ Z_T \int_0^T (b^\varepsilon(s, X_s) - b(s, X_s)) \nabla u(s, X_s) ds \right] \right| \\
 &\leq \underbrace{E[Z_T^\alpha]}_{\text{Lemma}} \left[ \left( \int_0^T |(b^\varepsilon - b)(s, X_s)|^2 ds \right)^{\frac{\alpha'}{2-\alpha'}} \right]^{\frac{2-\alpha'}{2\alpha'}} \underbrace{E \left[ \int_0^T |\nabla u(s, X_s)|^2 ds \right]^{\frac{1}{2}}}_{\text{Lemma(ii)}}.
 \end{aligned}$$

- We use Girsanov theorem to the middle term and similar arguments again. Then we obtain the term related to  $A_T(\varepsilon)$ .  $\square$

## Proposition 3

### Proposition

Let  $f \in C^3(\mathbb{R}^d) \cap C_{SI}(\mathbb{R}^d)$  and  $b_\varepsilon, \sigma \in C_b^{1,3}([0, T] \times \mathbb{R}^d)$ . Then we have

$$\left| E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq \frac{C}{n} \|b_\varepsilon\|_{3,\infty},$$

where  $C$  is a positive constant and  $\|b_\varepsilon\|_{3,\infty}$  is defined as follows:

$$\|b_\varepsilon\|_{3,\infty} = \sum_{j=0}^3 \|b_\varepsilon^{(j)}\|_\infty.$$

Note that we consider the Euler-Maruyama approximation with  $\Delta t = \frac{T}{n}$ .

# Proof of Proposition 3 (1)

Proof.

- Define

$$\hat{Z}_t^{b_\varepsilon} = \int_0^t b_\varepsilon^* \sigma^{-1}(s, Y_s) dW_s - \frac{1}{2} \int_0^t b_\varepsilon^* a^{-1} b_\varepsilon(s, Y_s) ds,$$

$$\tilde{Z}_t^{b_\varepsilon} = \int_0^t b_\varepsilon^* \sigma^{-1}(\phi(s), \bar{Y}_{\phi(s)}) dW_s - \frac{1}{2} \int_0^t b_\varepsilon^* a^{-1} b_\varepsilon(\phi(s), \bar{Y}_{\phi(s)}) ds,$$

where  $W_t$  is a Brownian motion and

$$Y_t = x + \int_0^t \sigma(s, Y_s) dW_s, \quad \bar{Y}_t = x + \int_0^t \sigma(\phi(s), \bar{Y}_{\phi(s)}) dW_s.$$

- $\hat{\mathcal{L}}^{b_\varepsilon}(Y_t) \sim \mathcal{L}(X_t^\varepsilon)$  and  $\tilde{\mathcal{L}}^{b_\varepsilon}(\bar{Y}_t) \sim \mathcal{L}(\bar{X}_t^\varepsilon)$  hold.
- Set  $g(y, z) = \exp(z)f(y)$ . Then

$$E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] = E[g(Y_T, \hat{Z}_T^{b_\varepsilon})] - E[g(\bar{Y}_T, \tilde{Z}_T^{b_\varepsilon})].$$

## Proof of Proposition 3 (2)

By using Taylor expansion,

$$\begin{aligned}
 &= E \left[ \nabla g(\theta Y_T + (1 - \theta) \bar{Y}_T, \theta \hat{Z}_T^{b_\varepsilon} + (1 - \theta) \tilde{Z}_T^{b_\varepsilon}) (Y_T - \bar{Y}_T) \right] \\
 &\quad + E \left[ \partial_z g(\theta' Y_T + (1 - \theta') \bar{Y}_T, \theta' \hat{Z}_T^{b_\varepsilon} + (1 - \theta') \tilde{Z}_T^{b_\varepsilon}) (\hat{Z}_T^{b_\varepsilon} - \tilde{Z}_T^{b_\varepsilon}) \right],
 \end{aligned} \tag{3}$$

where  $\theta, \theta' \sim U(0, 1)$  are independent of each other.

- $\mathcal{E}_t = Y_t - \bar{Y}_t$  is written as follows:

$$\begin{aligned}
 \mathcal{E}_t &= \int_0^t \alpha_s \mathcal{E}_s dW_s + \int_0^t G_s dW_s \\
 \Rightarrow \mathcal{E}_t &= U_t \int_0^t U_s^{-1} G_s dW_s - U_t \int_0^t U_s^{-1} \alpha(s) G_s ds,
 \end{aligned}$$

where set  $G_s = \sigma(s, \bar{Y}_s) - \sigma(\phi(s), \bar{Y}_{\phi(s)})$  and

$$U_t = 1 + \int_0^t \alpha_s U_s dW_s, \quad \alpha_s = \int_0^1 \partial_x \sigma(s, \xi Y_s + (1 - \xi) \bar{Y}_s) d\xi.$$

## Proof of Proposition 3 (3)

- Consider the first term of (3). (the rests are similar)

$$E \left[ \underbrace{\nabla g(\theta Y_T + (1 - \theta) \bar{Y}_T, \theta \hat{Z}_T^{b_\varepsilon} + (1 - \theta) \tilde{Z}_T^{b_\varepsilon})}_{=F} \varepsilon_T \right]$$

$$= E \left[ F \left\{ U_T \int_0^T U_s^{-1} G_s dW_s - U_T \int_0^T U_s^{-1} \alpha(s) G_s ds \right\} \right].$$

- By Taylor expansion,  $G_s$  is written as

$$G_s = \int_{\phi(s)}^s \partial_t \sigma(u, \bar{Y}_s) du \quad \left( \rightarrow \leq \frac{M}{n} \right)$$

$$+ \int_0^1 \nabla \sigma(\phi(s), \beta \bar{Y}_s + (1 - \beta) \bar{Y}_{\phi(s)}) \cdot \sigma(\phi(s), \bar{Y}_{\phi(s)}) \int_{\phi(s)}^s dW_u d\beta.$$

- By using the dual formula in the Malliavin calculus to the part

$$\int_{\phi(s)}^s dW_u, \text{ the second term also has } \frac{M}{n}. \quad \square$$

# Lemmas

## Lemma

For  $p > 2 \vee d$ , there exists some positive constant  $C_1(p, \Lambda, T)$  such that

$$\left| E[f(X_T)] - E[f(X_T^\varepsilon)] \right| \leq C_1(p, \Lambda, T) \sqrt{\text{Var}(f(x + B_T))} \|\mathbf{b} - \mathbf{b}_\varepsilon\|_{L^p}.$$

The proof is the similar to the following lemma.  $\square$

## Lemma

For  $p > 2$ , there exists some positive constant  $C_2(p, \Lambda, T)$  such that

$$\left| E[f(\bar{X}_T)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq C_2(p, \Lambda, T) \sqrt{\text{Var}(f(x + B_T))} \|\mathbf{b} - \mathbf{b}_\varepsilon\|_{L^p}.$$

## Proof of Second Lemma (1)

Proof.

- Set  $\beta(s) = b(x + B_{\phi(s)})$ ,  $\beta_{\varepsilon}(s) = b_{\varepsilon}(x + B_{\phi(s)})$  and define

$$Z_t = 1 + \int_0^t Z_s \beta(s) dB_s, \quad Z_t^{\varepsilon} = 1 + \int_0^t Z_s^{\varepsilon} \beta_{\varepsilon}(s) dB_s.$$

- $Z_t - Z_t^{\varepsilon}$  is written as follows:

$$Z_t - Z_t^{\varepsilon} = \int_0^t (Z_s - Z_s^{\varepsilon}) \beta(s) dB_s + \int_0^t Z_s^{\varepsilon} (\beta(s) - \beta_{\varepsilon}(s)) dB_s.$$

- Then from  $(a + b)^2 \leq 2a^2 + 2b^2$ , we have

$$\Delta_t = E \left[ |Z_t - Z_t^{\varepsilon}|^2 \right] \leq 2\Lambda^2 \int_0^t \Delta_s ds + 2E \left[ \int_0^t Z_s^{\varepsilon} (\beta(s) - \beta_{\varepsilon}(s))^2 ds \right].$$

- From (2), the second term in the RHS satisfies the following:  
( $C(p, \Lambda, T)$  is some positive constant)

$$E \left[ \int_0^T Z_s^{\varepsilon} (\beta(s) - \beta_{\varepsilon}(s))^2 ds \right] \leq C(p, \Lambda, T) E \left[ \int_0^T |\beta(s) - \beta_{\varepsilon}(s)|^p ds \right]^{\frac{2}{p}}.$$



## Proof of Second Lemma (2)

- By the Gronwall's inequality,

$$\Delta_T \leq C(p, \Lambda, T) e^{2\Lambda^2 T} E \left[ \int_0^T |\beta(s) - \beta_\varepsilon(s)|^p ds \right]^{\frac{2}{p}}.$$

- By using the similar argument to Proposition 1, we have: ( $\alpha, p > 2$ ,  $\frac{1}{\alpha} + \frac{1}{p} < \frac{1}{2}$ )

$$\begin{aligned} & \left| E[f(\bar{X}_T)] - E[f(\bar{X}_T^\varepsilon)] \right| \\ &= \left| E[Z_T f(x + B_T)] - E[Z_T^\varepsilon f(x + B_T)] \right| \\ &\leq C(\alpha, p, \Lambda, T) E \left[ \int_0^T |\beta(s) - \beta_\varepsilon(s)|^p ds \right]^{\frac{1}{p}} \sqrt{\text{Var}(f(x + B_T))}. \end{aligned}$$

- By using an upper Gaussian estimation to the middle term, we have: ( $\gamma > 1$ )

$$E \left[ \int_0^T |(b - b_\varepsilon)(x + B_{\phi(s)})|^p ds \right] \leq C'(T, \gamma) \|b - b_\varepsilon\|_{\frac{p\gamma}{\gamma-1}}^p$$

## Theorem 2

### Theorem

Let  $b$  be a bounded measurable function on  $\mathbb{R}^d$  which is Lipschitz except on a set  $G$  such that the Lebesgue measure  $\text{meas}(G(\varepsilon)) = O(\varepsilon^d)$ . Then for any  $f \in C_p^3(\mathbb{R}^d)$  and  $p > d \vee 2$ , we have

$$\left| E[f(X_T)] - E[f(\bar{X}_T)] \right| = O\left(n^{-\frac{d}{p+d}}\right).$$

### Proposition

(Theorem 1 in Mackevičius [4]) Let  $b_\varepsilon$  be a bounded and Lipschitz continuous function with constant  $\text{Lip}(b_\varepsilon)$  and  $f$  be in  $C_p^3(\mathbb{R}^d)$ . Then there exists some positive constant  $C(T, \Lambda, f)$  such that

$$\left| E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] \right| \leq \frac{C(T, \Lambda, f)}{n} \text{Lip}(b_\varepsilon).$$

## Proof of Theorem 2

### Proof.

- From the previous Proposition and two lemmas, for  $p > 2$ ,

$$\begin{aligned} & \left| E[f(X_T)] - E[f(\bar{X}_T)] \right| \\ & \leq \left| E[f(X_T)] - E[f(X_T^\varepsilon)] \right| + \left| E[f(X_T^\varepsilon)] - E[f(\bar{X}_T^\varepsilon)] \right| + \left| E[f(\bar{X}_T^\varepsilon)] - E[f(\bar{X}_T)] \right| \\ & \leq C(p, \Lambda, T) \sqrt{\text{Var}(f(x + B_T))} \|b - b_\varepsilon\|_{L^p} + \frac{C(\Lambda, T, f)}{n} \text{Lip}(b_\varepsilon). \end{aligned}$$

- From  $\text{Lip}(b_\varepsilon) = O(\frac{1}{\varepsilon})$  and  $\|b - b_\varepsilon\|_{L^p} = O(\varepsilon^{\frac{d}{p}})$ , we have






$$\left| E[f(X_T)] - E[f(\bar{X}_T)] \right| \leq \frac{C}{n\varepsilon} + C' \varepsilon^{\frac{d}{p}}.$$

- An optimal choice of  $\varepsilon$  is  $\varepsilon = O(n^{-\frac{p}{d+p}})$  and we obtain our consequence.  $\square$





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