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→ Some comments on financial modeling ①

① There are more general models:  
e.g. Stochastic Ginzburg Landau

$$dX_t = [dX_t - 8X_t^3]dt + [\beta X_t + \bar{\beta}]dW_t$$

not globally Lipschitz,  
however the existence & uniqueness  
has been shown

- CIR (Cox-Ingersoll-Ross) process  
used in interest rates

$$dX_t = [8 - d.X_t]dt + \beta\sqrt{X_t}dW_t$$

... Stochastic volatility models.

② Noise can be general Lévy process,  
might have discontinuities, i.e. jumps.

③ Many real world conditions might not be satisfied: ②

- transaction costs
- default risk (default of asset, counterparty default, ...)

→ Generalize to take into account these factors.

In conclusion, we will have some modeling error. → difficult to quantify.

Approximation error: Errors incurred through approximating the sol-n via some scheme.

Let us start with numerical approximations of SDEs (3)

## ① Euler-Mareyama (EM) scheme:

The SDE

$$dX_t = \mu(X_t) dt + \sigma(X_t) dW_t, X_0 = \xi$$

$t \in [0, T]$

$$\left[ X_t = \xi + \int_0^t \mu(X_s) ds + \int_0^t \sigma(X_s) dW_s \right]$$

Step Size  $h = \frac{T}{N}$  for some  $N \in \mathbb{N}$

$\gamma : \{0, 1, \dots, N\} \times \Omega \rightarrow \mathbb{R}^d$   
 discrete stochastic process, which  
 is given iteratively  
 $X_0 = \xi$

$$\begin{aligned} Y_{n+1} &= Y_n + \mu(Y_n) \cdot \frac{t^P}{N} + \\ &\quad \sigma(Y_n) \left( W_{\frac{(n+1)P}{N}} - W_{\frac{n P}{N}} \right) \\ &\quad t_{n+1} \end{aligned} \quad (4)$$

$t_{n+1} \in \{0, \dots, N-1\}$

$$= Y_n + h \cdot \mu(Y_n) + \sigma(Y_n) \cdot (W_{t_{n+1}} - W_{t_n})$$

Intuition:



to  $t_1 t_2 \dots$

$$\begin{aligned} X_{t_{n+1}} &= \xi + \int_0^{t_{n+1}} \mu(X_s) ds + \int_0^{t_{n+1}} \sigma(X_s) dW_s \\ &= \xi + \underbrace{\int_0^{t_n} \mu(X_s) ds}_{\text{Initial term}} + \underbrace{\int_{t_n}^{t_{n+1}} \mu(X_s) ds}_{\text{Numerical approximation}} + \end{aligned}$$

$$+ \int_0^{t_n} G(X_s) dW_s + \int_{t_n}^{t_{n+1}} G(X_s) dW_s \quad (5)$$

$$= X_{t_n} + \int_{t_n}^{t_{n+1}} \mu(X_s) ds + \int_{t_n}^{t_{n+1}} G(X_s) dW_s$$

$$X_{t_n} \approx Y_n$$

$$\int_{t_n}^{t_{n+1}} \mu(X_s) ds \approx \int_{t_n}^{t_{n+1}} \mu(Y_n) ds =$$

$$(t_{n+1} - t_n) \cdot \mu(Y_n) = h \cdot \mu(Y_n)$$

$$\int_{t_n}^{t_{n+1}} G(X_s) dW_s = \int_{t_n}^{t_{n+1}} G(Y_n) dW_s$$

$$= G(Y_n) [W_{t_{n+1}} - W_{t_n}]$$

$$Y_{t_{n+1}} = Y_n + h \cdot \mu(Y_n) + G(Y_n) \cdot [W_{t_{n+1}} - W_{t_n}] \quad (6)$$

We define linearly interpolated EM approximation by:

$$\bar{Y}: [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}^d, \quad \bar{Y}_0 = \xi$$

$$t \in \{0, 1, \dots, N-1\}, \quad t \in [t_n, t_{n+1}] = [n \cdot h, (n+1)h]$$

$$\begin{aligned} \bar{Y}_t &= \bar{Y}_{n \cdot h} + (t - n \cdot h) \cdot \mu(\bar{Y}_{n \cdot h}) \\ &\quad + \left( \frac{t}{h} - n \right) G(\bar{Y}_{n \cdot h}) (W_{t_{n+1}} - W_{t_n}) \end{aligned}$$

$$\bar{Y}_t = Y_n + \left( \frac{t}{h} - n \right) [\mu(Y_n) \cdot h + G(Y_n) \cdot (W_{t_{n+1}} - W_{t_n})]$$

Q: How good are these app-ns? ②

We have to differentiate several notions of convergence:

Def'n: Let  $Y^N: [0, T] \times \Omega \rightarrow \mathbb{R}^d$ ,  $N \in \mathbb{N}$ , be stochastic processes. We say that  $Y^N, N \in \mathbb{N}$  converges to  $X$  at time  $T$

(1) In the strong  $L^p$  sense ( $P \in (0, \infty)$ ) if

$$\left( \mathbb{E} \left[ \| Y_{\cdot, P}^N - X_{\cdot, P} \|_P^p \right] \right)^{1/p} \xrightarrow[N \rightarrow \infty]{} 0$$

$L^p$  error  $\xrightarrow[N \rightarrow \infty]{} 0$

with order  $de(0, \infty)$  if  $\exists C \in (0, \infty)$ :

$$\| Y_{\cdot, P}^N - X_{\cdot, P} \|_{L^p(P, \mathbb{R}^d)} \leq C \cdot N^{-\alpha} \quad \forall N \in \mathbb{N}$$

(2) P-a.s. if

$$P \left( \limsup_{N \rightarrow \infty} \| Y_{\cdot, P}^N - X_{\cdot, P} \|_{\mathbb{R}^d} = 0 \right) = 1.$$

With order  $de(0, \infty)$  if  $\exists C \in \mathbb{R} \rightarrow \mathbb{R}$  (random variable) s.t.

$$P \left( \| Y_{\cdot, P}^N - X_{\cdot, P} \| \leq C \cdot N^{-\alpha} \right) = 1.$$

(3) in probability if  $\forall \epsilon \in (0, \infty)$

$$\limsup_{N \rightarrow \infty} P \left( \| Y_{\cdot, P}^N - X_{\cdot, P} \| > \epsilon \right) = 0$$

(4) in numerically weak sense if  $\forall \psi \in C^\infty(\mathbb{R}^d, \mathbb{R})$  [test fns] with at most polynomially growing derivatives  $\mathbb{E}[\psi(Y_{\cdot, P}^N)] < \infty, \mathbb{E}[\psi(X_{\cdot, P})] < \infty$

$$[\mathbb{E}[\varphi(Y_P^N)] - \mathbb{E}[\varphi(X_P)]] \xrightarrow[N \rightarrow \infty]{(9)} 0$$

with order  $\mathcal{O}(0, \alpha)$  if:

$$\exists C \in (0, \infty) : \underbrace{|\mathbb{E}[\varphi(Y_P^N)] - \mathbb{E}[\varphi(X_P)]|}_{\mathbb{E}[\varphi(Y_P^N)]} \leq C \cdot N^{-\alpha}$$

weak error w.r.t.  $\varphi$ .

Recall:  $(E, \|\cdot\|_E)$ ,  $(F, \|\cdot\|_F)$  normed

spaces;  $f : E \rightarrow F$  grows at most polynomially if  $\exists C \in (0, \infty)$

$$\|f(x)\|_F \leq C \cdot (\|f\| \cdot \|x\|_E)^C$$

Theorem (Strong / uniform strong convergence of EM scheme).

Let  $p \in [2, \infty)$ ,  $\varphi \in L^p(P|_{F_0}; \mathbb{R}^d)$  and  $\mu$  and  $G$  be globally Lipschitz cont., i.e.

$$\begin{aligned} L_\mu &: \| \mu(x) - \mu(y) \| \leq L_\mu \cdot \|x - y\| \\ L_G &: \| G(x) - G(y) \|_{HS} \leq L_G \cdot \|x - y\|, \quad \forall x, y \in \mathbb{R}^d. \end{aligned}$$

[The same assumptions as for existence & uniqueness theorem]

then we have  $L^p$  convergence with order  $1/2$ :

$$\begin{aligned} (1) \quad & \sup_{t \in [0, T]} \| X_t - \bar{Y}_t \|_{L^p(P; \mathbb{R}^d)} \\ &= \sup_{t \in [0, T]} \left( \mathbb{E} [\| X_t - \bar{Y}_t \|_{\mathbb{R}^d}^p] \right)^{1/p} \leq \end{aligned}$$

$$\leq C(\lambda_\mu, \lambda_\beta, \mathcal{P}, p) \cdot \|X\|_{C^{1/2}([\zeta_0, \zeta_1], L^p)} \quad (1)$$

$$\frac{1}{\sqrt{N}}$$

$$\sup_{t,s} \left( \frac{\|X_t - Y_s\|_{L^p(\mathbb{P}; \mathbb{R}^d)}}{(t-s)^{1/2}} \right)$$

(i)  $\exists \tilde{C}$  s.t. uniform

$$\left\| \sup_{t \in [0, \zeta]} \|X_t - Y_t\|_{\mathbb{R}^d} \right\|_{L^p(\mathbb{P}; \mathbb{R})}$$

$$= \left( \mathbb{E} \left[ \left( \sup_{t \in [0, \zeta]} \|X_t - Y_t\|_{\mathbb{R}^d} \right)^p \right] \right)^{1/p}$$

$$\leq \tilde{C} \left( \sqrt{1 + \ln(N)} \right) \cdot \frac{1}{\sqrt{N}}$$

Smaller conv. order,  $\frac{1}{2} - \varepsilon$  (2)  
 $\forall \varepsilon \in (0, \infty)$ .

$$\frac{\ln(N)}{N^\varepsilon} \rightarrow 0 \quad \forall \varepsilon > 0$$

It has essentially order  $\frac{1}{2}$ .

Proof: (of) (i) uses discrete Gronwall lemma + Burkholder Davis-Gundy inequality (used for stochastic integral).

We will only prove (i) next time  
 increment tamed EM, higher orders (Milstein).