

# Convergence of the stochastic Euler scheme for locally Lipschitz coefficients

Arnulf Jentzen

Joint work with Martin Hutzenthaler

Department of Mathematics

Bielefeld University

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# Overview

- 1 Stochastic differential equations (SDEs)
- 2 Computational problem and the Monte Carlo Euler method
- 3 Convergence for SDEs with globally Lipschitz continuous coefficients
- 4 Convergence for SDEs with superlinearly growing coefficients

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- Consider
- a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  with a normal filtration  $(\mathcal{F}_t)_{t \in [0, T]}$  and  $T > 0$
  - a standard  $(\mathcal{F}_t)_{t \in [0, T]}$ -Brownian motion  $W : [0, T] \times \Omega \rightarrow \mathbb{R}$
  - continuous functions  $\mu, \sigma : \mathbb{R} \rightarrow \mathbb{R}$  and
  - a  $\mathcal{F}_0/\mathcal{B}(\mathbb{R})$ -measurable mapping  $\xi : \Omega \rightarrow \mathbb{R}$ .

Then let  $X : [0, T] \times \Omega \rightarrow \mathbb{R}$  be an adapted stochastic process with continuous sample paths which fulfills

$$X_t = \xi + \int_0^t \mu(X_s) ds + \int_0^t \sigma(X_s) dW_s \quad \mathbb{P}\text{-a.s.}$$

for all  $t \in [0, T]$ . Short form:

$$dX_t = \mu(X_t) dt + \sigma(X_t) dW_t, \quad X_0 = \xi, \quad t \in [0, T].$$

# Examples of SDEs I

**Black-Scholes model** with  $\bar{\mu}, \bar{\sigma}, x_0 \in (0, \infty)$ :

$$dX_t = \bar{\mu} X_t dt + \bar{\sigma} X_t dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

**A SDE with a cubic drift and additive noise:**

$$dX_t = -X_t^3 dt + dW_t, \quad X_0 = 0, \quad t \in [0, 1]$$

**A SDE with a cubic drift and multiplicative noise:**

$$dX_t = -X_t^3 dt + 6 X_t \circ dW_t, \quad X_0 = 1, \quad t \in [0, 3]$$

## Examples of SDEs II

A stochastic Verhulst equation with  $\eta, x_0 \in (0, \infty)$ :

$$dX_t = X_t (\eta - X_t) dt + X_t dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

A Feller diffusion with logistic growth with  $\eta, x_0 \in (0, \infty)$ :

$$dX_t = X_t (\eta - X_t) dt + \sqrt{X_t} dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

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# Weak approximation problem of the SDE (see e.g. Kloeden & Platen (1992))

Suppose we want to compute

$$\mathbb{E}\left[f(X_T)\right]$$

for a given smooth function  $f : \mathbb{R} \rightarrow \mathbb{R}$  whose derivatives grow at most polynomially.

For instance,  $f(x) = x^2$  for all  $x \in \mathbb{R}$  and we want to compute

$$\mathbb{E}\left[(X_T)^2\right]$$

the second moment of the SDE.



# Approximation of $\mathbb{E} [f(X_T)]$

The **stochastic Euler scheme**  $Y_k^N : \Omega \rightarrow \mathbb{R}$ ,  $k \in \{0, 1, \dots, N\}$ ,  $N \in \mathbb{N}$ , is given by  $Y_0^N(\omega) = \xi(\omega)$  and

$$\begin{aligned} & Y_{k+1}^N(\omega) \\ &= Y_k^N(\omega) + \frac{T}{N} \cdot \mu(Y_k^N(\omega)) + \sigma(Y_k^N(\omega)) \cdot \left( W_{\frac{(k+1)T}{N}}(\omega) - W_{\frac{kT}{N}}(\omega) \right) \end{aligned}$$

for all  $\omega \in \Omega$ ,  $k \in \{0, 1, \dots, N-1\}$  and all  $N \in \mathbb{N}$ . Let  $Y_k^{N,m} : \Omega \rightarrow \mathbb{R}$ ,  $k \in \{0, 1, \dots, N\}$ ,  $N \in \mathbb{N}$ , for  $m \in \mathbb{N}$  be independent copies of the Euler approximations. The **Monte Carlo Euler approximation** is then given by

$$\frac{1}{M} \left( \sum_{m=1}^M f(Y_N^{N,m}) \right) \approx \mathbb{E} [f(X_T)]$$

with  $N \in \mathbb{N}$  time steps and  $M \in \mathbb{N}$  Monte Carlo runs.

# Approximation of $\mathbb{E} [f(X_T)]$

The **stochastic Euler scheme**  $Y_k^N : \Omega \rightarrow \mathbb{R}$ ,  $k \in \{0, 1, \dots, N\}$ ,  $N \in \mathbb{N}$ , is given by  $Y_0^N(\omega) = \xi(\omega)$  and

$$\begin{aligned} Y_{k+1}^N(\omega) \\ = Y_k^N(\omega) + \frac{T}{N} \cdot \mu(Y_k^N(\omega)) + \sigma(Y_k^N(\omega)) \cdot \left( W_{\frac{(k+1)T}{N}}(\omega) - W_{\frac{kT}{N}}(\omega) \right) \end{aligned}$$

for all  $\omega \in \Omega$ ,  $k \in \{0, 1, \dots, N-1\}$  and all  $N \in \mathbb{N}$ . Let  $Y_k^{N,m} : \Omega \rightarrow \mathbb{R}$ ,  $k \in \{0, 1, \dots, N\}$ ,  $N \in \mathbb{N}$ , for  $m \in \mathbb{N}$  be independent copies of the Euler approximations. The **Monte Carlo Euler approximation** is then given by

$$\frac{1}{N^2} \left( \sum_{m=1}^{N^2} f(Y_N^{N,m}) \right) \approx \mathbb{E} [f(X_T)]$$

with  $N \in \mathbb{N}$  time steps and  $N^2 \in \mathbb{N}$  Monte Carlo runs.

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The triangle inequality shows

$$\begin{aligned}
 & \left| \mathbb{E} \left[ f(X_T) \right] - \frac{1}{N^2} \sum_{m=1}^{N^2} f(Y_N^{N,m}) \right| \\
 & \leq \underbrace{\left| \mathbb{E} \left[ f(X_T) \right] - \mathbb{E} \left[ f(Y_N^N) \right] \right|}_{\text{time discretization error}} + \underbrace{\left| \mathbb{E} \left[ f(Y_N^N) \right] - \frac{1}{N^2} \sum_{m=1}^{N^2} f(Y_N^{N,m}) \right|}_{\text{statistical error}} \quad (1)
 \end{aligned}$$

for all  $N \in \mathbb{N}$ .

The stochastic Euler scheme converges in the **numerically weak sense** if

$$\lim_{N \rightarrow \infty} \left| \mathbb{E} \left[ f(X_T) \right] - \mathbb{E} \left[ f(Y_N^N) \right] \right| = 0 \quad (2)$$

holds for every smooth function  $f : \mathbb{R} \rightarrow \mathbb{R}$  whose derivatives have at most polynomial growth (see e.g. Kloeden & Platen (1992), Milstein (1995), Talay (1996), Higham (2001), Rössler (2003)).

## Numerically weak convergence

Theorem (see e.g. Kloeden & Platen (1992))

Let  $\mu, \sigma, f : \mathbb{R} \rightarrow \mathbb{R}$  be four times continuously differentiable with at most polynomially growing derivatives. Moreover, let  $\mu, \sigma : \mathbb{R} \rightarrow \mathbb{R}$  be **globally Lipschitz continuous**. Then there is a real number  $C > 0$  such that

$$\left| \mathbb{E} \left[ f(X_T) \right] - \mathbb{E} \left[ f(Y_N^N) \right] \right| \leq C \cdot \frac{1}{N}$$

holds for all  $N \in \mathbb{N}$ .

*The stochastic Euler scheme converges in the numerically weak sense if the coefficients of the SDE are smooth and globally Lipschitz continuous.*

Numerically weak convergence yields

$$\begin{aligned}
 & \left| \mathbb{E} \left[ f(X_T) \right] - \frac{1}{N^2} \sum_{m=1}^{N^2} f(Y_N^{N,m}) \right| \\
 & \leq \left| \mathbb{E} \left[ f(X_T) \right] - \mathbb{E} \left[ f(Y_N^N) \right] \right| + \left| \mathbb{E} \left[ f(Y_N^N) \right] - \frac{1}{N^2} \sum_{m=1}^{N^2} f(Y_N^{N,m}) \right| \\
 & \leq C \cdot \frac{1}{N} + C_\varepsilon \cdot \frac{1}{N^{(1-\varepsilon)}} \leq (C + C_\varepsilon) \cdot \frac{1}{N^{(1-\varepsilon)}} \quad \mathbb{P} - \text{a.s.}
 \end{aligned}$$

for all  $N \in \mathbb{N}$  and all  $\varepsilon \in (0, 1)$  with an appropriate constant  $C \in (0, \infty)$  and appropriate random variables  $C_\varepsilon : \Omega \rightarrow [0, \infty)$ ,  $\varepsilon \in (0, 1)$ .

*The Monte Carlo Euler method converges if the coefficients of the SDE are smooth and globally Lipschitz continuous.*

# Examples of SDEs I

The global Lipschitz assumption on the coefficients of the SDE is a serious shortcoming:

**Black-Scholes model** with  $\bar{\mu}, \bar{\sigma}, x_0 \in (0, \infty)$ :

$$dX_t = \bar{\mu} X_t dt + \bar{\sigma} X_t dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

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## Theorem (Hutzenthaler &amp; J (2009))

Suppose  $\mathbb{P}[\sigma(\xi) \neq 0] > 0$  and let  $\alpha, C > 1$  be such that

$$|\mu(x)| \geq \frac{|x|^\alpha}{C} \quad \text{and} \quad |\sigma(x)| \leq C|x|$$

holds for all  $|x| \geq C$ . If the exact solution of the SDE satisfies

$\mathbb{E}[|X_T|^p] < \infty$  for one  $p \in [1, \infty)$ , then

$$\lim_{N \rightarrow \infty} \mathbb{E}[|X_T - Y_N^N|^p] = \infty, \quad \lim_{N \rightarrow \infty} \left| \mathbb{E}[|X_T|^p] - \mathbb{E}[|Y_N^N|^p] \right| = \infty$$

holds.

*Strong and numerically weak convergence fails to hold if the diffusion coefficient grows at most linearly and the drift coefficient grows superlinearly.*

# Examples of SDEs I

Divergence of Euler's method

$$\lim_{N \rightarrow \infty} \mathbb{E} |X_T - Y_N^N| = \infty, \quad \lim_{N \rightarrow \infty} \left| \mathbb{E} \left[ (X_T)^2 \right] - \mathbb{E} \left[ (Y_N^N)^2 \right] \right| = \infty$$

holds for:

**A SDE with a cubic drift and additive noise:**

$$dX_t = -X_t^3 dt + dW_t, \quad X_0 = 0, \quad t \in [0, 1]$$

**A SDE with a cubic drift and multiplicative noise:**

$$dX_t = -X_t^3 dt + 6 X_t \circ dW_t, \quad X_0 = 1, \quad t \in [0, 3]$$

## Examples of SDEs II

Divergence of Euler's method

$$\lim_{N \rightarrow \infty} \mathbb{E} |X_T - Y_N^N| = \infty, \quad \lim_{N \rightarrow \infty} \left| \mathbb{E} \left[ (X_T)^2 \right] - \mathbb{E} \left[ (Y_N^N)^2 \right] \right| = \infty$$

holds for:

A stochastic Verhulst equation with  $\eta, x_0 \in (0, \infty)$ :

$$dX_t = X_t (\eta - X_t) dt + X_t dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

A Feller diffusion with logistic growth with  $\eta, x_0 \in (0, \infty)$ :

$$dX_t = X_t (\eta - X_t) dt + \sqrt{X_t} dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

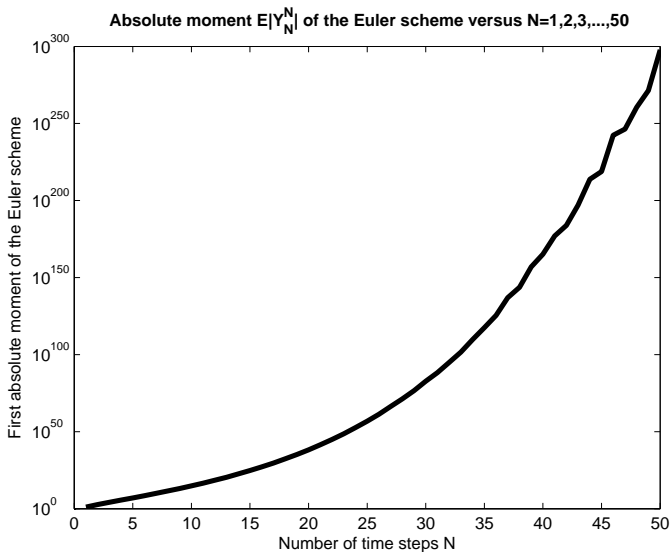
# Simulations of the first absolute moment of the solution of a SDE

Consider the SDE

$$dX_t = -10 \operatorname{sgn}(X_t) |X_t|^{1.1} dt + 4 dW_t, \quad X_0 = 0, \quad t \in [0, 10].$$

The first absolute moment of  $X_T$  with  $T = 10$  satisfies

$$\mathbb{E} \left[ |X_{10}| \right] \approx 0.7141 .$$



# Simulations for a SDE with a cubic drift and multiplicative noise

Consider the SDE

$$dX_t = -X_t^3 dt + 6 X_t \circ dW_t, \quad X_0 = 1, \quad t \in [0, 3].$$

The second moment of  $X_T$  with  $T = 3$  satisfies

$$\mathbb{E} [(X_3)^2] \approx 1.5423.$$

Different simulation values of the Monte Carlo Euler method with 300 time steps and 10 000 Monte Carlo runs:

NaN	0.5097	NaN	0.5378	0.5197
0.5243	NaN	NaN	0.5475	NaN

# Proof of divergence of Euler's method in the numerically weak sense

For simplicity we restrict our attention to the SDE

$$dX_t = -X_t^3 dt + dW_t, \quad X_0 = 0, \quad t \in [0, 1]$$

and show

$$\lim_{N \rightarrow \infty} \mathbb{E} \left[ |X_T - Y_N^N|^p \right] = \infty, \quad \lim_{N \rightarrow \infty} \left| \mathbb{E} \left[ |X_T|^p \right] - \mathbb{E} \left[ |Y_N^N|^p \right] \right| = \infty$$

for every  $p \in [1, \infty)$ . Of course, it remains to show

$$\lim_{N \rightarrow \infty} \mathbb{E} \left[ |Y_N^N| \right] = \infty.$$

Proof: Define

$$\Omega_N := \left\{ \omega \in \Omega \left| \sup_{k \in \{1, 2, \dots, N-1\}} \left| W_{\frac{k+1}{N}}(\omega) - W_{\frac{k}{N}}(\omega) \right| \leq 1, \right. \right. \\ \left. \left. \left| W_{\frac{1}{N}}(\omega) - W_0(\omega) \right| \geq 3N \right\}$$

for every  $N \in \mathbb{N}$ . Claim:

$$|Y_k^N(\omega)| \geq (3N)^{2^{(k-1)}} \quad \forall k \in \{1, 2, \dots, N\} \quad (3)$$

for every  $\omega \in \Omega_N$  and every  $N \in \mathbb{N}$ .

We fix  $N \in \mathbb{N}$ ,  $\omega \in \Omega_N$  and show (3) by induction on  $k \in \{1, 2, \dots, N\}$ .

$$\begin{aligned} |Y_1^N(\omega)| &= \left| Y_0^N(\omega) - \frac{1}{N} (Y_0^N(\omega))^3 + \left( W_{\frac{1}{N}}(\omega) - W_0(\omega) \right) \right| \\ &= \left| W_{\frac{1}{N}}(\omega) - W_0(\omega) \right| \geq 3N \end{aligned}$$



Induction hypothesis  $|Y_k^N(\omega)| \geq (3N)^{(2^{k-1})}$  for one  $k \in \{1, 2, \dots, N\}$ :

$$\begin{aligned}
 |Y_{k+1}^N(\omega)| &= \left| Y_k^N(\omega) - \frac{1}{N} (Y_k^N(\omega))^3 + \left( W_{\frac{k+1}{N}}(\omega) - W_{\frac{k}{N}}(\omega) \right) \right| \\
 &\geq \left| \frac{1}{N} (Y_k^N(\omega))^3 \right| - |Y_k^N(\omega)| - \left| W_{\frac{k+1}{N}}(\omega) - W_{\frac{k}{N}}(\omega) \right| \\
 &\geq \frac{1}{N} |Y_k^N(\omega)|^3 - |Y_k^N(\omega)| - 1 \\
 &\geq \frac{1}{N} |Y_k^N(\omega)|^3 - 2 |Y_k^N(\omega)|^2 \\
 &\geq |Y_k^N(\omega)|^2 \left( \frac{1}{N} |Y_k^N(\omega)| - 2 \right) \\
 &\geq |Y_k^N(\omega)|^2 \left( \frac{1}{N} 3N - 2 \right) = |Y_k^N(\omega)|^2 \\
 &\geq \left( (3N)^{(2^{k-1})} \right)^2 = (3N)^{(2^k)}
 \end{aligned}$$

In particular, we obtain

$$|Y_N^N(\omega)| \geq (3N)^{(2^{N-1})} \quad (4)$$

for all  $\omega \in \Omega_N$  and all  $N \in \mathbb{N}$ . Recall that

$$\Omega_N = \left\{ \omega \in \Omega \left| \sup_{k \in \{1, \dots, N-1\}} \left| W_{\frac{k+1}{N}}(\omega) - W_{\frac{k}{N}}(\omega) \right| \leq 1, \right. \right. \\ \left. \left. \left| W_{\frac{1}{N}}(\omega) - W_0(\omega) \right| \geq 3N \right\}$$

holds and therefore

$$\mathbb{P}[\Omega_N] \geq e^{-cN^3} \quad (5)$$

for all  $N \in \mathbb{N}$  with  $c \in (0, \infty)$  appropriate. Combining (4) and (5) shows

$$\mathbb{E}|Y_N^N| \geq \mathbb{P}[\Omega_N] \cdot (3N)^{(2^{N-1})} \geq e^{-cN^3} \cdot (3N)^{(2^{N-1})} \xrightarrow{N \rightarrow \infty} \infty. \quad \square$$

Do we need **new numerical methods** which converge in the numerically weak sense?

The Monte Carlo Euler method works very well **in practice!**

## Theorem (Hutzenthaler & J (2009))

Suppose that  $\mu, \sigma, f: \mathbb{R} \rightarrow \mathbb{R}$  are four times continuously differentiable functions with at most polynomially growing derivatives. Moreover, let  $\sigma$  be globally Lipschitz continuous and let  $\mu$  be **globally one-sided Lipschitz continuous**, i.e.,

$$(x - y) \cdot (\mu(x) - \mu(y)) \leq L(x - y)^2$$

holds for all  $x, y \in \mathbb{R}$ , where  $L \in (0, \infty)$  is a fixed constant. Then there are  $\mathcal{F}/\mathcal{B}([0, \infty))$ -measurable mappings  $C_\varepsilon: \Omega \rightarrow [0, \infty)$ ,  $\varepsilon \in (0, 1)$ , and a set  $\tilde{\Omega} \in \mathcal{F}$  with  $\mathbb{P}[\tilde{\Omega}] = 1$  such that

$$\left| \mathbb{E} \left[ f(X_T) \right] - \frac{1}{N^2} \left( \sum_{m=1}^{N^2} f(Y_N^{N,m}(\omega)) \right) \right| \leq C_\varepsilon(\omega) \cdot \frac{1}{N^{(1-\varepsilon)}}$$

holds for every  $\omega \in \tilde{\Omega}$ ,  $N \in \mathbb{N}$  and every  $\varepsilon \in (0, 1)$ .

## The theorem applies to ...

**Black-Scholes model** with  $\bar{\mu}, \bar{\sigma}, x_0 \in (0, \infty)$ :

$$dX_t = \bar{\mu} X_t dt + \bar{\sigma} X_t dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

**A SDE with a cubic drift and additive noise:**

$$dX_t = -X_t^3 dt + dW_t, \quad X_0 = 0, \quad t \in [0, 1]$$

**A SDE with a cubic drift and multiplicative noise:**

$$dX_t = -X_t^3 dt + 6 X_t \circ dW_t, \quad X_0 = 1, \quad t \in [0, 3]$$

**A stochastic Verhulst equation** with  $\eta, x_0 \in (0, \infty)$ :

$$dX_t = X_t (\eta - X_t) dt + X_t dW_t, \quad X_0 = x_0, \quad t \in [0, T]$$

Sketch of the proof:

For simplicity we restrict our attention again to the SDE

$$dX_t = -X_t^3 dt + dW_t, \quad X_0 = 0$$

for  $t \in [0, T]$  with  $T = 1$ .

Define the events  $\Omega_N \in \mathcal{F}$ ,  $N \in \mathbb{N}$ , given by

$$\Omega_N := \left\{ \omega \in \Omega \mid \sup_{0 \leq t \leq T} |W_t(\omega)| \leq \sqrt{N/2} \right\}$$

for all  $N \in \mathbb{N}$ . Moreover, define  $\tau_n^N : \Omega \rightarrow \{0, 1, \dots, N\}$  by

$$\tau_n^N(\omega) := \max \left( \{0\} \cup \left\{ k \in \{1, 2, \dots, n\} \mid \operatorname{sgn}(Y_{k-1}^N(\omega)) \neq \operatorname{sgn}(Y_k^N(\omega)) \right\} \right)$$

for every  $\omega \in \Omega$ ,  $n \in \{0, 1, \dots, N\}$  and every  $N \in \mathbb{N}$ .

Then we obtain

$$\begin{aligned}
 Y_n^N(\omega) &= Y_{\tau_n^N(\omega)}^N(\omega) + \sum_{k=\tau_n^N(\omega)}^{n-1} (Y_{k+1}^N(\omega) - Y_k^N(\omega)) \\
 &= Y_{\tau_n^N(\omega)}^N(\omega) + \sum_{k=\tau_n^N(\omega)}^{n-1} \left( -\frac{1}{N} (Y_k^N(\omega))^3 + \left( W_{\frac{k+1}{N}} - W_{\frac{k}{N}} \right) \right) \\
 &= Y_{\tau_n^N(\omega)}^N(\omega) - \frac{1}{N} \left( \sum_{k=\tau_n^N(\omega)}^{n-1} (Y_k^N(\omega))^3 \right) + \left( W_{\frac{n}{N}} - W_{\frac{\tau_n^N(\omega)}{N}} \right)
 \end{aligned}$$

for every  $\omega \in \Omega$ ,  $n \in \{0, 1, \dots, N\}$  and every  $N \in \mathbb{N}$ . This implies

$$\left| Y_n^N(\omega) \right| \leq \left| Y_{\tau_n^N(\omega)}^N(\omega) + \left( W_{\frac{n}{N}} - W_{\frac{\tau_n^N(\omega)}{N}} \right) \right|$$

for every  $\omega \in \Omega$ ,  $n \in \{0, 1, \dots, N\}$  and every  $N \in \mathbb{N}$ .

We have

$$\left| Y_n^N(\omega) \right| \leq \left| Y_{\tau_n^N(\omega)}^N(\omega) + \left( W_{\frac{n}{N}} - W_{\frac{\tau_n^N(\omega)}{N}} \right) \right|$$

for every  $\omega \in \Omega$ ,  $n \in \{0, 1, \dots, N\}$  and every  $N \in \mathbb{N}$ .

This enables us to show **the domination of Euler's method by twice the supremum of the Brownian motion**

$$\sup_{k \in \{0, 1, \dots, N\}} |Y_k^N(\omega)| \leq 2 \left( \sup_{0 \leq t \leq T} |W_t(\omega)| \right)$$

for all  $\omega \in \Omega_N$  and all  $N \in \mathbb{N}$ . The domination inequality can also be written as

$$\sup_{N \in \mathbb{N}} \sup_{k \in \{0, 1, \dots, N\}} \left( \mathbb{1}_{\Omega_N}(\omega) \cdot |Y_k^N(\omega)| \right) \leq 2 \left( \sup_{0 \leq t \leq T} |W_t(\omega)| \right)$$

for every  $\omega \in \Omega$ .



In particular, we obtain

$$\sup_{N \in \mathbb{N}} \mathbb{E} \left[ \mathbb{1}_{\Omega_N} |Y_N^N|^p \right] \leq 2^p \cdot \mathbb{E} \left[ \sup_{0 \leq t \leq T} |W_t|^p \right] < \infty$$

for all  $p \in [1, \infty)$ . This estimate complements the divergence

$$\lim_{N \rightarrow \infty} \mathbb{E} \left[ \mathbb{1}_{(\Omega_N)^c} |Y_N^N|^p \right] = \infty$$

for all  $p \in [1, \infty)$ . Using now that

$$\mathbb{P} \left[ (\Omega_N)^c \right] \leq e^{-cN}$$

holds for all  $N \in \mathbb{N}$  with an appropriate constant  $c \in (0, \infty)$ , an adaption of the arguments in the global Lipschitz case yields the convergence of the Monte Carlo Euler method. □

# Simulations for a SDE with a cubic drift and additive noise

Consider the SDE

$$dX_t = -X_t^3 dt + dW_t, \quad X_0 = 0, \quad t \in [0, 1].$$

The second moment of  $X_T$  with  $T = 1$  satisfies

$$\mathbb{E} [(X_1)^2] \approx 0.4529.$$

Different simulation values of the Monte Carlo Euler method:

$N = 2^0$	$N = 2^1$	$N = 2^2$	$N = 2^3$	$N = 2^4$
1.4516	0.5166	0.4329	0.5308	0.4285
$N = 2^5$	$N = 2^6$	$N = 2^7$	$N = 2^8$	$N = 2^9$
0.4452	0.4602	0.4517	0.4548	0.4537

## Summary

- **Counterexamples of numerically weak convergence** of the stochastic Euler scheme if the coefficients of the SDE grow superlinearly.
- **The Monte Carlo Euler method nevertheless converges** if the drift function is globally one-sided Lipschitz continuous, the diffusion function is globally Lipschitz continuous and both the drift and diffusion function are smooth with at most polynomially growing derivatives.

Remark: The situation is similar in the case of SPDEs and Multi-Level Monte Carlo.

## Conclusion

Strong and numerically weak error estimates are convenient, since stochastic calculus is an  $L^2$ -calculus (Itô isometry, etc.).

But, if Euler's method is used to solve one of the nonlinear problems above, then one needs different concepts such as

$$\left| X_T - Y_N^N \right| \xrightarrow{N \rightarrow \infty} 0 \quad \mathbb{P}\text{-a.s.}$$

for the strong approximation problem (Gyöngy (1998)) and

$$\left| \mathbb{E} \left[ f(X_T) \right] - \frac{1}{N^2} \left( \sum_{m=1}^{N^2} f(Y_N^N) \right) \right| \xrightarrow{N \rightarrow \infty} 0 \quad \mathbb{P}\text{-a.s.}$$

for the weak approximation problem (Hutzenthaler & J (2009)).

## References

- Hutzenthaler and J (2009), Non-globally Lipschitz Counterexamples for the stochastic Euler scheme.
- Hutzenthaler and J (2009), Convergence of the stochastic Euler scheme for locally Lipschitz coefficients.