



Computational Methods for SDEs

Introduction and information



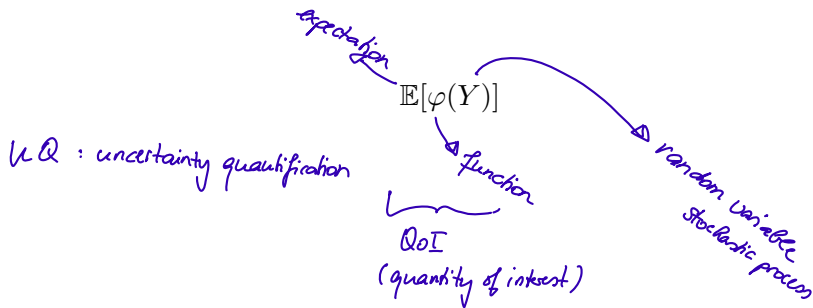
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Goal

Compute *efficiently* and *accurately*



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$$\mathbb{E}[\varphi(Y)]$$

e.g., Y is given by solution to

$$dX_t = b(t, X_t) dt + \sigma(t, X_t) dW_t$$

$$X_0 = x$$

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- How good are these approximations?
- How are we “sufficiently” efficient?

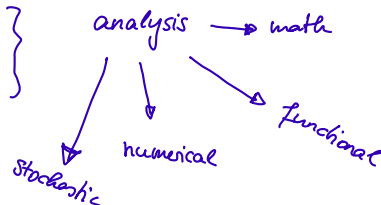
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- Theoretical derivations

- approximation
- convergence
- [regularity]



Approach

- Define our expectations of the course
- Theoretical derivations
 - approximation
 - convergence
 - [regularity]
- Computer simulations to test the theoretical findings
→ How do things work in practice?

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- Your chance (due to small group): give input and shape
- Your challenge: requires active participation, engagement and time

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 - If time admits, I pick out parts that are important to discuss from my point of view.
 - I will *not* go through the text/proofs if not explicitly requested.

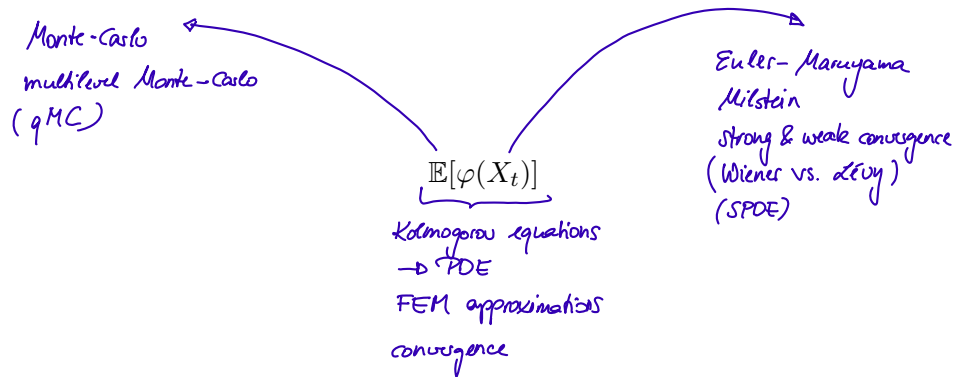
About me — About you

- Why are you here?
- What do you expect?
- What is your background?

Formalities

- *officially*: 4h exam, 2 projects with bonus points
- *teaching*: 4h lectures + 2 h exercise classes (Per Ljung)
 - *lectures*: Monday + Thursday, 10 - 12 in MVF33
 - *exercise classes*: Tuesday, 10 - 12 in MVF26
 - *exceptions*: Tuesday 28/1 (MVF32) and 11/2 lecture
Thursday 30/1 and 13/2 exercises

Back to mathematics



- [G] Emmanuel Gobet: Monte-Carlo Methods and Stochastic Processes: From Linear to Non-Linear, CRC, 2016
- [HRSW] Norbert Hilber, Oleg Reichmann, Christoph Schwab, Christoph Winter: Computational Methods for Quantitative Finance: Finite Element Methods for Derivative Pricing, Springer, 2013
- [KP] Peter Kloeden, Eckhard Platen: Numerical Solutions of Stochastic Differential Equations, Springer, 1992
- [Ø] Bernt Øksendal: Stochastic Differential Equations: An Introduction with Applications, Springer, 2003

Content

- Chapter 4–6 in [G]
- Chapter 3, 4, 8, 9 in [HRSW] (rewritten as lecture notes)

In words

- Review of Brownian motion, Itô integration, SDEs
- Feynman–Kac formulas
- Euler–Maruyama scheme, strong & weak convergence
- Statistical errors, (multilevel) Monte Carlo methods
- Review on FEM for parabolic PDEs
- FEM methods for PDEs from the Feynman–Kac formulas
- If time and interest: Applications

Recall on probability theory

- (Ω, \mathcal{A}, P) *probability space*
 - Ω set
 - \mathcal{A} σ -algebra
 - P probability measure
- $X : \Omega \rightarrow \mathbb{R}$ *random variable*
 - $\mathcal{B}(\mathbb{R}) = \sigma([a, b), a < b)$ Borel σ -algebra
 - X is $\mathcal{A}/\mathcal{B}(\mathbb{R})$ -measurable, i.e.

$$\forall B \in \mathcal{B}(\mathbb{R}) : \{\omega \in \Omega, X(\omega) \in B\} \in \mathcal{A}$$

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- $P_X(B) = P(\{\omega \in \Omega, X(\omega) \in B\})$ *image measure*, $B \in \mathcal{B}(\mathbb{R})$
- f *density* of X

$$P_X(B) = \int_B f(x) \, dx, \quad B \in \mathcal{B}(\mathbb{R})$$

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- $\mathbb{E}[X]$ *expectation* of X with

$$\mathbb{E}[X] = \int_{\Omega} X \, dP = \int_{-\infty}^{\infty} x f(x) \, dx$$

Random numbers

Do random numbers exist?

- philosophical question
- USB device uses *Johnson–Nyquist noise*
- *HERE* generation of *pseudo random numbers*

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Definition

- $U = (U^{(i)}, i \in \mathbb{N})$ sequence of independent, identically distributed random variables uniformly on $[0, 1)$
- *pseudo random number*:
 - sequence of numbers
 - generated by a (deterministic) algorithm
 - behaves like U

Random number generators

generate on $[0, 1)$ uniformly distributed random numbers

- *Algorithm K* of Knuth
- *linear congruent pseudo random number generator* of Lehmer

$$X_0 = \text{"seed"}$$

$$X_{n+1} = aX_n + c \bmod m$$

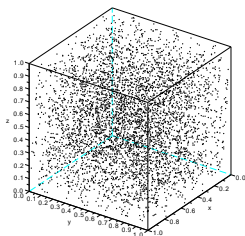
imitates roulette, output:

$$\frac{X_n}{m}$$

- *RANDU* by IBM ($m = 2^{31}$, $a = 2^{16} + 3$, $c = 0$)
- *Mother* by Marsaglia
- *Mersenne Twister* by Matsumoto & Nishimura
- *KISS* (Keep It Simple, Stupid) by Marsaglia & Zaman

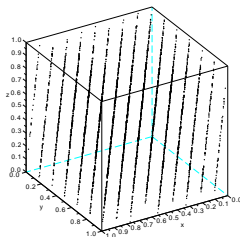
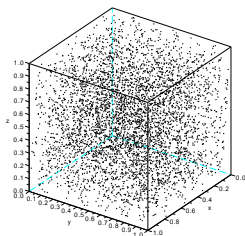
Test of RANDU

- generate random numbers $(U^{(i)}, i \in \mathbb{N}), U^{(i)} \sim \mathcal{U}([0, 1])$
- set triplets $(U^{(1)}, U^{(2)}, U^{(3)}), (U^{(4)}, U^{(5)}, U^{(6)}), \text{ etc.}$
- draw them into the cube $[0, 1] \times [0, 1] \times [0, 1]$



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Random numbers for given distributions

- general methods
 - inversion method

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- special methods
 - normal distribution
 - Poisson distribution
 - Gamma distribution
 - etc.

Questions for next lecture

While reading *Chapter 4.1–4.2* of [G], ask yourself:

- Which possibilities do you have to sample the same path of a Brownian motion with different accuracy/resolution?
- What is important for sample paths vs. distribution?
- How is the heat equation coupled to Brownian motion? In which sense?
- What is the naive idea of a filtration? How is it related to our daily life?
- Why can't we use “usual” integration for Brownian motion but have to define the Itô integral?
- What are the basic steps for the definition of the Itô integral? What do they tell us?
- In which sense of “uniqueness” should the Itô integral be interpreted?
- What are important properties of the Itô integral?