

Finite Difference Methods

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Outline

- 1 Partial Differential equations
 - Principle of Finite Difference
 - Resolution of PDEs arising in Finance
- 2 Simulation of SDEs
- 3 From PDE to SDE : Feynmann-Kac Formula
 - Feynmann-Kac Results
 - Proofs

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Principle of Finite Difference

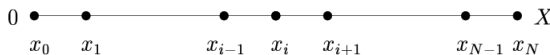
- A Partial Differential Equation (PDE) for a multivariate function $u(x_1, \dots, x_n)$ is an equation of the form

$$f\left(x_1, \dots, x_N; u, \frac{\partial u}{\partial x_1}, \dots, \frac{\partial u}{\partial x_n}; \frac{\partial^2 u}{\partial x_1 \partial x_1}, \dots, \frac{\partial^2 u}{\partial x_1 \partial x_n}; \dots\right) = 0$$

- Derivatives of u are approximated by linear combinations of the values of u at some points on a discretization grid

Example of a 1D grid on a domain $\Omega = (0, X)$

$i = 0, 1, \dots, N$ Mesh size = $\Delta x := \frac{X}{N}$ $x_i := i\Delta x$ $u_i := u(x_i)$

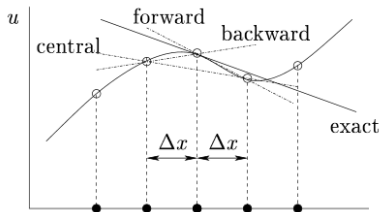




Approximation of 1st order derivatives

The theoretical 1st order derivative is defined by three equivalent expressions

$$\frac{\partial u}{\partial x}(x_i) = \begin{cases} \lim_{\Delta x \rightarrow 0} \frac{u(x_i + \Delta x) - u(x_i)}{\Delta x} \\ \lim_{\Delta x \rightarrow 0} \frac{u(x_i) - u(x_i - \Delta x)}{\Delta x} \\ \lim_{\Delta x \rightarrow 0} \frac{u(x_i + \Delta x) - u(x_i - \Delta x)}{2\Delta x} \end{cases} \quad (1)$$



$$\left(\frac{\partial u}{\partial x}\right)_i \approx \frac{u_{i+1} - u_i}{\Delta x} \quad \text{forward difference}$$

$$\left(\frac{\partial u}{\partial x}\right)_i \approx \frac{u_i - u_{i-1}}{\Delta x} \quad \text{backward difference}$$

$$\left(\frac{\partial u}{\partial x}\right)_i \approx \frac{u_{i+1} - u_{i-1}}{2\Delta x} \quad \text{forward difference}$$

Approximation of 2^{nd} order derivatives

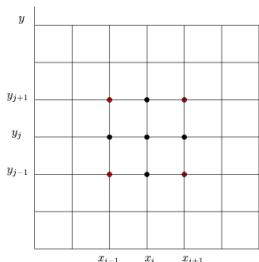
The second order discrete approximation can be obtained by two consecutive applications of 1^{st} order discretization.

$$\begin{aligned}
 \left(\frac{\partial^2 u}{\partial x^2}\right)_i &= \left[\frac{\partial}{\partial x} \left(\frac{\partial u}{\partial x}\right)\right]_i \\
 &= \lim_{\Delta x \rightarrow 0} \frac{\left(\frac{\partial u}{\partial x}\right)_{i+1/2} - \left(\frac{\partial u}{\partial x}\right)_{i-1/2}}{\Delta x} \\
 &\approx \frac{\frac{u_{i+1} - u_i}{\Delta x} - \frac{u_i - u_{i-1}}{\Delta x}}{\Delta x} \\
 &= \frac{u_{i+1} - 2u_i + u_{i-1}}{(\Delta x)^2}
 \end{aligned}$$

Mixed 2^{nd} order derivatives in 2D

Let $u : (x, y) \mapsto u(x, y)$. We have :

$$\begin{aligned} \left(\frac{\partial^2 u}{\partial x \partial y} \right)_{i,j} &= \frac{\left(\frac{\partial u}{\partial y} \right)_{i+1,j} - \left(\frac{\partial u}{\partial y} \right)_{i-1,j}}{2\Delta x} + \mathcal{O}(\Delta x)^2 \\ \left(\frac{\partial u}{\partial y} \right)_{i+1,j} &= \frac{u_{i+1,j+1} - u_{i+1,j-1}}{2\Delta y} + \mathcal{O}(\Delta y)^2 \\ \left(\frac{\partial u}{\partial y} \right)_{i-1,j} &= \frac{u_{i-1,j+1} - u_{i-1,j-1}}{2\Delta y} + \mathcal{O}(\Delta y)^2 \end{aligned}$$



2^{nd} order difference approximation

$$\left(\frac{\partial^2 u}{\partial x \partial y} \right)_{i,j} = \frac{u_{i+1,j+1} - u_{i+1,j-1} - u_{i-1,j+1} + u_{i-1,j-1}}{4\Delta x \Delta y} + \mathcal{O}[(\Delta x)^2, (\Delta y)^2]$$

PDEs arising in Finance

- Most one dimensional PDEs in Finance can be expressed in the following generic format:

$$\begin{cases} V_t + b(x, t)V_x + \frac{1}{2}a(x, t)V_{xx} - r(x, t)V + f(x, t) = 0 \\ V(x, T) = g(x), \quad (x, t) \in \mathbb{R} \times [0, T] \end{cases} \quad (2)$$

- f is called the source term, and may represent some revenue (dividends)
- x is the *space variable* and t the *time variable*
- We assume that the functions a , b and r are *continuous* and *bounded*, and that a is *nonnegative*



Pure diffusion equation

- The equation (2) becomes a pure diffusion equation when b and r are identically zero

$$\begin{cases} V_t + \frac{1}{2}a(x, t)V_{xx} + f(x, t) &= 0, & (x, t) \in \mathbb{R} \times [0, T] \\ V(x, T) &= g(x), & x \in \mathbb{R} \end{cases}$$

- Let the time step be $h_0 = T/N$, where N is a positive integer, and the space step be $h_1 > 0$
- For $j \in \mathbb{Z}$ and $k = 0$ to N , we denote

$$v_j^k := V(jh_1, kh_0), \quad a_j^k := a(jh_1, kh_0)$$

$$f_j^k := f(jh_1, kh_0), \quad g_j := g(jh_1)$$

Explicit Scheme for pure diffusion

The *Explicit* scheme of the pure diffusion equation is

$$\begin{cases} \frac{v_j^k - v_j^{k-1}}{h_0} + \frac{1}{2} a_j^k \frac{v_{j+1}^k + v_{j-1}^k - 2v_j^k}{h_1^2} + f_j^k = 0, & j \in \mathbb{Z}, k = 1, \dots, N \\ v_j^N = g_j, & j \in \mathbb{Z} \end{cases}$$

The *ordered form* (w.r.t. to the components of v^k) of the scheme is

$$v_j^{k-1} = \left(1 - \frac{h_0}{h_1^2} a_j^k\right) v_j^k + \frac{1}{2} \frac{h_0}{h_1^2} a_j^k (v_{j-1}^k + v_{j+1}^k) + h_0 f_j^k$$

- The r.h.s. is, apart from the source term $h_0 f_j^k$, a linear combination of the values at the previous step
- The coefficients have a sum equal to 1. They are *nonnegative* if the following *monotonicity condition* holds:

$$\frac{h_0}{h_1^2} \|a\|_\infty \leq 1$$

Implicit Scheme for pure diffusion

The standard *Implicit Scheme* for the pure diffusion equation is obtained by replacing the increment $(v_j^k - v_j^{k-1})$ in the *Explicit Scheme* by : $(v_j^{k+1} - v_j^k)$

$$\begin{cases} \frac{v_j^{k+1} - v_j^k}{h_0} + \frac{1}{2} a_j^k \frac{v_{j+1}^k + v_{j-1}^k - 2v_j^k}{h_1^2} + f_j^k = 0, & j \in \mathbb{Z}, k = 1, \dots, N \\ v_j^N = g_j, & j \in \mathbb{Z} \end{cases}$$

The first relation may be written in the *fixed-point form*

$$v_j^k = \left(1 + \frac{h_0}{h_1^2} a_j^k\right)^{-1} \left[\frac{1}{2} \frac{h_0}{h_1^2} a_j^k (v_{j-1}^k + v_{j+1}^k) + v_j^{k+1} + h_0 f_j^k \right]$$

Implicit Scheme - Stability

- In order to assess the stability, we set:

$$\gamma_j^k := \frac{h_0}{h_1^2} a_j^k \left(1 + \frac{h_0}{h_1^2} a_j^k \right)^{-1}, \quad \gamma^k := \sup_j \gamma_j^k$$

- Since $s \mapsto s/(1+s)$ is increasing with image in $(-1, 1)$, we have that

$$\gamma^k \leq \gamma(a, h) := \frac{h_0}{h_1^2} \|a\|_\infty \left(1 + \frac{h_0}{h_1^2} \|a\|_\infty \right)^{-1} < 1$$

- The contraction factor $\gamma(a, h) \leq 1 \implies$ *existence and uniqueness of the fixed-point*

Diffusion with actualization

- When r is not identically zero, the equation (2) becomes :

$$\begin{cases} V_t + \frac{1}{2}a(x, t)V_{xx} - r(x, t)v + f(x, t) &= 0, & (x, t) \in \mathbb{R} \times [0, T] \\ V(x, T) &= g(x), & x \in \mathbb{R} \end{cases}$$

- It is convenient to write the contribution of the actualization term as *implicit* (rather than *explicit*)

We set :

$$r_j^k := r(jh_1, kh_0)$$

Scheme with actualization

For $j \in \mathbb{Z}$ and $k = 1, \dots, N$, we have

$$\begin{cases} \frac{v_j^k - v_j^{k-1}}{h_0} + \frac{1}{2} a_j^k \frac{v_{j+1}^k + v_{j-1}^k - 2v_j^k}{h_1^2} - r_j^{k-1} v_j^{k-1} + f_j^k = 0 \\ v_j^N = g_j \end{cases}$$

The first relation may be written in the ordered form

$$v_j^{k-1} = (1 + h_0 r_j^{k-1})^{-1} \left[\left(1 - \frac{h_0}{h_1^2} a_j^k \right) v_j^k + \frac{1}{2} \frac{h_0}{h_1^2} a_j^k (v_{j-1}^k + v_{j+1}^k) + h_0 f_j^k \right]$$

We can see that the expression within the square brackets is the *explicit* scheme when $r = 0$



The family of θ schemes

For $\theta \in [0, 1]$, consider the following scheme for $j \in \mathbb{Z}$ and $k = 0, \dots, (N - 1)$

$$\begin{cases} \frac{v_j^{k+1} - v_j^k}{h_0} + \frac{1}{2}\theta a_j^k \frac{v_{j+1}^k + v_{j-1}^k - 2v_j^k}{h_1^2} + \frac{1}{2}(1 - \theta) a_j^{k+1} \frac{v_{j+1}^{k+1} + v_{j-1}^{k+1} - 2v_j^{k+1}}{h_1^2} + f_j^k = 0 \\ v_j^N = g_j \end{cases}$$

- The scheme is *explicit* for $\theta = 0$, and *implicit* for $\theta = 1$
- It can be seen as the combination of an explicit step followed by an implicit step, both of length h_0
- $\theta = \frac{1}{2} \implies$ *Cranck-Nicholson* scheme

The condition for a θ scheme to be simply monotone is

$$(1 - \theta) \frac{h_0}{h_1^2} \|a\|_{\infty} \leq 1$$

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Stochastic Differential Equations (SDEs)

- A *Stochastic Differential Equation* is a differential equation in which one or more of the terms is a Stochastic Process
- SDEs contain a variable which represents a random *White Noise*
- The *White Noise* is calculated as the derivative of a *Brownian motion* (or *Wiener Process*)

Definition

A Brownian Motion is a stochastic process $(B_t)_{t \geq 0}$ with continuous trajectories such that $B_0 = 0$ and for $0 \leq s \leq t$,

- $(B_t - B_s) \sim \mathcal{N}(0, t - s)$
- $(B_t - B_s)$ is independent of $B_r, \forall r \leq s$

Simulation of the Brownian Motion

The simulation relies on the probability distribution of increments

Simulation

Given times $t_1, t_2, \dots, t_k, \dots$, $(B_t)_{t \geq 0}$ is simulated by the following recurrent scheme

$$\begin{cases} B_{t_{k+1}} = B_{t_k} + \sqrt{t_{k+1} - t_k} G_{k+1} \\ B_0 = 0 \end{cases}$$

Where $(G_k)_{k \geq 1}$ is an *independent and identically distributed* sequence and

$$\forall k \geq 1, \quad G_k \sim \mathcal{N}(0, 1)$$

Solution of an SDE

Consider the following SDE

$$dX_t = b(X_t)dt + \sigma(X_t)dB_t, \quad X_0 \in \mathbb{R}^d$$

Existence and Uniqueness of the solution

If b and σ are Regular, locally Lipschitz, and verify the condition

$$\langle b(x), x \rangle + \frac{1}{2} \text{Tr}(\sigma \sigma')(x) \leq \lambda (1 + |x|^2)$$

Then the SDE has a unique solution : the *Markovian Process* $(X_t)_{t \geq 0}$ defined for all $t \geq 0$ by :

$$X_t = X_0 + \int_0^t b(X_s) ds + \int_0^t \sigma(X_s) dB_s$$

Euler Scheme

Let t_0, \dots, t_n be a partition of $[0, T]$. We have

$$\begin{aligned} X_{t_{k+1}} &= X_{t_k} + \int_{t_k}^{t_{k+1}} b(X_s) ds + \int_{t_k}^{t_{k+1}} \sigma(X_s) dB_s \\ &\approx X_{t_k} + b(X_{t_k})(t_{k+1} - t_k) + \sigma(X_{t_k})(B_{t_{k+1}} - B_{t_k}) \end{aligned}$$

The *Euler* scheme is therefore defined by the recurrence

$$\begin{cases} \bar{X}_{t_{k+1}} = \bar{X}_{t_k} + b(\bar{X}_{t_k})(t_{k+1} - t_k) + \sigma(\bar{X}_{t_k})(B_{t_{k+1}} - B_{t_k}) \\ \bar{X}_0 = X_0 \end{cases}$$

Milstein Scheme

The *Milstein* scheme is obtained by an enhancement of the Stochastic integral

$$\int_{t_k}^{t_{k+1}} \sigma(X_s) dB_s \approx \sigma(X_{t_k}) (B_{t_{k+1}} - B_{t_k}) + \frac{1}{2} \sigma \sigma' (X_{t_k}) \left[(B_{t_{k+1}} - B_{t_k})^2 - (t_{k+1} - t_k) \right]$$

The *Milstein* scheme is therefore defined by the following recurrence

$$\begin{aligned} \bar{X}_{t_{k+1}} = \bar{X}_{t_k} &+ \left(b - \frac{1}{2} \sigma \sigma' \right) (\bar{X}_{t_k}) (t_{k+1} - t_k) + \sigma (\bar{X}_{t_k}) (B_{t_{k+1}} - B_{t_k}) \\ &+ \frac{1}{2} \sigma \sigma' (\bar{X}_{t_k}) (B_{t_{k+1}} - B_{t_k})^2 \end{aligned}$$

Strong error for Euler and Milstein schemes

We define the L^2 strong error of the scheme \bar{X} by

$$\mathcal{E}_2^{strong} := \sqrt{\mathbb{E} \left[\left(\sup_{t_k} |X_{t_k} - \bar{X}_{t_k}| \right)^2 \right]}$$

Theorem

- For the *Euler* scheme with time step h , the strong error is of order $\frac{1}{2}$

$$\mathcal{E}_2^{strong} = \mathcal{O}(\sqrt{h})$$

- For the *Milstein* scheme with time step h , the strong error is of order 1

$$\mathcal{E}_2^{strong} = \mathcal{O}(h)$$

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 - Feynmann-Kac Results
 - Proofs

Feynmann-Kac results

- The expectation of a (function of) random variable can be obtained as a solution of an associated PDE
- Let $X_t = (X_t^1, \dots, X_t^d)$ be a stochastic process, solution of the following system of equations

$$dX_t^i = \mu_i(t, X_t) dt + \sigma_i(t, X_t) dB_t^i$$

Where B_t^1, \dots, B_t^d are Brownian motions with correlation

$$d\langle B^i, B^j \rangle_t = \rho_{ij} dt$$

- Let $H(x) = H(x_1, \dots, x_d)$ be some payoff

Feynmann-Kac Formula without interest rate

Link between PDEs and SDEs

The function

$$u(t, x) := \mathbb{E} [H(X_T) / X_t = x]$$

is solution of the PDE

$$\frac{\partial u}{\partial t} + \sum_{i=1}^d \mu(t, x) \frac{\partial u}{\partial x_i} + \frac{1}{2} \sum_{i,j=1}^d \rho_{ij} \sigma_i(t, x) \sigma_j(t, x) \frac{\partial^2 u}{\partial x_i \partial x_j} = 0$$

with final condition

$$u(T, x) = H(x)$$

Feynmann-Kac Formula with interest rate involved

- Let \mathcal{A} be the *generator* of the SDE, defined for every $f : \mathbb{R}^+ \times \mathbb{R}^d \rightarrow \mathbb{R}$ by

$$(\mathcal{A}f)(t, x) = \sum_{i=1}^d \mu_i(t, x) \frac{\partial f}{\partial x_i} + \frac{1}{2} \sum_{i,j=1}^d (\sigma \sigma^T)_{i,j}(t, x) \frac{\partial^2 f}{\partial x_i \partial x_j}$$

- Let $X_t^{t,x} = x$ be the initial condition of the SDE
- Let $u \in \mathcal{C}^{1,2}(\mathbb{R}^+ \times \mathbb{R}^d)$ satisfy the equation

$$\begin{cases} \frac{\partial u}{\partial t} + \mathcal{A}u - ru = 0, & \text{for all } (t, x) \in [0, T] \times \mathbb{R}^d \\ u(T, x) = f(x) \end{cases}$$

Then for all $(t, x) \in [0, T] \times \mathbb{R}^d$, the solution $u(t, x)$ is

$$u(t, x) = \mathbb{E} \left[e^{-\int_t^T r(s, X_s) ds} f(X_T) \middle| X_t = x \right] = \mathbb{E} \left[e^{-\int_t^T r(s, X_s^{t,x}) ds} f(X_T^{t,x}) \right]$$



Proof of the Feynmann-Kac formula

- Lets apply the Ito lemma to the function $F_t := e^{-\int_0^t r(s, X_s) ds} u(t, X_t)$
- Since $e^{-\int_0^s r(v, X_v) dv}$ is differentiable and therefore of bounded variation, we have $\langle e^{-\int_0^s r(v, X_v) dv}, u(s, X_s) \rangle = 0$

$$\begin{aligned}
 F_t &= F_0 + \int_0^t \left[d \left(e^{-\int_0^s r(v, X_v) dv} \right) u(s, X_s) + e^{-\int_0^s r(v, X_v) dv} du(s, X_s) + 0 \right] \\
 &= u(0, X_0) + \int_0^t \left[\left(e^{-\int_0^s r(v, X_v) dv} \right) u(s, X_s) (-r(s, X_s)) ds + e^{-\int_0^s r(v, X_v) dv} \frac{\partial u}{\partial t} ds \right] \\
 &\quad + \int_0^t e^{-\int_0^s r(v, X_v) dv} \left(\sum_{i=1}^d \frac{\partial u}{\partial x_i} dX_s^i + \frac{1}{2} \sum_{i,j=1}^d \frac{\partial^2 u}{\partial x_i \partial x_j} dX_s^i dX_s^j \right) \\
 &= u(0, X_0) + \int_0^t e^{-\int_0^s r(v, X_v) dv} \left[-ru + \frac{\partial u}{\partial t} + \sum_{i=1}^d \frac{\partial u}{\partial x_i} \mu_i(s, X_s) ds \right. \\
 &\quad \left. + \sum_{i=1}^d \frac{\partial u}{\partial x_i} \sum_k \sigma_{i,k}(s, X_s) dB_s^k + \sum_{i,j=1}^d \frac{\partial^2 u}{\partial x_i \partial x_j} \sum_{k,l} \sigma_{i,k} \sigma_{j,l} \underbrace{dB_s^k dB_s^l}_{=\delta_{k,l} ds} \right]
 \end{aligned}$$

Proof of the Feynmann-Kac formula

$$F_t = u(0, X_0) + \int_0^t e^{-\int_0^s r(v, X_v) dv} \left(-ru + \frac{\partial u}{\partial t} + \mathcal{A}u \right) ds + \int_0^t e^{-\int_0^s r(v, X_v) dv} \nabla u \cdot \sigma dB_s$$

Since the process $u(0, X_0) + \int_0^t e^{-\int_0^s r(v, X_v) dv} \nabla u \cdot \sigma dB_s$ is a martingale, then the process

$$M_t := e^{-\int_0^t r(s, X_s) ds} u(t, X_t) - \int_0^t e^{-\int_0^s r(v, X_v) dv} \left(\frac{\partial u}{\partial t} + \mathcal{A}u - ru \right) (s, X_s) ds$$

is a martingale. Hence the process $(M_{t'})_{t \leq t' \leq T}$ given by

$$\begin{aligned} M_{t'} : &= e^{-\int_t^{t'} r(s, X_s^{t,x}) ds} u(t', X_{t'}^{t,x}) - \int_t^{t'} e^{-\int_t^s r(v, X_v^{t,x}) dv} \underbrace{\left(\frac{\partial u}{\partial t} + \mathcal{A}u - ru \right)}_{=0} (s, X_s^{t,x}) ds \\ &= e^{-\int_t^{t'} r(s, X_s^{t,x}) ds} u(t', X_{t'}^{t,x}) \quad \text{is also a martingale.} \end{aligned}$$

Proof of the Feynmann-Kac formula

$$\begin{aligned}u(t, x) &= M_t \\&= \mathbb{E} [M_t] \\&= \mathbb{E} [M_T] \\&= \mathbb{E} \left[e^{-\int_t^T r(s, X_s^{t,x}) ds} u \left(T, X_T^{t,x} \right) \right] \\&= \mathbb{E} \left[e^{-\int_t^T r(s, X_s^{t,x}) ds} f \left(X_T^{t,x} \right) \right]\end{aligned}$$

Feynmann-Kac with a source term

For some function g , by rewriting $M_{t'}$ as

$$M_{t'} := e^{-\int_t^{t'} r(s, X_s^{t,x}) ds} u(t', X_{t'}^{t,x}) - \int_t^{t'} e^{-\int_t^s r(v, X_v^{t,x}) dv} \left(\frac{\partial u}{\partial t} + \mathcal{A}u - ru \right) (s, X_s^{t,x}) ds - \int_t^{t'} e^{-\int_t^s r(v, X_v^{t,x}) dv} g(s, X_s^{t,x}) ds$$

The solution of the PDE

$$\begin{cases} \frac{\partial u}{\partial t} + \mathcal{A}u - ru = g \\ v(T, x) = f(x) \end{cases}$$

is obtained as

$$v(t, x) := \mathbb{E} \left[e^{-\int_t^T r(s, X_s^{t,x}) ds} f(X_T^{t,x}) - \int_t^T e^{-\int_t^s r(v, X_v^{t,x}) dv} g(s, X_s^{t,x}) ds \right]$$