# **Stochastic Numerical Analysis**

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# **Mean-square stability analysis**

Today we are looking at the numerical analysis in

D.J. Higham. 'Mean-square and asymptotic stability of the stochastic theta method'. *SIAM Journal of Numerical Analysis*, 38(3):753-769, 2000

M.B. Giles, C. Reisinger. 'Stochastic finite differences and multilevel Monte Carlo for a class of SPDEs in finance'. *SIAM Journal of Financial Mathematics*, 3(1):572-592, 2012.

What's new?

- new numerical methods
- new definition and analysis of numerical stability

# **Stochastic theta method**

The stochastic theta method for approximating the SDE

$$\mathrm{d}X_t = f(X_t) \,\mathrm{d}t + g(X_t) \,\mathrm{d}W_t$$

is

$$\widehat{X}_{n+1} = \widehat{X}_n + (1-\theta)f(\widehat{X}_n)h + \theta f(\widehat{X}_{n+1})h + g(\widehat{X}_n)\Delta W_n$$

#### $\bullet$ $\theta = 0$ is Euler-Maruyama method

- $\theta = 1$  is drift-implicit method
- $\theta = 1/2$  is stochastic equivalent of Crank-Nicholson method

The linear ODE:

$$\mathrm{d}X_t = -\lambda \, X_t \, \mathrm{d}t$$

has a solution which decays exponentially if  $\lambda > 0$ .

The numerical approximation

$$\widehat{X}_{n+1} = \widehat{X}_n - (1-\theta)\lambda \,h\,\widehat{X}_n - \theta\,\lambda\,h\,\widehat{X}_{n+1}$$

also decays exponentially if

$$\left|\frac{1-(1\!-\!\theta)\lambda\,h}{1+\theta\lambda\,h}\right|<1$$

so need either  $\theta \ge 1/2$ , or  $\lambda h < 2/(1-2\theta)$ .

What about the corresponding SDE?

$$\mathrm{d}X_t = -\lambda \, X_t \, \mathrm{d}t + \mu \, X_t \, \mathrm{d}W_t$$

First of all, how does the analytic solution behave? Itô calculus gives us

$$dX_t^2 = -2(\lambda - \frac{1}{2}\mu^2) X_t^2 dt + 2\mu X_t^2 dW_t$$

and hence

$$d\left(\mathbb{E}[X_t^2]\right) = -2\left(\lambda - \frac{1}{2}\mu^2\right) \mathbb{E}[X_t^2] dt$$

so  $\mathbb{E}[X_t^2]$  decays exponentially if  $\lambda > \frac{1}{2}\mu^2$ 

The numerical approximation is

$$\widehat{X}_{n+1} = \widehat{X}_n - (1-\theta)\lambda h \,\widehat{X}_n - \theta \,\lambda h \,\widehat{X}_{n+1} + \mu \,\widehat{X}_n \,\Delta W_n$$

Setting  $\Delta W_n = h^{1/2}Z_n$  where  $Z_n$  is a standard Normal r.v., we can re-arrange to get

$$\widehat{X}_{n+1} = (a+b\,Z_n)\,\widehat{X}_n$$

where

$$a = \frac{1 - (1 - \theta)\lambda h}{1 + \theta\lambda h}, \quad b = \frac{\mu h^{1/2}}{1 + \theta\lambda h}$$

Since

$$\widehat{X}_{n+1}^2 = (a+b\,Z_n)^2\,\widehat{X}_n^2$$

it follows that

$$\mathbb{E}[\widehat{X}_{n+1}^2] = (a^2 + b^2) \ \mathbb{E}[\widehat{X}_n^2]$$

so  $\mathbb{E}[\widehat{X}_n^2]$  decays exponentially iff  $a^2 + b^2 < 1$ , which corresponds to

$$(1-2\theta)\lambda^2 h < 2(\lambda - \frac{1}{2}\mu^2)$$

If  $\lambda - \frac{1}{2}\mu^2 > 0$ , then it's unconditionally stable for  $\theta \ge 1/2$ , while for  $\theta < 1/2$  the timestep stability limit is

$$h < \frac{2\left(\lambda - \frac{1}{2}\mu^2\right)}{\left(1 - 2\,\theta\right)\lambda^2}$$

Generalisation to vector systems - the algorithm

$$\widehat{X}_{n+1} = (A + Z_n B) \ \widehat{X}_n$$

with scalar  $Z_n$ , vector  $\widehat{X}_n$  and matrices A, B, leads to

$$\widehat{X}_{n+1}^T \widehat{X}_{n+1} = \widehat{X}_n^T (A + Z_n B)^T (A + Z_n B) \ \widehat{X}_n$$

and hence

$$\mathbb{E}\left[\widehat{X}_{n+1}^T\widehat{X}_{n+1}\right] = \mathbb{E}\left[\widehat{X}_n^T(A^TA + B^TB)\widehat{X}_n\right]$$

 $A^T A + B^T B$  is symmetric and positive (semi-)definite, so a sufficient condition for mean-square stability is that the largest eigenvalue is less than 1.

It can be further generalised to

$$\widehat{X}_{n+1} = (A + Z_n B + W_n C) \ \widehat{X}_n$$

where  $W_n$  is an additional, independent Normal r.v.

This leads to

$$\mathbb{E}\left[\widehat{X}_{n+1}^T \widehat{X}_{n+1}\right] = \mathbb{E}\left[\widehat{X}_n^T (A^T A + B^T B + C^T C)\widehat{X}_n\right]$$

with a similar test for mean-square stability.

Unusual parabolic SPDE arises in CDO modelling (Bush, Hambly, Haworth & Reisinger)

$$\mathrm{d}p = -\mu \,\frac{\partial p}{\partial x} \,\mathrm{d}t + \frac{1}{2} \,\frac{\partial^2 p}{\partial x^2} \,\mathrm{d}t + \sqrt{\rho} \,\frac{\partial p}{\partial x} \,\mathrm{d}W$$

with absorbing boundary p(0,t) = 0

- $\bullet$  x is distance to default
- p(x,t) is probability density function
- $\bullet$  dW term corresponds to systemic risk
- $\partial^2 p / \partial x^2$  comes from idiosyncratic risk

Milstein and central difference discretisation leads to

$$p_{j}^{n+1} = p_{j}^{n} - \frac{\mu k + \sqrt{\rho k} Z_{n}}{2h} \left( p_{j+1}^{n} - p_{j-1}^{n} \right) \\ + \frac{(1-\rho) k + \rho k Z_{n}^{2}}{2h^{2}} \left( p_{j+1}^{n} - 2p_{j}^{n} + p_{j-1}^{n} \right)$$

where k is the timestep, h is the uniform grid spacing, and  $Z_n \sim {\cal N}(0,1),$ 

Considering a Fourier mode

$$p_j^n = g_n \exp(ij\theta), \quad |\theta| \le \pi$$

leads to ...

$$g_{n+1} = \left(a(\theta) + b(\theta) Z_n + c(\theta) Z_n^2\right) g_n,$$

where

$$a(\theta) = 1 - \frac{i\mu k}{h} \sin \theta - \frac{2(1-\rho)k}{h^2} \sin^2 \frac{\theta}{2},$$
  

$$b(\theta) = -\frac{i\sqrt{\rho k}}{h} \sin \theta,$$
  

$$c(\theta) = -\frac{2\rho k}{h^2} \sin^2 \frac{\theta}{2}.$$

Following Higham's mean-square stability analysis approach,

$$\mathbb{E}[|g_{n+1}|^2] = \mathbb{E}\left[(a+bZ_n+cZ_n^2)(a^*+b^*Z_n+c^*Z_n^2)|g_n|^2\right]$$
$$= \left(|a+c|^2+|b|^2+2|c|^2\right) \mathbb{E}\left[|g_n|^2\right]$$

so stability requires  $|a+c|^2 + |b|^2 + 2|c|^2 \leq 1$  for all  $\theta$ , which leads to a timestep stability limit:

$$\mu^{2}k \leq 1 - \rho, 
\frac{k}{h^{2}} \leq (1 + 2\rho^{2})^{-1}.$$

This can be extended to finite domains using matrix stability analysis, writing the discrete equations as

$$P_{n+1} = (A + B Z_n + C Z_n^2) P_n$$
, where

$$A = I - \frac{\mu k}{2h} D_1 + \frac{(1-\rho) k}{2h^2} D_2, \quad B = -\frac{\sqrt{\rho k}}{2h} D_1, \quad C = \frac{\rho k}{2h^2} D_2,$$

and  $D_1$  and  $D_2$  look like

$$D_{1} = \begin{pmatrix} 0 & 1 & & \\ -1 & 0 & 1 & \\ & -1 & 0 & 1 \\ & & -1 & 0 \end{pmatrix}, \quad D_{2} = \begin{pmatrix} -2 & 1 & & \\ 1 & -2 & 1 & \\ & 1 & -2 & 1 \\ & & 1 & -2 \end{pmatrix}$$

$$\mathbb{E}[P_{n+1}^T P_{n+1}] = \mathbb{E}\left[P_n^T (A^T + B^T Z_n + C^T Z_n^2)(A + B Z_n + C Z_n^2) P_n\right]$$
  
=  $\mathbb{E}\left[P_n^T \left((A + C)^T (A + C) + B^T B + 2 C^T C\right) P_n\right]$ 

 $D_1$  is anti-symmetric and  $D_2$  is symmetric, and

$$D_1D_2 - D_2D_1 = E_1 - E_2, \quad D_1^2 = D_3 + E_1 + E_2$$

where  $D_3$  looks like

$$D_3 = \begin{pmatrix} -3 & 0 & 1 \\ 0 & -2 & 0 & 1 \\ 1 & 0 & -2 & 0 \\ & 1 & 0 & -3 \end{pmatrix},$$

and  $E_1$  and  $E_2$  are zero apart from one corner element,

$$E_1 = \begin{pmatrix} 2 \\ & \end{pmatrix}, \quad E_2 = \begin{pmatrix} & & \\ & & 2 \end{pmatrix}$$

This leads to

$$\mathbb{E} \left[ V_n^T \left( (A+C)^T (A+C) + B^T B + 2 C^T C \right) V_n \right] \\ = \mathbb{E} \left[ V_n^T M V_n \right] - (e_1 + e_2) \mathbb{E} [(v_1^n)^2] - (e_1 - e_2) \mathbb{E} [(v_{J-1}^n)^2],$$

where  $e_1$  and  $e_2$  are scalars and

$$M = I - \frac{k}{h^2} D_2 + \frac{k^2}{4 h^4} D_2^2 - \left(\frac{\rho k}{4 h^2} + \frac{\mu^2 k^2}{4 h^2}\right) D_3.$$
 Stoch. NA, Lecture 11 – p. 16

It can be verified that the  $m^{th}$  eigenvector of M is a Fourier mode and the associated eigenvalue is

$$|a(\theta_m) + c(\theta_m)|^2 + |b(\theta_m)|^2 + 2|c(\theta_m)|^2$$

where  $a(\theta), b(\theta), c(\theta)$  are the same functions as before.

In the limit  $h, k/h \rightarrow 0$ ,  $e_1 \pm e_2 > 0$ , and therefore the Fourier stability condition

$$\sup_{\theta} \left\{ |a(\theta) + c(\theta)|^2 + |b(\theta)|^2 + 2|c(\theta)|^2 \right\} \le 1$$

is also a sufficient condition for mean-square matrix stability.

This turns out to be a good application for multilevel MC:

- coarsest level of approximation uses 1 timestep per quarter, and 10 spatial points
- each finer level uses four times as many timesteps, and twice as many spatial points – ratio is due to numerical stability constraints
- computational cost  $C_{\ell} \propto 8^{\ell}$
- numerical results suggest variance  $V_\ell \propto 8^{-\ell}$
- can prove  $V_\ell \propto 16^{-\ell}$  when no absorbing boundary

Fractional loss on equity tranche of a 5-year CDO:



Stoch. NA, Lecture 11 - p. 19

Fractional loss on equity tranche of a 5-year CDO:

