

Two-sided error estimates for strong Ito approximations of SODEs

Special case: stochastic theta method

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The stochastic ordinary differential equation (SODE)

We consider for $t \in [0, T]$

$$dX(t) = b^0(t, X(t))dt + \sum_{k=1}^m b^k(t, X(t))dW^k(t) \quad (\text{SODE})$$
$$X(0) = X_0,$$

where

- ▶ $b^k : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}^d$ measurable,
- ▶ W^k real, pairwise independent, standard Brownian motions, adapted to filtration $(\mathcal{F}_t)_{t \in [0, T]}$,
- ▶ X_0 initial value: \mathcal{F}_0 -mb. with values in \mathbb{R}^d .

The stochastic theta method

For $\theta \in [0, 1]$ the **STM** is given by

$$\begin{aligned}0 &= X_h(t_i) - X_h(t_{i-1}) - h(1 - \theta)b^0(t_{i-1}, X_h(t_{i-1})) \\ &\quad - h\theta b^0(t_i, X_h(t_i)) \\ &\quad - \sum_{k=1}^m b^k(t_{i-1}, X_h(t_{i-1}))\Delta_h W^k(t_i), \quad 1 \leq i \leq N, \\ 0 &= X_h(t_0) - X_0,\end{aligned}$$

where

- ▶ $h = \frac{T}{N}$, $N \in \mathbb{N}$, equidistant step size,
- ▶ $\Delta_h W^k(t_i) = W^k(t_i) - W^k(t_{i-1})$.

Note: $\theta = 0 \Rightarrow$ *Euler-Maruyama* method.

Assumptions

(A1) $\mathbb{E}(|X_0|^2) < \infty$

(A2) There exists $K > 0$ such that

$$|b^k(t, x)| \leq K(1 + |x|)$$

and

$$|b^k(t, x) - b^k(t, y)| \leq K|x - y|$$

for all $k = 0, \dots, m$ and $x, y \in \mathbb{R}^d$, $t \in [0, T]$.

(A3) There exists $K > 0$ such that

$$|b^k(t, x) - b^k(s, x)| \leq K(1 + |x|)\sqrt{|t - s|}$$

for all $k = 0, \dots, m$ and $t, s \in [0, T]$, $x \in \mathbb{R}^d$.

Existence and uniqueness result

Theorem (L. Arnold, 1974)

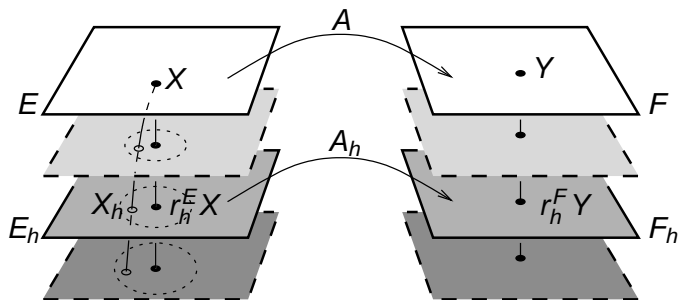
Under assumptions (A1) + (A2) there exists a unique solution to (SODE) with

$$X(t) = X_0 + \int_0^t b^0(s, X(s)) ds + \sum_{k=1}^m \int_0^t b^k(s, X(s)) dW^k(s)$$

for $t \in [0, T]$.

Discrete approximation theory

Schematic



To solve:

$$AX = Y$$

Numerical method:

$$A_h X_h = r_h^F Y$$

Embedment of the STM

The operator $A : E \rightarrow F$ is given by

- ▶ $E := \{X\}$,
- ▶ $F := \{Y\} = \{(X_0, 0)\}$,
- ▶ $AX :=$
 $(X(0), X(0) - \int_0^\cdot b^0(s, X(s))ds - \sum_{k=1}^m \int_0^\cdot b^k(s, X(s))dW^k(s)).$

Discrete space

Let

$$\tau_h := \{t_i \mid t_i = ih, i = 0, \dots, N\}$$

be the time grid. Denote by

$$\mathcal{G}_h := \mathcal{G}(\tau_h, L^2(\Omega, \mathcal{F}, P; \mathbb{R}^d))$$

set of adapted and $L^2(\Omega)$ -valued grid functions.

Here $Z_h \in \mathcal{G}_h$ is adapted if $Z_h(t_i)$ is \mathcal{F}_{t_i} measurable for all $t_i \in \tau_h$.

Metric space E_h

Restriction operators:

$$r_h^E : \begin{array}{l} E \rightarrow \mathcal{G}_h \\ X \mapsto r_h^E X \end{array}$$

with

$$[r_h^E X](t_i) = X(t_i).$$

We define

$$E_h := \overline{B}_\rho(r_h^E X) \subset \mathcal{G}_h$$

measured in the norm

$$\|Z_h\|_{0,h} := \max_{0 \leq i \leq N} \|Z_h(t_i)\|_{L^2(\Omega)}.$$

Metric space F_h

Restriction operators:

$$r_h^F : \begin{array}{l} F \rightarrow \mathcal{G}_h \\ Y \mapsto r_h^E Y \end{array}$$

with

$$[r_h^F Y](t_0) = X_0, \quad [r_h^F Y](t_i) = 0, \quad 1 \leq i \leq N.$$

We define

$$F_h := \overline{B}_\sigma(r_h^F Y) \subset \mathcal{G}_h$$

measured in the stochastic **Spijker-norm**

$$\|Z_h\|_{-1,h} := \max_{0 \leq i \leq N} \left\| \sum_{j=0}^i Z_h(t_j) \right\|_{L^2(\Omega)}.$$

Residual mapping and the operator A_h

- ▶ Residual mapping $\text{res}_h : \mathcal{G}_h \rightarrow \mathcal{G}_h$ of the STM

$$\text{res}_h(\mathbf{Z}_h)(t_0) = \mathbf{Z}_h(t_0) - \mathbf{X}_0,$$

$$\begin{aligned} \text{res}_h(\mathbf{Z}_h)(t_i) &= \mathbf{Z}_h(t_i) - \mathbf{Z}_h(t_{i-1}) - h(1 - \theta)\mathbf{b}^0(t_{i-1}, \mathbf{Z}_h(t_{i-1})) \\ &\quad - h\theta\mathbf{b}^0(t_i, \mathbf{Z}_h(t_i)) \\ &\quad - \sum_{k=1}^m \mathbf{b}^k(t_{i-1}, \mathbf{Z}_h(t_{i-1}))\Delta_h \mathbf{W}^k(t_i), \quad 1 \leq i \leq N. \end{aligned}$$

- ▶ Note that if X_h is a solution to **STM** then $\text{res}_h(X_h) = 0$.
- ▶ Operator $A_h : D(A_h) \rightarrow F_h$ is defined by

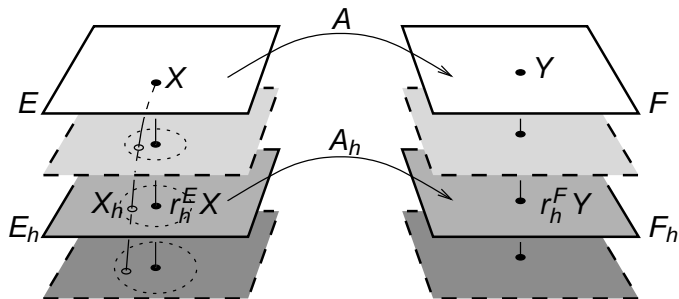
$$A_h X_h = \text{res}_h(X_h) + r_h^F Y$$

with domain of definition

$$D(A_h) := \{ \mathbf{Z}_h \in E_h \mid \|\text{res}_h(\mathbf{Z}_h)\|_{-1,h} \leq \sigma \} \subset E_h.$$

Discrete approximation theory

Schematic



To solve:

$$AX = Y$$

Numerical method:

$$A_h X_h = r_h^F Y$$

Question: Relationship between X and the numerical solutions X_h ?

Consistency

Definition

A one-step method is called **consistent** of order $\gamma > 0$, if there exists a constant $C > 0$ and an upper step size bound \bar{h} , s.t.

$$\left\| A_h r_h^E X - r_h^F A X \right\|_{-1,h} \leq C h^\gamma$$

for all $h \leq \bar{h}$.

Theorem (Beyn, Kruse 2009)

Under the assumptions (A1) - (A3) the stochastic theta method is consistent of order $\gamma = \frac{1}{2}$.

Bistability

Definition

A one-step method is called **bistable**, if there exist constants $C, \tilde{C} > 0$ and an upper step size bound $\bar{h} > 0$ such that the operators $A_h : D(A_h) \rightarrow F_h$ are bijective and the inequality

$$C\|A_h Z_h - A_h \tilde{Z}_h\|_{-1,h} \leq \|Z_h - \tilde{Z}_h\|_{0,h} \leq \tilde{C}\|A_h Z_h - A_h \tilde{Z}_h\|_{-1,h}$$

holds for all $h < \bar{h}$ and $Z_h, \tilde{Z}_h \in D(A_h)$.

Theorem (Beyn, Kruse 2009)

Under the assumptions (A1) - (A3) there exist parameter values $\rho, \sigma > 0$ such that the stochastic theta method is bistable.

Convergence

Definition

A one-step method is called **convergent** with order $\gamma > 0$ if there exist an upper step size bound $\bar{h} > 0$ and a constant $C > 0$ such that the operators $A_h : D(A_h) \rightarrow F_h$ are bijective and

$$\|X_h - r_h^E X\|_{0,h} \leq Ch^\gamma$$

for all $h \leq \bar{h}$. Here X_h denotes the solution to $A_h X_h = r_h^F AX$.

Two-sided error estimate

Let X_h be the solution to $A_h X_h = r_h^F A X$.

Theorem (Beyn, Kruse 2009)

Let the assumptions (A1) - (A3) hold and choose parameter values $L, \rho, \sigma > 0$ such that the stochastic theta method is bistable. Then the two-sided error estimate

$$C \|A_h X_h - A_h r_h^E X\|_{-1,h} \leq \|X_h - r_h^E X\|_{0,h} \leq \tilde{C} \|A_h X_h - A_h r_h^E X\|_{-1,h}$$

holds for all $h < \bar{h}$. In particular, the stochastic theta method is convergent of order $\gamma = \frac{1}{2}$.

Maximum order of convergence

Example (Clark, Cameron 1980)

Consider the SODE

$$dX(t) = d \begin{pmatrix} X_1(t) \\ X_2(t) \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & X_1(t) \end{pmatrix} d \begin{pmatrix} W^1(t) \\ W^2(t) \end{pmatrix}$$
$$X(0) = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

For the solution

$$X(t) = \begin{pmatrix} W^1(t) \\ \int_0^t W^1(s) dW^2(s) \end{pmatrix}$$

one calculates

$$\|A_h r_h^E X - r_h^F A X\|_{-1,h} = \sqrt{\frac{1}{2} Th}.$$

Summary

- ▶ Discrete approximation theory provides “new” notion of **consistency**, stability and convergence.
- ▶ **Stochastic Spijker-norm** gives two-sided error estimate.

- ▶ Outlook
 - ▶ Stochastic delay equations
 - ▶ SPDE (partially done for heat equation and finite difference method)

Second order estimate

Theorem (Arnold 1973)

Under assumptions (A1) and (A2) there exists $C_1 > 0$ s.t.

$$\mathbb{E}(|X(t)|^2) \leq (1 + \mathbb{E}(|X_0|^2))e^{C_1 t}$$

and there exists $C_2 > 0$ s.t.

$$\mathbb{E}(|X(t) - X(s)|^2) \leq C_2 |t - s|$$

for $t, s \in [0, T]$.