

3.3 Stochastic Differential Equations

Session 17
Nov 1, 2018

usual first order ordinary differential equation (ODE):

$$\frac{dx(t)}{dt} = f(x(t), t)$$

integral form: $x(t) = x(0) + \int_0^t f(x(s), s) ds$

stochastic version (SDE):

$$X(t) = X(0) + \int_0^t f(X(s), s) ds + \underbrace{\int_0^t g(X(s), s) dW(s)}_{\substack{\rightarrow \text{Brownian motion increments} \\ \text{stochastic integral (always starts from} \\ \text{now on)}}}$$

short-hand notation: $dX(t) = f(X(t), t) dt + g(X(t), t) dW(t)$

Ex.: $dS(t) = \mu S(t) dt + \sigma S(t) dW(t)$, $S(0) = S_0$

next time: this is solved by geom. Brownian motion

$$S(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma W(t)}$$

integral form: $S(t) - S_0 = \mu \int_0^t S(v) dv + \sigma \int_0^t S(v) dW(v)$

from this we can compute $\mathbb{E}(S(t))$:

$$\mathbb{E}(S(t)) - S_0 = \mu \int_0^t \mathbb{E}(S(u)) du + \sigma \int_0^t \underbrace{\mathbb{E}(S(u) dW(u))}_{= \mathbb{E}(S(u)) \underbrace{\mathbb{E}(dW(u))}_{=0}}$$

so

$$\mathbb{E}(S(t)) = S_0 + \mu \int_0^t \mathbb{E}(S(u)) du$$

$$\left(\frac{d\mathbb{E}(S(t))}{dt} = \mu \mathbb{E}(S(t)) \right)$$

$$\Rightarrow \mathbb{E}(S(t)) = e^{\mu t}$$

Usual ODE can be solved numerically with Euler's method:

$$\text{discretize ODE: } \frac{x_{n+1} - x_n}{\Delta t} = f(x_n, t_n) \quad , \Delta t = \frac{t}{n}$$

$$\text{or } x_{n+1} = x_n + f(x_n, t) \Delta t$$

error in one step:

$$\bullet \text{ Euler: } x_1 = x_0 + f(x_0, t) \Delta t$$

$$\bullet \text{ exact solution (with Taylor): } x(\Delta t) = x(0) + \Delta t \overbrace{x'(0)} = f(x_0, 0) + \frac{(\Delta t)^2}{2} x''(0) + O(\Delta t^3)$$

$$\Rightarrow x(\Delta t) - x_1 = \frac{(\Delta t)^2}{2} x''(0) + O((\Delta t)^3) \approx c (\Delta t)^2$$

total error: $|X(t) - x_n| \sim c(t) \Delta t$, $\Delta t = \frac{t}{n}$

the generalization to SDEs is called **Euler-Maruyama** method:

$$X_{n+1} = X_n + f(X_n, t_n) \Delta t + g(X_n, t_n) \Delta W_n$$

for error we want to compare X_n to exact sol. $X(t)$.

one distinguishes two types of errors:

- **strong error**: $\mathbb{E}(|X_n - X(t)|) \sim c_s (\Delta t)^\alpha$

α = strong order of convergence

note: relevance for individual paths via Markov's inequality

$$\mathbb{P}(|X| > a) \leq \frac{\mathbb{E}(|X|)}{a}$$

Proof:

$$\mathbb{E}(|X|) = \int_{-\infty}^{\infty} |x| \underbrace{\rho(x)}_{\text{probability density}} dx = \int_{-a}^a |x| \rho(x) dx + \int_{-\infty}^{-a} |x| \rho(x) dx + \int_a^{\infty} |x| \rho(x) dx$$

$$\geq \int_{-\infty}^{-a} |x| \rho(x) dx + \int_a^{\infty} |x| \rho(x) dx$$

use $|x| > a$
integral

$$\geq a \left(\int_{-\infty}^{-a} \rho(x) dx + \int_a^{\infty} \rho(x) dx \right)$$

$$\underbrace{\hspace{10em}}_{\mathbb{P}(|X| > a)}$$

Then in our case:

$$\Rightarrow \mathbb{P}(|X_u - X(t)| > (\Delta t)^{\frac{\alpha}{2}}) \leq \frac{C_s (\Delta t)^\alpha}{(\Delta t)^{\frac{\alpha}{2}}} = C_s (\Delta t)^{\frac{\alpha}{2}}$$

probability of a large error small for individual paths

• weak error: $|\mathbb{E}(X_u) - \mathbb{E}(X(t))| \sim c_w (\Delta t)^\beta$, $\beta =$ weak order of convergence

$$\begin{aligned} \text{note: } |\mathbb{E}(X_u) - \mathbb{E}(X(t))| &= |\mathbb{E}(X_u - X(t))| \\ &\leq |\mathbb{E}(|X_u - X(t)|)| \end{aligned}$$

so weak error \leq strong error

Ex.: compare $X(t) = 0$ to $X_u = \begin{cases} +1 & \text{with prob. } \frac{1}{2} \\ -1 & \text{with prob. } \frac{1}{2} \end{cases}$

$$\text{weak error: } |0 - 0| = 0$$

$$\text{strong error: } \frac{1}{2} + \frac{1}{2} = 1$$