

## 8. Stochastic Differential Equations as limits of Markov Chains

Instead of a random walk which has increments or steps whose distributions are independent of their current position, we can have Markov Chains moving in  $R$ , that take small steps, but the distribution of the steps depend on the current position of the Markov Chain. We think of a small parameter  $h > 0$  as the unit of time and the Markov Chain from the position  $X_n^h$  at time  $nh$  moves to its next position  $X_{n+1}^h$  with a step of or increment of  $Y_{n,n+1}^h = X_{n+1}^h - X_n^h$ . We anticipate that in the limit as  $h \rightarrow 0$  only the mean and variance of the increment  $Y_{n,n+1}^h$  will matter. Assuming the transition probabilities to be stationary in time, we denote by

$$\begin{aligned} b^h(x) &= E[Y_{n,n+1}^h | X_n^h = x] \\ a^h(x) &= E[(Y_{n,n+1}^h)^2 | X_n^h = x] \\ \Delta^h(x) &= E[|Y_{n,n+1}^h|^3 | X_n^h = x] \end{aligned}$$

We saw earlier that if  $b^h(x) = o(h)$ ,  $a^h(x) = h + o(h)$  and  $\Delta^h(x) = o(h)$ , then the distribution of  $X_n^h$  converges to a Normal distribution with mean  $X_0 = x$  and variance  $t$ , provided  $nh \rightarrow t$ . One can improve this to the convergence of  $X_n^h$  to the Brownian Motion  $x + \beta(t)$ , in the sense that the joint distributions of  $\{X_{n_i}^h : 1 \leq i \leq k\}$  converges to the joint distributions of  $\{x + \beta(t_i) : 1 \leq i \leq k\}$  provided  $n_i h \rightarrow t_i$  for  $i = 1, \dots, k$ . We will now assume that

$$\begin{aligned} b^h(x) &= hb(x) + o(h) \\ a^h(x) &= ha(x) + o(h) \\ \Delta^h(x) &= o(h) \end{aligned}$$

Although  $a^h(x)$  is only the second moment and not the variance, the difference which is the square of the mean is  $(b^h(x))^2$  and is  $O(h^2) = o(h)$  and can be ignored. One way to model such a situation (by no means unique) is to assume

$$X_{n+1}^h = X_n^h + hb(x) + \sqrt{a(x)}\sqrt{h}\xi_n$$

where  $\{\xi_n\}$  i.i.d. standard normals. Or one can replace  $\sqrt{h}\xi_n$  by  $\beta((n+1)h) - \beta(nh)$  to get

$$X_{n+1}^h = X_n^h + hb(X_n^h) + \sqrt{a(X_n^h)}(\beta((n+1)h) - \beta(nh))$$

We can take a formal limit here to arrive at

$$dX(t) = b(X(t))dt + \sqrt{a(X(t))}d\beta(t)$$

This equation cannot be treated as a standard ODE.  $\beta(t)$  as we saw is not of bounded variation and even in the integrated form

$$(1) \quad X(t) = X(0) + \int_0^t b(X(s))ds + \int_0^t \sqrt{a(X(s))}d\beta(s)$$

does not make sense at the first glance.

There is a theory developed by K.Itô that treats this. The main ideas are the following steps the details of which we will not go into.

**Step 1.** Approximate integrals of the form  $\int_0^t F(s)d\beta(s)$  by

$$\mathcal{I}_n = \sum_{j=0}^{n-1} F(t_j)[\beta(t_{j+1}) - \beta(t_j)] : 0 = t_0 < t_1 < \dots < t_n = t$$

sticking the increments always in the future. If  $F(s)$  only depends on the past history upto time  $t$  then  $F(t_j)$  is independent of  $\beta(t_{j+1}) - \beta(t_j)$  and a simple calculation yields

$$\begin{aligned} E[\mathcal{I}_n] &= 0 \\ E[\mathcal{I}_n^2] &= \sum_{j=0}^{n-1} E[F^2(t_j)(t_{j+1} - t_j)] \end{aligned}$$

suggesting a definition of

$$\mathcal{I} = \int_0^t F(s)d\beta(s)$$

for random functions  $F(s)$  that depend only on past history such that

$$\begin{aligned} E[\mathcal{I}] &= 0 \\ E[\mathcal{I}^2] &= E\left[\int_0^t F^2(s)ds\right] \end{aligned}$$

**Step 2.** Define iteratively

$$X_{n+1}(t) = x + \int_0^t b(X_n(s))ds + \int_0^t \sqrt{a(X_n(s))}d\beta(s)$$

**Step 3.** Using the above iteration, similar to Picard iteration for ODE, prove that  $X_n(\cdot)$  has a limit  $X(\cdot)$ , that satisfies the equation (1). Prove uniqueness. One makes the assumption that  $b(x)$  and  $\sqrt{a(x)}$  satisfy the Lipshitz condition

$$\begin{aligned} |b(x) - b(y)| &\leq A|x - y| \\ |\sqrt{a(x)} - \sqrt{a(y)}| &\leq A|x - y| \end{aligned}$$

**Step 4.** Develop a calculus. (Itô Calculus). If we expand

$$\begin{aligned}
f(\beta(t)) - f(\beta(0)) &= \sum [f(\beta((j+1)h)) - f(\beta(jh))] \\
&= \sum_j f'(\beta(jh))[\beta(j+1)h - \beta(jh)] \\
&\quad + \sum_j \frac{1}{2} f''(\beta(jh))[\beta(j+1)h - \beta(jh)]^2 \\
&\quad + \sum_j O(|\beta(j+1)h - \beta(jh)|^3) \\
&= \int_0^t f'(\beta(s))d\beta(s) + \frac{1}{2} \int_0^t f''(\beta(s))ds
\end{aligned}$$

We have used the properties that refining an interval  $[0, t]$  into finer and finer partitions leads to

$$\sum [\beta(t_{j+1}) - \beta(t_j)]^2 \rightarrow t$$

and

$$\sum |\beta(t_{j+1}) - \beta(t_j)|^3 = nO(n^{-\frac{3}{2}}) \rightarrow 0$$

Formally  $[d\beta(t)]^2 = dt$  and  $[d\beta(t)]^k = 0$  for  $k \geq 3$ . In Taylor expansion we always keep two terms. Any mixed term  $d\beta dt$  is equal to 0. With this rule one can start with

$$dX(t) = b(X(t))dt + \sqrt{a(X(t))}d\beta(t)$$

and get

$$[dX(t)]^2 = a(X(t))dt$$

or

$$\begin{aligned}
du(t, X(t)) &= u_t(t, X(t))dt + u_x(t, X(t))dX(t) + \frac{1}{2}a(X(t))u_{xx}(t, X(t))dt \\
&= u_t(t, X(t))dt + u_x(t, X(t))[\sqrt{a(X(t))}d\beta(t) + b(X(t))dt] \\
&\quad + \frac{1}{2}a(X(t))u_{xx}(t, X(t))dt
\end{aligned}$$

This is to be interpreted as the identity

$$\begin{aligned}
u(t, X(t)) - u(0, x) &= \int_0^t u_x(s, X(s))\sqrt{a(X(s))}d\beta(s) \\
&\quad + \int_0^t g(s, X(s))ds
\end{aligned}$$

with  $g(t, x) = u_t(t, x) + b(x)u_x(t, x) + \frac{1}{2}a(x)u_{xx}(t, x)$ .

**Examples.**

1. Let  $f(x) = x^2$ . Then

$$\beta(t)^2 - \beta(0)^2 = 2 \int_0^t \beta(s) d\beta(s) + t$$

This can be directly verified by approximation and using the relation

$$\sum_j [\beta(t_{j+1}) - \beta(t_j)]^2 \rightarrow t$$

2\*. Show that the solution of  $dX(t) = X(t)d\beta(t)$  is  $X(t) = X(0)\exp[\beta(t) - \frac{t}{2}]$  and not  $X(0)\exp[\beta(t)]$ .

3\*. If  $u(t, x)$  satisfies the PDE

$$u_t(t, x) + b(x)u_x(t, x) + \frac{a(x)}{2}u_{xx}(t, x) \equiv 0 \quad \text{for } 0 \leq s \leq T \quad \text{and} \quad u(T, x) = f(x)$$

and  $X(t)$  satisfies

$$X(t) = x + \int_0^t b(X(s))ds + \int_0^t \sqrt{a(X(s))}d\beta(s)$$

then use Itô calculus and the fact that  $E[\int_0^T F(s)d\beta(s)] = 0$ , to show that

$$u(0, x) = E[f(X(T))]$$

**Remark:** Technically one needs to know that

$$E[\int_0^T [F(s)]^2 ds] < \infty$$

to define the integral  $\int_0^T F(s)d\beta(s)$  and show that it has mean 0 and its variance is equal to  $E[\int_0^T [F(s)]^2 ds]$ . Although this can be relaxed somewhat in order to define the stochastic integral, the mean of the integral may cease to exist or may exist and be different from 0 if  $E[\int_0^T [F(s)]^2 ds] = \infty$