

Markov Processes

Definition: A stochastic process $X(t)$ is called a Markov process if for every n and for any $t_1 < t_2 < \dots < t_n$, its conditional probability satisfies

$$P\{X(t_n) \leq x_n \mid X(t_{n-1}), X(t_{n-2}), \dots, X(t_1)\} = P\{X(t_n) \leq x_n \mid X(t_{n-1})\}.$$

In other words

$$P\{X(t_n) \leq x_n \mid X(t) \text{ for all } t \leq t_{n-1}\} = P\{X(t_n) \leq x_n \mid X(t_{n-1})\}.$$

Properties:

- i) If $X(t)$ is a Markov process, then it is also Markov in reverse. That is, $P\{X(t_1) \leq x_1 \mid X(t) \text{ for all } t \geq t_2\} = P\{X(t_1) \leq x_1 \mid X(t_2)\}$.
- ii) For a Markov process, the future is independent of the past under the given condition of present.
- iii) If for any $t_1 < t_2$, $X(t_2) - X(t_1)$ be independent of $X(t)$ for $t \leq t_1$, then $X(t)$ is a Markov process. Thus, independent increment processes (such as Poisson and Wiener-Levy processes) are Markov processes.
- iv) If $X(t)$ is a Markov process, then $E\{X(t_n) \mid X(t_{n-1}), \dots, X(t_1)\} = E\{X(t_n) \mid X(t_{n-1})\}$.
- v) A Markov process $X(t)$ is always associated with a first-order equation

$$\frac{dX}{dt} - \beta(X, t) = j(t), \text{ with } j(t) = \frac{dW}{dt} \text{ or } j(t)dt = dW,$$

where $W(t)$ is an independent increment process (i.e. $j(t_1), j(t_2), \dots, j(t_n)$ are independent random variables for any t_1, t_2, \dots, t_n and any n).

The solution to the first-order equation is formally given as

$$X(t) = X(t_0) + \int_{t_0}^t \beta(X(\tau), \tau) d\tau + \int_{t_0}^t j(\tau) d\tau.$$

Thus $X(t_1)$ is uniquely determined from $X(t_0)$ and $j(t)$ with $t_0 < t \leq t_1$. $X(t_0)$ depends on $j(t)$ for $t \leq t_0$ and hence is independent of $j(t)$ for $t > t_0$. Thus, given $X(t_0)$ the past of the process $X(t)$ (i.e. $X(t)$ for $t < t_0$) has no effect on the future of $X(t)$ (i.e. for $t > t_0$). That is, $X(t)$ is a Markov process.

- vi) A continuous random process $X(t)$ is said to Markovian if its conditional probability density satisfies the relation

$$f_X(x_n, t_n \mid x_{n-1}, t_{n-1}; \dots; x_2, t_2; x_1, t_1) = f_X(x_n, t_n \mid x_{n-1}, t_{n-1}) \text{ for any } t_1 < t_2 < \dots < t_n.$$

vii) The following relationships hold for a Markov process:

$$a. f_X(x_1, t_1; x_2, t_2; x_3, t_3) = f_X(x_3, t_3 | x_2, t_2) f_X(x_2, t_2 | x_1, t_1) f_X(x_1, t_1),$$

$$b. f_X(x_1, t_1; \dots; x_n, t_n) = f_X(x_n, t_n | x_{n-1}, t_{n-1}) \dots f_X(x_2, t_2 | x_1, t_1) f_X(x_1, t_1),$$

where $f_X(x_n, t_n | x_{n-1}, t_{n-1})$ is called the transition probability density.

$$c. \text{ If } X(0) = x_0, \text{ then } f_X(x_1, t_1) = f_X(x_1, t_1 | x_0, 0).$$

Thus, a Markov process $X(t)$ is fully specified in any of the following three equivalent ways:

- i) Given the first-order density and the transition probability density.
- ii) Given the second-order density $f_X(x_1, t_1; x_2, t_2)$.
- iii) Given the transition probability density and $X(0)$.

The Chapman-Kolmogorov-Smoluchowski Equation

For any continuous random process

$$\begin{aligned} f(x, t | x_0, t_0) &= \int_{-\infty}^{+\infty} f(x, t; x_1, t_1 | x_0, t_0) dx_1 \\ &= \int_{-\infty}^{+\infty} f(x, t | x_1, t_1; x_0, t_0) f(x_1, t_1 | x_0, t_0) dx_1 \end{aligned}$$

For a Markov process

$$f(x, t | x_1, t_1; x_0, t_0) = f(x, t | x_1, t_1).$$

Thus,

$$f(x, t | x_0, t_0) = \int_{-\infty}^{+\infty} f(x, t | x_1, t_1) f(x_1, t_1 | x_0, t_0) dx_1.$$

This integral equation for the transition probability density of a Markov process is called the Chapman-Kolmogorov-Smoluchowski equation.

Fokker-Planck Equation

It may be shown that the transition probability density must satisfy the following (forward) Fokker-Planck equation

$$\frac{\partial f}{\partial t} = -\frac{\partial}{\partial x}[\alpha_1(x,t)f] + \frac{1}{2}\frac{\partial^2}{\partial x^2}[\alpha_{11}(x,t)f].$$

Here α_1 and α_{11} are the incremental moments defined as

$$\alpha_1(x,t) = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{dX(t) | X(t) = x\},$$

$$\alpha_{11}(x,t) = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{[dX(t)]^2 | X(t) = x\}.$$

The Kolmogorov (Backward) equation is given as

$$\frac{\partial f}{\partial t_0} + \alpha_1(x_0, t_0) \frac{\partial f}{\partial x_0} + \frac{\alpha_{11}(x_0, t_0)}{2} \frac{\partial^2 f}{\partial x_0^2} = 0$$

Note that

$$f = f(x, t | x_0, t_0).$$

Example: Determine the Fokker-Planck equation for the Wiener-Levy process and find the transition probability density function.

Recalling that

$$E\{W(t)\} = 0, \quad E\{W^2(t)\} = 2Dt, \quad R_{ww}(t_1, t_2) = \begin{cases} 2Dt_1 & t_2 \geq t_1 \\ 2Dt_2 & t_1 \geq t_2 \end{cases},$$

and

$$E\{W(t_2) - W(t_1)\} = 0, \quad E\{[W(t_2) - W(t_1)]^2\} = 2D(t_2 - t_1) \text{ for } t_2 > t_1.$$

Let

$$t_2 = t + dt, \quad t_1 = t, \quad dW = W(t + dt) - W(t)$$

Thus

$$E\{dW\} = 0, \quad E\{(dW)^2\} = 2Ddt$$

Now

$$\alpha_1 = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{dW | W\} = 0,$$

$$\alpha_{11} = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{(dW)^2 | W\} = 2D.$$

The corresponding Fokker-Planck equation then becomes

$$\frac{\partial f}{\partial t} = -\frac{\partial}{\partial x}(\alpha_1 f) + \frac{1}{2} \frac{\partial^2}{\partial x^2}(\alpha_{11} f) = D \frac{\partial^2 f}{\partial x^2}.$$

Using w for Wiener process instead of x , it follows that

$$\frac{\partial f}{\partial t} = D \frac{\partial^2 f}{\partial W^2}.$$

For $f(w, t_o / w_o, t_o) = \delta(w - w_o)$, the solution becomes

$$f = \frac{e^{-\frac{(w-w_o)^2}{4D(t-t_o)}}}{\sqrt{4\pi D(t-t_o)}}.$$

Fokker-Planck Equation for a Vector Markov Process

The transition probability density function of a vector Markov process $\mathbf{X}(t)$ satisfies the following Fokker-Planck equation:

$$\frac{\partial f}{\partial t} = -\sum_{j=1}^n \frac{\partial}{\partial x_j} [\alpha_j(\mathbf{x}, t) f] + \frac{1}{2} \sum_i \sum_j \frac{\partial^2}{\partial x_i \partial x_j} [\alpha_{ij}(\mathbf{x}, t) f].$$

The incremental moments α_j and α_{ij} are given as

$$\alpha_j = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{dX_j(t) | \mathbf{X}(t) = \mathbf{x}\},$$

$$\alpha_{ij} = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{dX_i(t) dX_j(t) | \mathbf{X}(t) = \mathbf{x}\}.$$

Fokker-Planck Equation for Ito's Equation

Consider Ito's equation

$$\frac{d\mathbf{X}}{dt} = \mathbf{g}(\mathbf{X}, t) + \mathbf{G}(\mathbf{x}, t) \cdot \mathbf{n}(t)$$

or

$$\frac{dX_i}{dt} = g_i(\mathbf{X}, t) + \sum_j G_{ij}(\mathbf{X}, t) n_j(t)$$

or

$$d\mathbf{X} = \mathbf{g}(\mathbf{X}, t)dt + \mathbf{G}(\mathbf{X}, t) \cdot d\mathbf{W}.$$

Here, \mathbf{n} and \mathbf{W} are vector white noise and Wiener process with

$$E\{n_i\} = E\{dW_i\} = 0$$

$$E\{n_i(t + \tau)n_j(t)\} = 2D_{ij}\delta(\tau), \quad E\{dW_i dW_j\} = 2D_{ij}dt.$$

The incremental moments are then given as

$$a_j = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{dX_j | \mathbf{X} = \mathbf{x}\} = g_j(x, t),$$

$$a_{ij} = \lim_{dt \rightarrow 0} \frac{1}{dt} E\{dX_i dX_j | \mathbf{X} = \mathbf{x}\},$$

$$\begin{aligned} dX_i dX_j &= g_i g_j (dt)^2 + g_i \sum_k G_{jk} dW_k dt \\ &\quad + g_j \sum_k G_{ik} dW_k dt + \sum_k \sum_\ell G_{ik} G_{j\ell} dW_k dW_\ell. \end{aligned}$$

Then

$$\alpha_{ij} = 2 \sum_k \sum_\ell G_{ik} G_{j\ell} D_{k\ell} = 2(\mathbf{G} \cdot \mathbf{D} \cdot \mathbf{G}^T)_{ij}$$

The Fokker-Planck equation then becomes

$$\frac{\partial f}{\partial t} = - \sum_j \frac{\partial}{\partial x_j} [g_j(\mathbf{x}, t) f] + \sum_i \sum_j \frac{\partial^2}{\partial x_i \partial x_j} [(\mathbf{G} \cdot \mathbf{D} \cdot \mathbf{G}^T)_{ij} f].$$

Example

Consider a first order system

$$\frac{dx}{dt} = g(x,t) + G(x,t) \frac{dW}{dt}. \quad E\{(dW)^2\} = 2Ddt.$$

The Fokker-Planck equation is given by

$$\frac{\partial f}{\partial t} = -\frac{\partial}{\partial x}(gf) + D \frac{\partial^2}{\partial x^2}(G^2 f).$$

For stationary solution we find,

$$\begin{aligned} \frac{d}{dx} \left[-gf + D \frac{d}{dx}(G^2 f) \right] &= 0, \\ -gf + D \frac{d}{dx}(G^2 f) &= c_1 = 0, \end{aligned}$$

Let

$$G^2 f = F,$$

$$D \frac{dF}{dx} = \frac{g}{G^2} F,$$

$$\frac{dF}{F} = \frac{g}{DG^2} dx,$$

$$F = C \exp \left\{ + \int_0^x \frac{g(x_1)}{DG^2(x_1)} dx_1 \right\},$$

and finally

$$f = \frac{c}{G^2} \exp \left\{ \int_0^x \frac{g(x_1)}{DG^2(x_1)} dx_1 \right\}.$$