

We start with the SDE in \mathbb{R}^N :

$$dX_t = f(X_t)dt + g dW_t$$

Here g is an $N \times N$ invertible matrix. Let

$$\phi(y) = y + f(y)h.$$

Assuming that f is Lipschitz we see that ϕ is invertible for sufficiently small h ; this follows from

$$D\phi(y) = I + Df(y)h.$$

Discretizing the SDE in time, we obtain

$$X_{n+1} = X_n + f(X_n)h + gh^{1/2}Z_{n+1}.$$

Here Z_{n+1} is a sequence of independent multivariate Gaussians, each with mean vector 0 and covariance matrix equal to the identity matrix I . Hence X_{n+1} given $X_n = y$ has multivariate Gaussian density with mean vector $\phi(y)$ and covariance matrix hgg^T . Now moving from sample paths to densities, we have

$$\tilde{p}(x, t_{n+1}) = \int_{y \in \mathbb{R}^N} G(x - \phi(y); hgg^T) \tilde{p}(y, t_n) dy.$$

Let

$$G(x - \phi(y); hgg^T) = \frac{1}{\sqrt{(2\pi h)^N |g|^2}} \exp \left(-\frac{1}{2h} (x - \phi(y))^T (gg^T)^{-1} (x - \phi(y)) \right).$$

Now we let $z = \phi(y)$ so that $dz = D\phi(y) dy$. Then

$$\tilde{p}(x, t_{n+1}) = \int_{z \in \mathbb{R}^N} G(x - z; hgg^T) \underbrace{\tilde{p}(\phi^{-1}(z), t_n) [D\phi(\phi^{-1}(z))]^{-1}}_{\psi_n(z)} dz.$$

We now have a convolution!