

Problem 1.5. (*) This exercise is based on [107]. Suppose the function F of Problem 1.4 has the form

$$F = f(X(T)),$$

where $X = X(t)$, $t \in [0, T]$, is an Itô diffusion given by

$$dX(t) = b(X(t))dt + \sigma(X(t))dW(t); \quad X(0) = x \in \mathbb{R}.$$

Here $b: \mathbb{R} \rightarrow \mathbb{R}$ and $\sigma: \mathbb{R} \rightarrow \mathbb{R}$ are given Lipschitz continuous functions of at most linear growth, so there exists a unique strong solution $X(t) = X^x(t)$, $t \in [0, T]$. Then there is a useful formula for the process φ in the Itô representation theorem. This formula is achieved as follows. If g is a real function such that

$$E[|g(X^x(t))|] < \infty,$$

then we define

$$u(t, x) := P_t g(x) := E[g(X^x(t))], \quad t \in [0, T], \quad x \in \mathbb{R}.$$

Suppose that there exists $\delta > 0$ such that

$$|\sigma(x)| \geq \delta \quad \text{for all } x \in \mathbb{R}. \quad (1.28)$$

Then $u(t, x) \in C^{1,2}(\mathbb{R}^+ \times \mathbb{R})$ and

$$\frac{\partial u}{\partial t} = b(x) \frac{\partial u}{\partial x} + \frac{1}{2} \sigma^2(x) \frac{\partial^2 u}{\partial x^2}$$

(this is the Kolmogorov backward equation, see, for example, [74, Volume 1, Theorem 5.11, p. 162 and Volume 2, Theorem 13.18, p. 53], [176, Theorem 8.1] for details on this issue).

(a) Use the Itô formula for the process

$$Y(t) = g(t, X(t)), \quad t \in [0, T], \quad \text{with } g(t, x) = P_{T-t} f(x)$$

to show that

$$f(X(T)) = P_T f(x) + \int_0^T \left[\sigma(\xi) \frac{\partial}{\partial \xi} P_{T-t} f(\xi) \right]_{|\xi=X(t)} dW(t), \quad (1.29)$$

for all $f \in C^2(\mathbb{R})$. In other words, with the notation of Problem 1.4, we have shown that if $F = f(X(T))$, then

$$E[F] = P_T f(x) \quad \text{and} \quad \varphi(t) = \left[\sigma(\xi) \frac{\partial}{\partial \xi} P_{T-t} f(\xi) \right]_{|\xi=X(t)}. \quad (1.30)$$

Note that P_+ is the transition probability. P_0 is the identity matrix.
Also,

$$g(T, X_T) = P_0 f(X(T)) = f(X(T))$$

By Itô's formula,

$$\begin{aligned} dY_t &= \partial_t g(t, x) dt + \partial_x g(t, x) dX_t + \frac{1}{2} \partial_x^2 g(t, x) [dX_t, dX_t] \\ &= \left(\partial_t g(t, x) + b(x) \partial_x g(t, x) + \frac{1}{2} \sigma^2(x) \partial_x^2 g(t, x) \right) dt + \sigma(x) \partial_x g(t, x) dW_t \end{aligned}$$

Hence,

$$Y_T - Y_0 = \int_0^T \sigma(x) \partial_x g(t, x) dW_t$$

and

$$Y_T = P_T f(x) + \int_0^T \sigma(z) \partial_z P_{T-t} f(z) dW_t$$

(b) Use (1.30) to compute $E[F]$ and find φ in the Itô representation of the following random variables:

(b.1) $F = W^2(T)$

(b.2) $F = W^3(T)$

(b.3) $F = X(T)$, where $X(t)$, $t \in [0, T]$, is the geometric Brownian motion, that is,

$$dX(t) = \rho X(t)dt + \alpha X(t)dW(t); \quad X(0) = x \in \mathbb{R} \quad (\rho, \alpha \text{ constants}).$$

(b.1) Goal: write $W^2(T) = P_T f(x) + \int_0^T \varphi(t) dW_t$

Let $z = x + W_t$. By Itô's formula,

$$d(W_t^2) = dt + 2W_t dW_t$$

Since $f(z) = z^2$, we have

$$P_T f(z) = E[f(W_T^z)] = E^z[W_T^2] = T + z^2$$

And

$$\varphi(t) = \frac{\partial}{\partial z} P_{T-t} f(z) = \frac{\partial}{\partial z} [z^2 + T] = 2z = 2(W_t + x)$$

(b.2) Let $f(t, \zeta) = \zeta^3$ and $X_t = x + W_t$. Then

$$P_T f(\zeta) = E^\zeta[X_T^3] = E^\zeta[x^3 + 3x^2 W_t + 3x W_t^2 + W_t^3] = \zeta^3 + 3\zeta T$$

we have

$$E[F] = P_T f(x) = x^3 + 3xT$$

and

$$\varphi(t) = \frac{\partial}{\partial \zeta} P_{T-t} f(\zeta) = \frac{\partial}{\partial \zeta} [\zeta^3 + 3(T-t)\zeta] = 3\zeta^2 + 3(T-t)$$

$$= 3(x + W_t)^2 + 3(T-t)$$

(b.3) Given that $f(\zeta) = \zeta$, we have

GBM: $E[X_t] = X_0 e^{\rho t}$

$$P_T f(\zeta) = E[f(X_T)] = E^\zeta[X_T] = \zeta e^{\rho T} \Rightarrow E[F] = P_T f(x) = x e^{\rho T}$$

and

$$\varphi(t) = \alpha \zeta \frac{\partial}{\partial \zeta} P_{T-t} f(\zeta) = \alpha \zeta \frac{\partial}{\partial \zeta} [\zeta e^{\rho(T-t)}] = \alpha X_t e^{\rho(T-t)}$$

- (c) Extend formula (1.30) to the case when $X(t) \in \mathbb{R}^n$, $t \in [0, T]$, and $f : \mathbb{R}^n \rightarrow \mathbb{R}$. In this case, condition (1.28) must be replaced by the *uniform ellipticity* condition

$$\eta^T \sigma^T(x) \sigma(x) \eta \geq \delta |\eta|^2 \quad \text{for all } x \in \mathbb{R}^n, \eta \in \mathbb{R}^n, \quad (1.31)$$

where $\sigma^T(x)$ denotes the transposed of the $m \times n$ -matrix $\sigma(x)$.

Using Itô's formula,

$$dY = \frac{\partial g}{\partial t}(t, X_t) dt + \sum_i \frac{\partial g}{\partial x_i}(t, X_t) dX_i + \frac{1}{2} \sum_{i,j} \frac{\partial^2 g}{\partial x_i \partial x_j}(t, X_t) dX_i dX_j$$

~~$$= \left(\frac{\partial g}{\partial t} + \sum_i b(x_t) \frac{\partial g}{\partial x_i} + \frac{1}{2} \sum_{i,j} (\sigma^T)(x_t) \frac{\partial^2 g}{\partial x_i \partial x_j} \right) + \sum_i \sigma^T(x_t) \frac{\partial g}{\partial x_i} dW_i(t)$$~~

Hence,

$$dY(t) = \sigma^T(X_t) \nabla P_{T-t} f(X_t) dW_t$$

and

$$Y(t) = P_T f(x) + \int_0^t \sigma^T(x) \nabla P_{T-t} f(x) dW_t$$

□