

AMATH 562: Homework 6

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March 4, 2018

1. (a) Poisson process is the special case of compound poisson process. Here, the jump can only be of size one.

$$\begin{aligned}
 v(U) &= \mathbb{E}N(1, U) = \mathbb{E} \sum_{0 \leq s \leq 1} \mathbb{1}_{\Delta P \in U} \\
 &= \mathbb{E} \sum_1^{P_1} \mathbb{1}_{1 \in U} \\
 &= \mathbb{E} \mathbb{E} \left[\sum_1^{P_1} \mathbb{1}_{1 \in U} | P_1 \right] \\
 &= \mathbb{E} \left[\sum_1^{P_1} \mathbb{E}[\mathbb{1}_{1 \in U} | P_1] \right] \\
 &= \mathbb{E}[P_1 \mathbb{E}[\mathbb{1}_{1 \in U} | P_1]] \\
 &= \mathbb{E}[P_1 \delta_1(U)] \\
 &= \delta_1(U) \mathbb{E}[P_1] \\
 &= \delta_1(U) \lambda
 \end{aligned}$$

(b)

$$dX_t = dP_t$$

If $X_t = x$,

$$\begin{aligned}
 X_T &= P_T - P_t + x \\
 u(t, x) &= \mathbb{E}[\phi(P_T - P_t + x) | X_t = x] \\
 &= \sum_n \phi(n + x) \mathbb{P}(P_T - P_t = n) \\
 &= \sum_n \phi(n + x) \mathbb{P}(P_{T-t} = n) \\
 &= \sum_n \phi(n + x) \frac{(\lambda(T-t))^n}{n!} e^{-\lambda(T-t)} \\
 \mathbf{A}(t)\phi(x) &= \lim_{s \downarrow t} \frac{P(s, t)\phi(x) - \phi(x)}{s - t} \\
 &= \lim_{s \downarrow t} \frac{\mathbb{E}[\phi(X_s) | X_t = x] - \phi(x)}{s - t}
 \end{aligned}$$

As t goes to s , there can either be a jump of size one or no jump.

$$\begin{aligned}
\mathbf{A}(t)\phi(x) &= \lim_{s \downarrow t} \frac{P(s, t)\phi(x) - \phi(x)}{s - t} \\
&= \lim_{s \downarrow t} \frac{\mathbb{E}[\phi(X_s)|X_t = x] - \phi(x)}{s - t} \\
&= \lim_{dt \rightarrow 0} \frac{\phi(x+1)(\lambda dt e^{-\lambda dt}) + \phi(x)(e^{-\lambda dt}) - \phi(x)}{dt} \\
&= \lim_{dt \rightarrow 0} \frac{\phi(x+1)(\lambda dt(1 - \lambda dt + \dots)) + \phi(x)(1 - \lambda dt + \dots) - \phi(x)}{dt} \\
&= \phi(x+1)\lambda - \lambda\phi(x) \\
\partial_t u(t, x) &= \sum_n \lambda \phi(n+x) \frac{(\lambda(T-t))^n}{n!} e^{-(T-t)} + \lambda \phi(n+x+1) \frac{(\lambda(T-t))^n}{n!} e^{-(T-t)} \\
&= \lambda u(t, x) - \lambda u(t, x+1) \\
&= -\mathbf{A}(t, x)u(t, x)
\end{aligned}$$

Thus, it satisfies the KBE.

2. (a)

$$Z_t = \frac{X_t}{Y_t}$$

This looks like a great place to use Ito's multi-dimensional formula.

$$\begin{aligned}
f_{X_t} &= \frac{1}{Y_t}, f_{Y_t} = -\frac{X_t}{Y_t^2} \\
f_{XX} &= 0, f_{YY} = \frac{2X_t}{Y_t^3}, f_{XY} = f_{YX} = -\frac{1}{Y_t^2} \\
f(X_{t-} + (e^{\gamma_t(z)} - 1)X_{t-}, Y_{t-} + (e^{g_t(z)} - 1)Y_{t-}) &= \frac{X_{t-} + (e^{\gamma_t(z)} - 1)X_{t-}}{Y_{t-} + (e^{g_t(z)} - 1)Y_{t-}} = Z_{t-} e^{\gamma_t(z) - g_t(z)} \\
dZ_t &= (\mu_t \frac{X_t}{Y_t} - b_t \frac{X_t}{Y_t} - 2\frac{1}{2}\sigma_t a_t \frac{X_t}{Y_t} + a_t^2 \frac{X_t}{Y_t})dt \\
&\quad + (\sigma_t \frac{X_t}{Y_t} - a_t \frac{X_t}{Y_t})dW_t \\
&\quad + \int_R Z_{t-} e^{\gamma_t(z) - g_t(z)} \tilde{N}(dt, dz) \\
&\quad + \int_R (Z_{t-} e^{\gamma_t(z) - g_t(z)} - (e^{\gamma_t(z)} - 1)Z_{t-} + (e^{g_t(z)} - 1)Z_{t-})v(dz)dt \\
dZ_t &= (\mu_t - b_t - \sigma_t a_t + a_t^2)Z_t dt + (\sigma_t - a_t)Z_t dW_t \\
&\quad + \int_R Z_{t-} e^{\gamma_t(z) - g_t(z)} \tilde{N}(dt, dz) \\
&\quad + \int_R (e^{\gamma_t(z) - g_t(z)} + (e^{g_t(z)} - e^{\gamma_t(z)}))v(dz)Z_{t-} dt
\end{aligned}$$

(b) For Z_t to be a martingale, it should have no drift Thus

$$\mu_t = b_t + \sigma_t a_t + a_t^2 - \frac{\int_R (e^{\gamma_t(z) - g_t(z)} + (e^{g_t(z)} - e^{\gamma_t(z)})) v(dz) Z_{t-}}{Z_t}$$

3. (a)

$$dX_t = \kappa(\theta - X_t)dt + d\eta_t$$

$$Y_t = X_t - \theta$$

$$dY_t = -\kappa Y_t dt + d\eta_t$$

$$f = e^{kt} Y_t$$

$$df = k e^t Y_t + e^{kt} dY_t$$

$$df = k e^t Y_t - \kappa e^{kt} Y_t + e^{kt} d\eta_t$$

$$df = e^{kt} d\eta_t$$

$$f_t = f_0 + \int_0^t e^{ks} d\eta_s$$

$$Y_t = e^{-kt} f_0 + \int_0^t e^{-k(t-s)} d\eta_s$$

$$Y_t = e^{-kt} Y_0 + \int_0^t e^{-k(t-s)} d\eta_s$$

$$X_t = \theta + e^{-kt} (X_0 - \theta) + \int_0^t e^{-k(t-s)} d\eta_s$$

$$X_t = \theta + e^{-kt} (X_0 - \theta) + \int_0^t e^{-k(t-s)} \sigma dW_s + \int_0^t \int_R e^{-k(t-s)} z \tilde{N}(ds, dz)$$

(b)

$$m(t) = \mathbb{E}[X_t] = \theta + e^{-kt} (X_0 - \theta)$$

Here, we assume the X_0 is a constant and a random variable.

$$\mathbb{E}[(X_s - m(s))(X_t - m(t))] = \mathbb{E}[(X_s - m(s))(X_t - m(t))]$$

$$Z_s = e^{ks} (X_s - m(s)) = \int_0^t e^{kr} \sigma dW_r + \int_0^t \int_R e^{kr} z \tilde{N}(dr, dz)$$

So, this process has no drift and we can do something similar to Ito Isometry.

$$f(Z_s, Z_t) = Z_s Z_t$$

If $s < t$, $I(t) = g(I(s))$ and vice versa. Thus we can use Ito's multidimensional formula.

$$\partial_{Z_s} f(Z_s, Z_t) = Z_t$$

$$\partial_{Z_s} \partial_{Z_s} f(Z_s, Z_t) = 0$$

$$\partial_{Z_t} \partial_{Z_s} f(Z_s, Z_t) = 1$$

$$f(Z_{s-} + \gamma_s, Z_{t-} + \gamma_t) - f(Z_{s-}, Z_{t-}) - \gamma \cdot \nabla f(Z_s, Z_t)$$

$$\begin{aligned}
&= Z_{s-}Z_{t-} + \gamma^2 + \gamma Z_{t-} + \gamma Z_{s-} - Z_{s-}Z_{t-} - \gamma Z_{t-} + -\gamma Z_{s-} \\
&= \gamma^2 = e^{2kr} z^2
\end{aligned}$$

$$\frac{1}{2} \sum_{i=1}^2 \sum_{j=1}^2 \sigma_{eff} \sigma_{eff}^T(i, j) \partial_{Z_i} \partial_{Z_j} f(Z_s, Z_t) = \sigma_{eff}^2 = e^{2kr} \sigma^2$$

$$df(Z_s, Z_t) = e^{2kr} \sigma^2 dr + \int_{\mathbb{R}} e^{2kr} z^2 v(dz) dr + \int_{\mathbb{R}} (\dots) \tilde{N}(dt, dz) + (\dots) dW_t$$

$$d(Z_s Z_t) = e^{2kr} \sigma^2 dr + \int_{\mathbb{R}} e^{2kr} z^2 v(dz) dr + \int_{\mathbb{R}} (\dots) \tilde{N}(dt, dz) + (\dots) dW_t$$

$$\begin{aligned}
\mathbb{E}[Z_s Z_t] &= \mathbb{E} \int_0^T e^{2kr} \sigma^2 dr + \int_0^T \int_{\mathbb{R}} e^{2kr} z^2 v(dz) dr \\
&= \frac{(e^{2kT} - 1) \sigma^2}{2k} + \frac{(e^{2kT} - 1)}{2k} \int_{\mathbb{R}} z^2 v(dz)
\end{aligned}$$

$$\mathbb{E}[Z_s Z_t] = \mathbb{E}[e^{k(t+s)} (X_s - m(s))(X_t - m(t))]$$

$$\begin{aligned}
c(t, s) &= \mathbb{E}[(X_s - m(s))(X_t - m(t))] = \mathbb{E}[e^{-k(t+s)} Z_s Z_t] = e^{-k(t+s)} \mathbb{E}[Z_s Z_t] \\
&= \frac{e^{-k(t+s)} (e^{2kT} - 1) \sigma^2}{2k} + \frac{e^{-k(t+s)} (e^{2kT} - 1)}{2k} \int_{\mathbb{R}} z^2 v(dz)
\end{aligned}$$

4.

$$dX_t = \mu dt + \sigma dW_t + \int_{\mathbb{R}} \gamma \tilde{N}(t, dz)$$

$$\begin{aligned}
d\phi(X_t) &= (\mu_t \phi'(X_t) + \frac{1}{2} \sigma^2 \phi''(X_t)) dt + \int_{\mathbb{R}} (\phi(X_{t-} + \gamma_t(z)) - \phi(X_{t-}) - \gamma_t(z) \phi'(X_t)) v(dz) dt \\
&\quad + \int_{\mathbb{R}} (\dots) \tilde{N}(dt, dz) + (\dots) dW_t
\end{aligned}$$

$$\begin{aligned}
\phi(X_s) &= \phi(x) + \int_t^s (\mu_r \phi'(X_r) + \frac{1}{2} \sigma^2 \phi''(X_r)) dr + \int_t^s \int_{\mathbb{R}} (\phi(X_{r-} + \gamma_r(z)) - \phi(X_{r-}) - \gamma_r(z) \phi'(X_r)) v(dz) dr \\
&\quad + \int_t^s \int_{\mathbb{R}} (\dots) \tilde{N}(dr, dz) + \int_t^s (\dots) dW_r
\end{aligned}$$

$$\mathbb{E}[\phi(X_s) | X_t = x] = \phi(x) + \int_t^s \mathbb{E}[(\mu_r \phi'(X_r) + \frac{1}{2} \sigma^2 \phi''(X_r)) dr | X_t = x]$$

$$+ \int_t^s \mathbb{E}[\int_{\mathbb{R}} (\phi(X_{r-} + \gamma_r(z)) - \phi(X_{r-}) - \gamma_r(z) \phi'(X_r)) v(dz) dr | X_t = x]$$

$$+ 0 + 0$$

$$\mathbb{E}[\phi(X_s) | X_t = x] - \phi(x) = \int_t^s \mathbb{E}[(\mu_r \phi'(X_r) + \frac{1}{2} \sigma^2 \phi''(X_r)) dr | X_t = x]$$

$$+ \int_t^s \mathbb{E}[\int_{\mathbb{R}} (\phi(X_{r-} + \gamma_r(z)) - \phi(X_{r-}) - \gamma_r(z) \phi'(X_r)) v(dz) dr | X_t = x]$$

$$\lim_{s \downarrow t} \frac{1}{s - t} \left(\mathbb{E}[\phi(X_s) | X_t = x] - \phi(x) \right) = \lim_{s \downarrow t} \frac{1}{s - t} \int_t^s \mathbb{E}[(\mu_r \phi'(X_r) + \frac{1}{2} \sigma^2 \phi''(X_r)) dr | X_t = x]$$

$$+ \lim_{s \downarrow t} \frac{1}{s-t} \int_t^s \mathbb{E} \left[\int_{\mathbb{R}} (\phi(X_{r-} + \gamma_r(z)) - \phi(X_{r-}) - \gamma_r(z) \phi'(X_r)) v(dz) dr \middle| X_t = x \right]$$

Thus,

$$\begin{aligned} \mathbf{A}(t) \phi(x) &= \\ &= \mathbb{E} \left[(\mu_r \phi'(X_t) + \frac{1}{2} \sigma^2 \phi''(X_t)) \middle| X_t = x \right] \\ &\quad + \mathbb{E} \left[\int_{\mathbb{R}} (\phi(X_{t-} + \gamma_t(z)) - \phi(X_{t-}) - \gamma_t(z) \phi'(X_t)) v(dz) \middle| X_t = x \right] \\ &= (\mu_t \phi'(x) + \frac{1}{2} \sigma^2 \phi''(x)) + \int_{\mathbb{R}} (\phi(x + \gamma_t(z)) - \phi(x) - \gamma_t(z) \phi'(x)) v(dz) \end{aligned}$$