

# Mathematical Finance

## Solution sheet 4

**Solution 4.1** The covariation of  $X$  and  $A$  can be expressed as a Lebesgue-Stieltjes integral

$$\begin{aligned} [X, A]_t &= \lim_n \sum_{k=1}^n (X_{kt/n} - X_{(k-1)t/n})(A_{kt/n} - A_{(k-1)t/n}) \\ &= \lim_n \sum_{k=1}^n \int_0^t \mathbb{1}_{\{(k-1)t/n < s \leq kt/n\}} (X_{kt/n} - X_{(k-1)t/n}) dA_s \\ &= \int_0^t \lim_n \sum_{k=1}^n \mathbb{1}_{\{(k-1)t/n < s \leq kt/n\}} (X_{kt/n} - X_{(k-1)t/n}) dA_s \\ &= \int_0^t \Delta X_s dA_s, \end{aligned}$$

where we used the boundedness of  $X$ . For each  $\omega$ , the set  $S_t(\omega) = \{s \leq t : \Delta X(\omega)_s \neq 0\}$  is at most countable, and the boundedness of  $X$  can be used to evaluate the integral

$$\begin{aligned} \int_0^t \Delta X_s dA_s &= \int_0^t \sum_{s \in S_t} \Delta X_s \mathbb{1}_{\{s=u\}} dA_u \\ &= \sum_{s \in S_t} \Delta X_s \int_0^t \mathbb{1}_{\{s=u\}} dA_u \\ &= \sum_{s \leq t} \Delta X_s \Delta A_s. \end{aligned}$$

**Solution 4.2** For  $\lambda \in \mathbb{R}$  and

$$M_t := \exp\left(iX_t + \frac{1}{2}|\lambda|^2 t\right),$$

by Itô's formula,

$$\begin{aligned} M_t &= M_0 + \int_0^t iM_s dX_s + \int_0^t M_s \frac{1}{2}|\lambda|^2 ds + \frac{1}{2} \int_0^t M_s i^2 \lambda^2 d[X, X]_s \\ &= M_0 + \int_0^t iM_s dX_s. \end{aligned}$$

Since

$$\sup_{s \leq t} |M_s| = \exp\left(\frac{1}{2}|\lambda|^2 t\right) < \infty,$$

the process  $M$  is a martingale, and from

$$E\left[\frac{M_t}{M_s} \mid \mathcal{F}_s\right] = 1,$$

we obtain

$$E\left[e^{i\lambda(X_t - X_s)} \mid \mathcal{F}_s\right] = \exp\left(-\frac{1}{2}|\lambda|^2(t-s)\right),$$

where the right-hand side is the characteristic function of the normal distribution  $\mathcal{N}(0, t - s)$ . The process  $X$  is a Brownian motion.

**Solution 4.3** Denote  $\sup_n E[|M_1^{\pi^n}|^2] < \infty$  by  $C$  and  $\bigcup_n \pi^n$  by  $D$ . The family  $\left\{ \frac{1}{C} \mathbb{1}_{\{C \neq 0\}} M_1^{\pi^n} \right\}$  is contained in the unit ball of  $L^2 := L^2(\Omega, \mathcal{F}_1, P)$ , so, by Banach-Alaoglu theorem (in conjunction with Eberlein-Šmulian theorem), there exists a subsequence  $(\pi^{n_k})$  such that  $(M_1^{\pi^{n_k}})$  converges weakly to some  $\xi \in L^2$ . We have  $M_t^{\pi^{n_k}} \rightarrow M_t$  for  $t \in D$ . On the other hand, for every  $t \in D$ , we have  $M_t^{\pi^{n_k}} = E[M_1^{\pi^{n_k}} | \mathcal{F}_t] \rightarrow E[\xi | \mathcal{F}_t]$  weakly. Two limits must coincide, so, we have  $M_t = E[\xi | \mathcal{F}_t]$ ,  $t \in D$ . Let  $0 \leq s < t < 1$  and  $(s_n), (t_n) \subset D$  be such that  $s < s_n < t < t_n$ ,  $s_n \downarrow s$  and  $t_n \downarrow t$ . For any  $A \in \mathcal{F}_s$ , we have

$$E[M_{s_n} \mathbb{1}_A] = E[M_{t_n} \mathbb{1}_A]. \quad (1)$$

Because  $(M_{s_n})$  and  $(M_{t_n})$  are uniformly integrable, letting  $n \rightarrow \infty$  in both sides of (1) yields

$$E[M_s \mathbb{1}_A] = E[M_t \mathbb{1}_A],$$

i.e.,  $M$  is a martingale on  $[0, 1[$  with  $M_t = E[\xi | \mathcal{F}_t]$  for  $t \in [0, 1[$ .

#### Solution 4.4

```

1 import numpy
2
3 from poisson import poisson
4 from brownian import brownian
5
6
7 #Define a function to compute the quadratic variation of rows of mxN-matrix x
8 def qv(x, m, N):
9
10     y = numpy.empty(x.shape)
11
12     for i in range(m):
13         for j in range(N):
14             y[i, j+1] = y[i, j] + (x[i, j+1] - x[i, j])**2
15     return y.mean(axis=0)[N]
16
17
18 def main():
19
20     # The Wiener process parameter.
21     delta = 1
22     # The Poisson process parameter.
23     intensity = 1
24     # Total time.
25     T = 1.0
26     # Number of steps.
27     N = 1000
28     # Time step size
29     dt = T/N
30     # Number of realizations to generate.
31     m = 1000
32     # Create empty arrays to store the realizations.
33     x = numpy.empty((m, N+1))
34     y = numpy.empty((m, N+1))

```

```
35 z = numpy.empty((m,N+1))
36 # Initial values of x,y,z.
37 x[:, 0] = 0
38 y[:, 0] = 0
39 z[:, 0] = 0
40
41 # Simulate the paths
42 brownian(x[:,0], N, dt, delta, out=x[:,1:])
43 poisson(y[:,0], N, dt, intensity, compensated=False, out=y[:,1:])
44 poisson(z[:,0], N, dt, intensity, compensated=True, out=z[:,1:])
45
46 print qv(x,m,N), qv(y,m,N), qv(z,m,N)
47
48 if __name__ == "__main__":
49     main()
```