Mathematical Finance

Solution sheet 7

Solution 7.1 First let $p: X \to \mathbb{R}$ be a sublinear functional on a vector space. If p is linear and $f(x) \leq p(x)$ for all $x \in X$ for some linear functional $f: X \to \mathbb{R}$, then $-f(x) = f(-x) \leq p(-x) = -p(x)$, so $p(x) \leq f(x)$ for all $x \in X$, i.e., f = p. Now assume that p dominates exactly one linear functional on X and that p is not linear. Then there exists some $x_0 \neq 0$ such that $-p(-x_0) < p(x_0)$. Let $M := \{\lambda x_0 : \lambda \in \mathbb{R}\}$ be the vector space generated by x_0 and define the linear functionals $f, g: M \to \mathbb{R}$ by $f(\lambda x_0) = \lambda p(x_0)$ and $g(\lambda x_0) = -\lambda p(-x_0)$. From $f(x_0) = p(x_0)$ and $g(x_0) = -p(-x_0)$ we see that $f \neq g$. Next, notice that $f(z) \leq p(z)$ and $g(z) \leq p(z)$ for each $z \in M$, that is, p dominates both f and g on the subspace M. Now, by the Hahn-Banach theorem, the two distinct linear functionals f and g have linear extensions to all of X dominated there by p, a contradiction.

Solution 7.2 Let Q be an equivalent martingale measure for P which exists by (NA). By Doob's maximal inequality, for every 1-admissible H, we have

$$Q((|H \circ X)_T^*| > K) \leq \frac{2E_Q[(H \circ X)_T^-]}{K} \leq \frac{2}{K}$$

for K > 0, so, the family $\{(H \circ X)_T : H \text{ is 1-admissible}\}$ is bounded in Q and consequently in P, i.e., (NUPBR) holds.

Solution 7.3 Let P be the Lebesgue measure on $\Omega := [0, 1]$. Define

$$X^{n,k} := n^2 \mathbb{1}_{](k-1)/n,k/n]}, \ k = 1, \dots, n \in \mathbb{N}.$$

We have

$$P(X^{n,k} > K) = \begin{cases} 1/n & \text{if } n > \sqrt{K}, \\ 0 & \text{otherwise,} \end{cases}$$

so, the family $\{X^{n,k}\}$ is bounded in probability, but since

$$\sum_{k=1}^{n} \frac{1}{n} X^{n,k} = n \in \operatorname{co}(X^{n,k}), \ n \in \mathbb{N},$$

the convex hull of $\{X^{n,k}\}$ is not bounded in probability.

Solution 7.4 Let B and C be two independent Brownian motions. Define

$$L_t := \exp\left(B_t - \frac{1}{2}t\right)$$
 and $N_t := \exp\left(C_t - \frac{1}{2}t\right)$

and

$$\tau := \inf \left\{ t \ge 0 : L_t = \frac{1}{2} \right\} \text{ and } \sigma := \inf \left\{ t \ge 0 : N_t = 2 \right\}.$$

By the properties of Brownian motion, we get

$$P(\tau = \infty) = 0$$
 and $P(\sigma = \infty) = P(\sigma < \infty) = \frac{1}{2}$.

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Let $X = L^{\tau \wedge \sigma}$ and $Y = N^{\tau \wedge \sigma}$. From above, we conclude that $X_{\infty} > 0$ a.s. and $Y_{\infty} > 0$ a.s. Moreover, we have

$$E[X_{\tau \wedge \sigma}] = E[L_{\tau \wedge \sigma}] = E[L_{\tau} 1_{\{\sigma = \infty\}}] + E[L_{\tau \wedge \sigma} 1_{\{\sigma < \infty\}}].$$

For the first term, we get

$$E[L_{\tau}1_{\{\sigma=\infty\}}] = P(\sigma=\infty)E[L_{\tau}] = \frac{1}{4}$$

by independence, and for the second term,

$$E[L_{\tau \wedge \sigma} 1_{\{\sigma < \infty\}}] = \int_0^\infty P(\sigma \in dt) E[L_{\tau \wedge t}] = \int_0^\infty P(\sigma \in dt) = P(\sigma < \infty) = \frac{1}{2}$$

by independence and the optional stopping theorem. Hence,

$$E[X_{\infty}] = E[X_{\tau \wedge \sigma}] = \frac{1}{4} + \frac{1}{2} = \frac{3}{4} < 1,$$

and so we conclude that X is a strict local martingale. However, the process $Y = (N^{\sigma})^{\tau}$ is a uniformly bounded martingale (since N^{σ} is) and the product XY is a uniformly integrable martingale. Indeed, we have

$$E[X_{\infty}Y_{\infty}] = E[L_{\tau \wedge \sigma}N_{\tau \wedge \sigma}] = E[L_{\tau \wedge \sigma}N_{\sigma}] = 2E[L_{\tau \wedge \sigma}\mathbb{1}_{\{\sigma < \infty\}}] = 2P(\sigma < \infty) = 1.$$

Finally, define the process S as $dS = dM + d\langle M, M \rangle$, where $X = \mathcal{E}(-M)$. The measure Q defined as

$$dQ = X_{\infty}Y_{\infty}dP$$

is an equivalent local martingale measure for S. The density X_{∞} does not define a probability measure.

Solution 7.5 The discounted asset prices X^1 and X^2 satisfy

$$dX^{1} = X^{1}dB + \frac{1}{2}X^{1}dt$$
 and $dX^{2} = \frac{1}{2}X^{2}dB + \frac{1}{8}X^{2}dt$,

so, we try

$$H^1 = \frac{X^2}{X^1}$$
 and $H^2 = -2$.

```
1 import numpy
2 from pylab import hist, show
3 from matplotlib.pyplot import subplot
5 from brownian import brownian
#Function computes the forward integral of rows of a mxN-matrix w.r.t. another
 def integral(x,y,m,N,out=None):
9
10
      if out is None:
          out = numpy.empty(x.shape)
12
      for i in range(m):
14
    for j in range(N):
15
      out[i,j+1]=out[i,j]+x[i,j]*(y[i,j+1]-y[i,j])
16
```

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```
17
      return out
18
19
20
21 def main():
22
      # The Wiener process parameter.
23
      delta = 1
24
25
      # Total time.
      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 = 5000
32
      # Create empty arrays to store the realizations and integrals.
33
      x = numpy.empty((m, N+1))
34
      y = numpy.empty((m, N+1))
35
36
      z = numpy.empty((m, N+1))
      # Initial values of x,y,z,w.
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
44
      # Compute the integrals
45
      integral(numpy.exp(.5*x)/numpy.exp(x),numpy.exp(x),m,N,out=y)
46
      integral(-2.0*numpy.ones((m,N+1)),numpy.exp(.5*x),m,N,out=z)
47
48
      # Plot the terminal distribution
49
      hist(y[:,N]+z[:,N],normed=True,bins='auto')
50
      show()
51
52
53 if __name__ == "__main__":
      main()
54
```