

# ASP

## Solution to Assignment 8

1. For  $(X_t)$ , we verify the four conditions in the definition of SBM:

- (a)  $X_0 = \frac{1}{c}B_0 = 0$ .
- (b) for any  $s, t \geq 0$ ,

$$X_{t+s} - X_t = \frac{1}{c}B_{c^2(t+s)} - \frac{1}{c}B_{c^2t} = \frac{1}{c}(B_{c^2(t+s)} - B_{c^2t}).$$

But  $B_{c^2(t+s)} - B_{c^2t} \sim N(0, c^2s)$ . So  $X_{t+s} - X_t$  is normal with mean 0 and variance

$$\text{Var}(X_{t+s} - X_t) = \frac{1}{c^2}\text{Var}(B_{c^2(t+s)} - B_{c^2t}) = \frac{1}{c^2}c^2s = s,$$

i.e.,

$$X_{t+s} - X_t \sim N(0, s), \quad (1)$$

showing that  $(X_t)$  has stationary increment.

- (c) Suppose  $0 \leq t_0 < \dots < t_n$ . Note that for  $i = 1, \dots, n$ ,

$$X_{t_i} - X_{t_{i-1}} = \frac{1}{c}B_{c^2t_i} - \frac{1}{c}B_{c^2t_{i-1}} = \frac{1}{c}(B_{c^2t_i} - B_{c^2t_{i-1}}).$$

So

$$X_{t_1} - X_{t_0}, X_{t_2} - X_{t_1}, \dots, X_{t_n} - X_{t_{n-1}}$$

are mutually independent, since

$$B_{c^2t_1} - B_{c^2t_0}, B_{c^2t_2} - B_{c^2t_1}, \dots, B_{c^2t_n} - B_{c^2t_{n-1}}$$

are mutually independent. This means that  $(X_t)$  has independent increment.

- (d) Since the function  $t \mapsto B_t$  is a continuous function of  $t$ , it follows that  $t \mapsto \frac{1}{c}B_{c^2t}$  is also a continuous function of  $t$ .

2. Similarly to the previous problem, for  $(\tilde{B}_t)$ , we verify the four conditions in the definition of SBM:

- (a)  $\tilde{B}_0 = B_{t_0} - B_{t_0} = 0$ .
- (b) for any  $s, t \geq 0$ ,

$$\tilde{B}_{t+s} - \tilde{B}_t = (B_{t+s+t_0} - B_{t_0}) - (B_{t+t_0} - B_{t_0}) = B_{t+s+t_0} - B_{t+t_0} \sim N(0, s), \quad (2)$$

showing that  $(\tilde{B}_t)$  has stationary increment.

(c) Suppose  $0 \leq t_0 < \dots < t_n$ . For  $i = 1, \dots, n$ ,

$$\tilde{B}_{t_i} - \tilde{B}_{t_{i-1}} = (B_{t_i+t_0} - B_{t_0}) - (B_{t_{i-1}+t_0} - B_{t_0}) = B_{t_i+t_0} - B_{t_{i-1}+t_0}.$$

So

$$\tilde{B}_{t_1} - \tilde{B}_{t_0}, \tilde{B}_{t_2} - \tilde{B}_{t_1}, \dots, \tilde{B}_{t_n} - \tilde{B}_{t_{n-1}}$$

are mutually independent, as  $(B_t)$  is a SBM and has independent increment.

(d) Since the function  $t \mapsto B_t$  is a continuous function of  $t$ , it follows that  $t \mapsto B_{t+t_0} - B_{t_0}$  is also a continuous function of  $t$ .

3.

(a) Obviously,  $E(X_t) = E(B_t - tB_1) = E(B_t) - tE(B_1) = 0$ . So for  $s, t \in [0, 1]$ ,

$$\begin{aligned} E(X_s X_t) &= E(X_s X_t) - E(X_s)E(X_t) \\ &= \text{Cov}(X_s, X_t) \\ &= \text{Cov}(B_s - sB_1, B_t - tB_1) \\ &= \text{Cov}(B_s, B_t) - s\text{Cov}(B_1, B_t) - t\text{Cov}(B_s, B_1) + st\text{Cov}(B_1, B_1) \\ &= \min(s, t) - st - st + st \\ &= \min(s, t) - st. \end{aligned}$$

(b) Suppose  $t \in [0, 1]$ . Since

$$\begin{aligned} X_t &= B_t - tB_1 = B_t - t(B_1 - B_t + B_t) \\ &= (1-t)B_t - t(B_1 - B_t) \\ &= (1-t, -t) \begin{pmatrix} B_t \\ B_1 - B_t \end{pmatrix} \end{aligned}$$

and  $(B_t, B_1 - B_t)^\top$  is a normal random vector,  $X_t$ , as a linear transform of a normal random vector, is again normal with mean 0 and variance

$$\text{Var}(X_t) = E(X_t X_t) = \min(t, t) - t \cdot t = t - t^2.$$

4.

(a) We have

$$\begin{aligned} E[e^{uB_t}] &= \int_{\mathbb{R}} e^{ux} \cdot \frac{1}{\sqrt{2\pi t}} e^{-x^2/(2t)} dx \\ &= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi t}} e^{ux - x^2/(2t)} dx \\ &= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi t}} e^{-(2t)^{-1}(x-ut)^2 + 2^{-1}u^2 t} dx \\ &= \exp\left(\frac{1}{2}u^2 t\right) \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi t}} e^{-(x-ut)^2/(2t)} dx. \end{aligned}$$

Since  $\frac{1}{\sqrt{2\pi t}}e^{-u^2/(2t)}$  is the density function of  $B_t$ , using the change of variables  $y = x - ut$ , we get

$$\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi t}} e^{-(x-ut)^2/(2t)} dx = \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi t}} e^{-y^2/(2t)} dy = 1.$$

So

$$E[e^{uB_t}] = \exp\left(\frac{1}{2}u^2t\right), \quad \text{for all } u \in \mathbb{R}. \quad (3)$$

(b) Considering the power series expansion of the exponential function on both sides of (3), we have

$$E[e^{uB_t}] = E\left[\sum_{n=0}^{\infty} \frac{(uB_t)^n}{n!}\right] = \sum_{n=0}^{\infty} \frac{E[(B_t)^n]}{n!} \cdot u^n$$

and

$$\exp\left(\frac{1}{2}u^2t\right) = \sum_{k=0}^{\infty} \frac{(u^2t/2)^k}{k!} = \sum_{k=0}^{\infty} \frac{(t/2)^k}{k!} u^{2k}.$$

So (3) implies

$$\sum_{n=0}^{\infty} \frac{E[(B_t)^n]}{n!} \cdot u^n = \sum_{k=0}^{\infty} \frac{(t/2)^k}{k!} u^{2k}, \quad \text{for all } u \in \mathbb{R}.$$

Comparing the coefficients of the polynomials on both sides, we get

$$\frac{E[(B_t)^{2n}]}{2n!} = \frac{(t/2)^n}{n!}$$

or

$$E[(B_t)^{2n}] = \frac{(t/2)^n}{n!} 2n! = \frac{(2n)!}{2^n \cdot n!} t^n.$$

(c) We prove the assertion by induction. First, we have

$$E[(B_t)^2] = t,$$

which is equal to  $\frac{(2)!}{2^1 \cdot 1!} t^1 = t$ . So the assertion is true for  $n = 1$ . Suppose now that the assertion is true for  $n$ , i.e.,

$$E[(B_t)^{2n}] = \frac{(2n)!}{2^n \cdot n!} t^n. \quad (4)$$

Then by integration by parts,

$$\begin{aligned}
E \left[ (B_t)^{2(n+1)} \right] &= \frac{1}{\sqrt{2\pi t}} \int_{\mathbb{R}} x^{2(n+1)} e^{-\frac{x^2}{2t}} dx \\
&= \frac{-t}{\sqrt{2\pi t}} \int_{\mathbb{R}} x^{2n+1} d \left( e^{-\frac{x^2}{2t}} \right) \\
&= \frac{-t}{\sqrt{2\pi t}} x^{2n+1} e^{-\frac{x^2}{2t}} \Big|_{-\infty}^{\infty} + \frac{(2n+1)t}{\sqrt{2\pi t}} \int_{\mathbb{R}} x^{2n} e^{-\frac{x^2}{2t}} dx \\
&= 0 + (2n+1)t \cdot E \left[ (B_t)^{2n} \right] \\
&\stackrel{(4)}{=} (2n+1)t \cdot \frac{(2n)!}{2^n \cdot n!} t^n \\
&= \frac{(2n+2)!}{2^{n+1} \cdot (n+1)!} t^{n+1},
\end{aligned}$$

showing that the assertion is also true for  $n+1$ . By induction, the statement holds for any  $n \in \mathbb{N}$ .

5. Let  $X := B_1, Y := B_2 - B_1, Z := B_3 - B_2$ . Then  $X, Y, Z$  are mutually independent,  $E(X) = E(Y) = E(Z) = 0$  and

$$B_2 = X + Y, \quad B_3 = X + Y + Z.$$

So

$$\begin{aligned}
E(B_1^2 B_2 B_3) &= E \left[ X^2 (X + Y)(X + Y + Z) \right] \\
&= E \left[ X^4 + X^3 Y + X^3 Z + X^3 Y + X^2 Y^2 + X^2 Y Z \right] \\
&= E \left[ X^4 \right] + E \left[ X^3 Y \right] + E \left[ X^3 Z \right] + E \left[ X^3 Y \right] + E \left[ X^2 Y^2 \right] + E \left[ X^2 Y Z \right] \\
&= E \left[ X^4 \right] + E \left[ X^3 \right] E \left[ Y \right] + E \left[ X^3 \right] E \left[ Z \right] \\
&\quad + E \left[ X^3 \right] E \left[ Y \right] + E \left[ X^2 \right] E \left[ Y^2 \right] + E \left[ X^2 \right] E \left[ Y \right] E \left[ Z \right] \\
&= E \left[ X^4 \right] + E \left[ X^2 \right] E \left[ Y^2 \right] \\
&= 3 + 1 \cdot 1 = 4,
\end{aligned}$$

where we have used  $E \left[ X^4 \right] = E \left[ B_1^4 \right] = 3$  as shown in Problem 4.

6.  $(B_t^2 - t)_{t \geq 0}$  is a martingale, since:

- (a)  $B_t \sim N(0, t) \Rightarrow E(|B_t^2 - t|) \leq E(B_t^2 + t) = t + t = 2t < \infty$ .
- (b) Note  $\mathcal{F}_t = \sigma(B_s, 0 \leq s \leq t)$ . So  $B_t^2 - t$  is  $\mathcal{F}_t$ -measurable. Thus  $(B_t^2 - t)_{t \geq 0}$  is  $\mathcal{F}_t$ -adapted.

(c) If  $s < t$ , then

$$\begin{aligned}
\mathbb{E}[B_t^2 - t \mid \mathcal{F}_s] &= \mathbb{E}[(B_t - B_s + B_s)^2 - t \mid \mathcal{F}_s] \\
&= \mathbb{E}[(B_t - B_s)^2 + 2(B_t - B_s)B_s + B_s^2 - t \mid \mathcal{F}_s] \\
&= \mathbb{E}[(B_t - B_s)^2 \mid \mathcal{F}_s] + \mathbb{E}[2(B_t - B_s)B_s \mid \mathcal{F}_s] + \mathbb{E}[B_s^2 \mid \mathcal{F}_s] - t \\
&= t - s + B_s \mathbb{E}[2(B_t - B_s) \mid \mathcal{F}_s] + B_s^2 - t \quad [Taking out known] \\
&= B_s^2 - s.
\end{aligned}$$

7. (a) Note that  $B_t = B_s + B_t - B_s$ . So  $B_t^2 = B_s^2 + (B_t - B_s)^2 + 2B_s(B_t - B_s)$ . Therefore, by taking out what is known and the role of independence, we have

$$E(B_t^2 \mid \mathcal{F}_s) = B_s^2 + E(B_t - B_s)^2 + 2B_s E(B_t - B_s) = B_s^2 + t - s$$

(b)

$$\begin{aligned}
B_t^3 &= (B_s + B_t - B_s)^3 \\
&= 3B_s^2(B_t - B_s) + B_s^3 + (B_t - B_s)^3 + 3B_s(B_t - B_s)^2
\end{aligned}$$

Hence,

$$E[B_t^3 \mid \mathcal{F}_s] = B_s^3 + 3(t - s)B_s$$

(c)

$$\begin{aligned}
B_t^4 &= 3B_s^2(B_t - B_s)^2 + 3B_s^3(B_t - B_s) + B_s^4 + B_s^3(B_t - B_s) \\
&\quad + (B_t - B_s)^4 + B_s(B_t - B_s)^3 + 3B_s^2(B_t - B_s)^2 + 3B_s(B_t - B_s)^3 \\
&= 6B_s^2(B_t - B_s)^2 + 4B_s^3(B_t - B_s) + B_s^4 + (B_t - B_s)^4 + 4B_s(B_t - B_s)^3
\end{aligned}$$

$$\begin{aligned}
E[B_t^4 \mid \mathcal{F}_s] &= 6B_s^2 E(B_t - B_s)^2 + 4B_s^3 E(B_t - B_s) + B_s^4 + E(B_t - B_s)^4 + 4B_s E(B_t - B_s)^3 \\
&= 6(t - s)B_s^2 + B_s^4 + 3(t - s)^2,
\end{aligned}$$

where we have used that if  $\xi \sim N(0, \sigma^2)$ , then  $E[\xi^4] = 3\sigma^4$ , thus  $E(B_t - B_s)^4 = 3(t - s)^2$ .

- (d) Notice that  $e^{4B_t - 2} = e^{-2}e^{4(B_t - B_s + B_s)} = e^{-2}e^{4B_s}e^{4(B_t - B_s)}$ , then

$$E[e^{4B_t - 2} \mid \mathcal{F}_s] = e^{-2}e^{4B_s}E[e^{4(B_t - B_s)}] = e^{-2}e^{4B_s}e^{8(t - s)}$$

8.

(a) Yes. In fact, for any  $n \in \mathbb{N}$  and

$$0 \leq t_1 < t_2 < \cdots < t_n,$$

we have

$$\begin{aligned} (Y_{t_1}, \dots, Y_{t_n})^\top &= (t_1 B_{1/t_1}, t_2 B_{1/t_2}, \dots, t_n \cdot B_{1/t_n})^\top \\ &= \begin{pmatrix} 0 & \cdots & \cdots & t_1 \\ 0 & \cdots & t_2 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ t_n & 0 & \cdots & 0 \end{pmatrix} \begin{pmatrix} B_{1/t_n} \\ B_{1/t_{n-1}} \\ \vdots \\ B_{1/t_1} \end{pmatrix}. \end{aligned}$$

(b) Since  $(B_{1/t_n}, \dots, B_{1/t_1})^\top$  is multi-dimensional normal,  $(Y_{t_1}, \dots, Y_{t_n})^\top$  is also normal. So  $(Y_t)$  is a Gaussian process.

$$\begin{aligned} \text{Cov}(Y_s, Y_t) &= \text{Cov}(s B_{1/s}, t B_{1/t}) \\ &= st \cdot \text{Cov}(B_{1/s}, B_{1/t}) \end{aligned}$$

If  $s \leq t$ ,  $\text{Cov}(Y_s, Y_t) = s \cdot t \cdot \frac{1}{t} = s$ , and if  $s > t$   $\text{Cov}(Y_s, Y_t) = st \cdot \frac{1}{s} = t$ . So

$$\text{Cov}(Y_s, Y_t) = \min(s, t)$$

(c) Yes. Similar to (a), we can easily verify that  $(Y_t)$  has independent increments. It remains to show that  $Y_t$  has normal increments. For  $0 \leq s < t$ , we have

$$\begin{aligned} Y_t - Y_s &= t \cdot B_{1/t} - s \cdot B_{1/s} \\ &= t \cdot B_{1/t} - s \cdot (B_{1/s} - B_{1/t} + B_{1/t}) \\ &= t \cdot B_{1/t} - s \cdot (B_{1/s} - B_{1/t}) - s \cdot B_{1/t} \\ &= (t - s) B_{1/t} - s (B_{1/s} - B_{1/t}) \\ &= (t - s, -s) \cdot \begin{pmatrix} B_{1/t} \\ B_{1/s} - B_{1/t} \end{pmatrix}. \end{aligned}$$

Since  $(B_{1/t}, B_{1/s} - B_{1/t})^\top \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \frac{1}{t} & 0 \\ 0 & \frac{1}{s} - \frac{1}{t} \end{pmatrix}\right)$ ,  $Y_t - Y_s$  is normal with mean 0 and

$$\begin{aligned} \text{Var}(Y_t - Y_s) &= (t - s)^2 \cdot \frac{1}{t} + s^2 \cdot \left(\frac{1}{s} - \frac{1}{t}\right) \\ &= (t - s) \cdot \frac{(t - s) + s}{t} = t - s. \end{aligned}$$

9. (a)

$$P(B_3 \geq 1/2) = P\left(\sqrt{3}B_1 \geq \frac{1}{2}\right) = P\left(B_1 \geq \sqrt{3}/6\right) = 1 - \Phi(\sqrt{3}/6) \approx 0.386$$

(b)

$$P(B_1 \leq 1/2, B_3 \geq B_1 + 2) = P(B_1 \leq \frac{1}{2}, B_3 - B_1 \geq 2) = \Phi(1/2)(1 - \Phi(\sqrt{2})) = 0.055$$

(c)

$$1 - P\left(\max_{0 \leq s \leq 10} B_s \geq 6\right) = 1 - 2P(B_{10} \geq 6) = 2\Phi(\sqrt{6}/10) - 1 \approx 0.196$$

(d) Note that

$$P(B_4 \leq 0 \mid B_2 \geq 0) = \frac{P(B_2 \geq 0, B_4 \leq 0)}{P(B_2 \geq 0)}$$

and  $P(B_2 \geq 0) = \frac{1}{2}$ . So

$$\begin{aligned} P(B_2 \geq 0, B_4 \leq 0) &= \int_0^\infty P(B_4 \leq 0 \mid B_2 = x) dP(B_2 = x) \\ &= \int_0^\infty P(B_4 - B_2 < -x) \frac{1}{\sqrt{4\pi}} e^{-\frac{x^2}{4}} dx \\ &= \int_0^{+\infty} \int_{-\infty}^{-x} \frac{1}{4\pi} e^{-\frac{x^2+y^2}{4}} dy dx \\ &= \int_0^{+\infty} \int_{-\pi/4}^{-\pi/2} \frac{1}{4\pi} e^{-\frac{r^2}{4}} r d\theta dr \\ &= 1/8 \end{aligned}$$

Therefore,  $P(B_4 \leq 0 \mid B_2 \geq 0) = 1/4$

10. Let  $\mathcal{F}_t = \sigma(B_s : 0 \leq s \leq t)$ . Then  $M_t = e^{\sigma B_t - \frac{\sigma^2 t}{2}}$  can be written as  $M_t = \phi(t, B_t)$ . So  $M_t$  is adapted w.r.t.  $\mathcal{F}_t$ . Because  $B_t \sim N(0, t)$ ,

$$E[|M_t|] = E\left[\left|e^{\sigma B_t - \frac{\sigma^2 t}{2}}\right|\right] = E\left[e^{\sigma B_t - \frac{\sigma^2 t}{2}}\right] = e^{-\frac{\sigma^2 t}{2} + \frac{\sigma^2 t}{2}} = e^0 = 1 < \infty.$$

Suppose  $s > 0$ , then

$$\begin{aligned}
E[M_{t+s} \mid M_t] &= E \left[ e^{\sigma B_{t+s} - \frac{\sigma^2(t+s)}{2}} \mid \mathcal{F}_t \right] \\
&= E \left[ e^{\sigma(B_{t+s} - B_t + B_t) - \frac{\sigma^2 t}{2} - \frac{\sigma^2 s}{2}} \mid \mathcal{F}_t \right] \\
&= e^{B_t - \frac{\sigma^2 t}{2}} \cdot E \left[ e^{\sigma(B_{t+s} - B_t) - \frac{\sigma^2 s}{2}} \mid \mathcal{F}_t \right] \\
&= M_t \cdot E \left[ e^{\sigma(B_{t+s} - B_t) - \frac{\sigma^2 s}{2}} \right] = M_t.
\end{aligned}$$

Hence  $M_t$  is a martingale w.r.t.  $\mathcal{F}_t$ .

11. Consider the cumulative distribution function of  $M$ ,

$$\begin{aligned}
F_M(m) &= P(M \leq m) = 1 - P(M > m) = 1 - P \left( \max_{0 \leq t \leq 1} B_t > m \right) \\
&= 1 - 2P(B_1 > m) = 2\Phi(m) - 1.
\end{aligned}$$

Note that  $F_M(0) = 2\phi(0) - 1 = 0$ , i.e.  $P(M \leq 0) = 0$ . So the probability density function of  $M$  is

$$f_M(m) = F'_M(m) = \begin{cases} \sqrt{\frac{2}{\pi}} e^{-\frac{m^2}{2}}, & m > 0; \\ 0, & \text{otherwise.} \end{cases}$$

Then

$$\begin{aligned}
E(M) &= \int_0^\infty m \cdot \sqrt{\frac{2}{\pi}} e^{-\frac{m^2}{2}} dm = -\sqrt{\frac{2}{\pi}} \int_0^\infty e^{-\frac{m^2}{2}} d \left( -\frac{m^2}{2} \right) = -\sqrt{\frac{2}{\pi}} e^{-\frac{m^2}{2}} \Big|_0^\infty = \sqrt{\frac{2}{\pi}}, \\
E(M^2) &= \int_0^\infty m^2 \cdot \sqrt{\frac{2}{\pi}} e^{-\frac{m^2}{2}} dm = \sqrt{\frac{2}{\pi}} \int_0^\infty -m de^{-\frac{m^2}{2}} = \sqrt{\frac{2}{\pi}} \left[ -me^{-\frac{m^2}{2}} \Big|_0^\infty + \int_0^\infty e^{-\frac{m^2}{2}} dm \right] \\
&= 0 + 2 \int_0^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{m^2}{2}} dm = 2 \cdot 1/2 = 1,
\end{aligned}$$

and thus  $\text{Var}(M) = E(M^2) - E^2(M) = 1 - \frac{2}{\pi}$ .

12. Since  $(X_t)$  and  $(Y_t)$  are independent standard 1-dimensional Brownian motions, the probability density function of  $B_t$  is  $f(x, y) = \frac{1}{2\pi t} e^{-\frac{x^2+y^2}{2t}}$ . Then the probability

$$\begin{aligned}
P(B_t \in D_\rho) &= \iint_{\sqrt{x^2+y^2} < \rho} f(x, y) dx dy = \iint_{\sqrt{x^2+y^2} < \rho} \frac{1}{2\pi t} e^{-\frac{x^2+y^2}{2t}} dx dy \\
&= \int_0^\rho \int_0^{2\pi} \frac{1}{2\pi t} e^{-\frac{r^2}{2t}} \cdot r dr d\theta = -e^{-\frac{r^2}{2t}} \Big|_0^\rho \\
&= 1 - e^{-\frac{\rho^2}{2t}}.
\end{aligned}$$