

## Solutions for Exercise sheet 5: Markov processes (v2)

### Solution 1 — Counter-example.

- (1) Consider the filtration  $\mathcal{F}_t = \sigma(X_s, 0 \leq s \leq t)$ . Then we can write  $X_{t+s} = X_t + (B_{t+s} - B_t) \mathbb{1}[A \neq 0]$ . But almost surely,  $\mathbb{1}[A \neq 0] = \mathbb{1}[X_t \neq 0]$ , which means that we can rewrite  $X_{t+s} = X_t + (B_{t+s} - B_t) \mathbb{1}[X_t \neq 0]$ . Since  $X_t \in \mathcal{F}_t$  and  $B_{t+s} - B_t \perp\!\!\!\perp \mathcal{F}_t$ , we get the Markov property with

$$p_t(x, dy) = \delta_0(dy) \text{ if } x = 0 \text{ and } \mathbb{P}(x + B_t \in dy) \text{ otherwise.}$$

- (2) If it did, then it would mean that the process sticks to 0 after its first hitting time of 0, which is indeed not the case.

### Solution 2 — The stationary Ornstein-Uhlenbeck process.

Firstly,  $\text{Cov}(X_t, X_s) = e^{-|t-s|}$ . So at each time  $t$ ,  $X_t$  is a standard Gaussian. For the Markov property, start from the standard filtration  $\mathcal{F}$  of  $B$ . The standard filtration of  $X$  is then  $t \mapsto \mathcal{F}_{e^{2t}}$ . Then we easily compute

$$\mathbb{P}(X_{t+s} \in dy \mid \mathcal{F}_{e^{2t}}) = \mathbb{P}(e^{-s}x + B_{1-e^{-2s}} \in dy) = \frac{1}{\sqrt{2\pi(1-e^{-2s})}} \exp\left(-\frac{(y - e^{-s}x)^2}{2(1-e^{-2s})}\right) dy.$$

### Solution 3 — Brownian bridges.

Here we denote  $p(t, x, y)$  the Brownian transition kernel density  $p(t, x, y) = \frac{1}{\sqrt{2\pi t}} e^{-(x-y)^2/(2t)}$  for  $t > 0$ .

- (1) Set  $X_t = x + B_t$  and  $\beta x, y_t = x + B_t - tB_1 + t(y - x)$ . Remark that  $\beta_t^{x,y} = \beta_t^{x,0} + yt$ . But  $X_t = \beta_t^{x,0} + tX_1$ . Since  $\beta^{x,0}$  is independent from  $X_1$ , it comes that  $\mathbb{E}[H(X_{|[0,1]}) | X_1] = \mathbb{E}[H(\beta_t^{x,0} + ty)]_{y=X_1} = \mathbb{E}[H(\beta^{x,y})]_{y=X_1}$ . Hence the claim that  $\mathbb{P}(X_{|[0,1]} \in \cdot | X_1 \in dy) = \mathbb{P}(\beta^{x,y} \in \cdot)$ .
- (2) The Markov property at  $a$  tells us that

$$\mathbb{E}[(H(X_{|[0,a]}, X_1))] = \int_{\mathcal{C}([0,a])} \mathbb{P}(X_{|[0,a]} \in d\phi) \int_{\mathbb{R}} dy p(1-a, \phi(a), y) H(\phi, y).$$

But then, multiplying and dividing by  $p_1(x, y) = \frac{\mathbb{P}(X_1 \in dy)}{dy}$ , and using Fubini

$$\begin{aligned} \mathbb{E}[(H(X_{|[0,a]}, X_1))] &= \int_{\mathbb{R}} dy p(1, x, y) \int_{\mathcal{C}([0,a])} \mathbb{P}(X_{|[0,a]} \in d\phi) \frac{p(1-a, \phi(a), y)}{p(1, x, y)} H(\phi, y). \\ &= \int_{\mathbb{R}} \mathbb{P}(X_1 \in dy) \int_{\mathcal{C}([0,a])} \mathbb{P}(X_{|[0,a]} \in d\phi) \frac{p(1-a, \phi(a), y)}{p(1, x, y)} H(\phi, y). \\ &= \int_{\mathbb{R}} \mathbb{P}(X_1 \in dy) \int_{\mathcal{C}([0,a])} U(y, d\phi) H(\phi, y) \end{aligned}$$

But we recognize a desintegration of measure formula as in the definition of conditional probability<sup>1</sup>, with the conditional probability kernel  $U(y, d\phi) = \mathbb{P}(X_{|[0,a]} \in d\phi) \frac{p(1-a, \phi(a), y)}{p(1, x, y)}$ . Hence we have

$$\mathbb{P}(X_{|[0,a]} \in d\phi | X_1 \in dy) = \mathbb{P}(X_{|[0,a]} \in d\phi) \frac{p(1, \phi(a), y)}{p(1, x, y)}.$$

On the other hand, the previous question gives us (restricting a process is a measurable transformation), that

$$\mathbb{P}(X_{|[0,a]} \in d\phi | X_1 \in dy) = \mathbb{P}(\beta_{|[0,a]}^{x,y} \in d\phi).$$

- (3) The rhs of the last two equations are measure-valued functions of  $y$  that are  $\mathbb{P}(X_1 \in dy)$ -a.e. equal. Since the distribution of  $X_1$  and Lebesgue are mutually absolutely continuous, then they are equal  $dy$ -a.e. Now we claim that they are both continuous (measure valued, with the narrow convergence topology) functions of  $y$ . For the first one, it follows from Scheffé's lemma. For the second one, it is because as  $y_n \rightarrow y$ ,  $\beta^{x, y_n} \rightarrow \beta^{x, y}$  in  $\mathcal{C}([0, 1])$  for every  $\omega$  and of course  $\omega$ -wise convergence implies convergence in distribution. Hence for every  $y$ ,

$$\mathbb{P}(\beta_{|[0,a]}^{x,y} \in d\phi) = \mathbb{P}(X_{|[0,a]} \in d\phi) \frac{p(1, \phi(a), y)}{p(1, x, y)}.$$

In particular, if  $\beta = \beta^{0,0}$  denotes a standard Brownian bridge,

$$\frac{\mathbb{P}(\beta_{|[0,a]} \in d\phi)}{\mathbb{P}(B_{|[0,a]} \in d\phi)} = \frac{\exp\left(\frac{\phi(a)^2}{2(1-a)}\right)}{\sqrt{1-a}}.$$

---

<sup>1</sup>To go back to the main definition of conditional probability distributions and precisely show that  $\mathbb{E}[F(X_{|[0,1]}) | X_1] = \int U(X_1, d\phi) F(\phi) d\phi$ , you can test with  $H$  in the product form  $H(\phi, y) = F(\phi)G(y)$ .

**Solution 4** — *Cauchy process.*

- (1) We have  $C_a = B_{T_a}^{(2)} = \Psi(B^{(2)}, T_a)$  where  $\Psi(\phi, t) = \phi_t$  is a measurable (actually continuous) functional  $\mathcal{C}(\mathbb{R}_+) \times \mathbb{R}_+ \rightarrow \mathbb{R}$ . Then for some positive measurable  $H$ ,

$$\begin{aligned} E[H(C_a)] &= \mathbb{E}[H(\Psi(B^{(2)}, T_a))] = \int_{\mathbb{R}_+} \mathbb{P}(T_a \in dt) \int_{\mathcal{C}(\mathbb{R}_+)} \mathbb{P}(B^{(2)} \in d\phi) H(\Psi(\phi, t)) \\ &= \int_{\mathbb{R}_+} \mathbb{P}(T_a \in dt) \mathbb{E}[H(B_t^{(2)})] = \int_{\mathbb{R}_+} \mathbb{P}(T_a \in dt) \int_{\mathbb{R}} \mathbb{P}(B_t \in du) H(u) \\ &= \int_{\mathbb{R}} H(u) \left( \int_{\mathbb{R}_+} \frac{\mathbb{P}(T_a \in dt) \mathbb{P}(B_t \in du)}{dt \, du} dt \right) du. \end{aligned}$$

(Fubini has been used several times). Hence the thing inside the parenthesis is the density of  $C_a$  at  $u$ . Let's compute it

$$\begin{aligned} \frac{\mathbb{P}(C_a \in du)}{du} &= \int_{\mathbb{R}_+} \frac{\mathbb{P}(T_a \in dt) \mathbb{P}(B_t \in du)}{dt \, du} dt \\ &= \int_{\mathbb{R}_+} \frac{a}{\sqrt{2\pi t^3/2}} e^{-a^2/2t} \frac{1}{\sqrt{2\pi t}} e^{-x^2/2t} dt = \frac{a}{\pi(x^2 + a^2)} \end{aligned}$$

- (2) We have that  $(C_{a+} - C_a)$  is constructed from  $B_{T_{a+}} - B_{T_a}$  the same way  $C$  is constructed from  $B$ . Hence the first claim follows from the strong Markov property of  $B$ . Now  $C_{t+s} = C_t + C_{t+s} - C_t$ , and  $C_{t+s} - C_t$  is independent of  $\sigma(C_u, u \leq t) \subset F_{T_a}$ , hence  $\mathbb{P}(C_{t+s} \in dy | C_t \in dx) = \mathbb{P}(x + C_s \in dy) = \frac{s}{\pi((y-x)^2 + s^2)} dy$  (The usual stuff with Lévy processes)
- (3)  $C$  is càglàd because  $T$  is. Let  $G = T_{B^{(1)*}(1)}$  and  $D = T_{B^{(1)*}(1)_+}$ . Then almost surely  $G < 1 < D$ . If  $C$  were continuous, we'd get  $B^{(2)}(G) = B^{(2)}(D)$  almost surely, negating the independence of  $B^{(2)}$  and  $(G, D) \in \sigma(B^{(1)})$ .