Applied Stochastic Analysis Homework assignment 7

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Exercise 1

Since every Y_t^i , $i=1,\ldots,d$, is a linear combination of continuous independent (centered) Gaussian processes then every Y_t^i is a (centered) Gaussian process too. Hence, we only need to examine its covariance function. We have

$$\mathbb{E}[Y_s^i Y_t^j] = \sum_{k=1}^d \sum_{n=1}^d Q_{ik} Q_{jn} \, \mathbb{E}[W_s^k W_t^n] = (s \wedge t) \sum_{k=1}^d \sum_{n=1}^d Q_{ik} Q_{jn} \delta_{kn}$$
$$= (s \wedge t) \sum_{k=1}^d Q_{ik} Q_{jk} = (s \wedge t) (Q \cdot Q^t)_{ij} = (s \wedge t) \delta_{ij}.$$

The above concludes the proof that $\mathbf{Y}_t = (Y_t^1, \dots, Y_t^d)$ is a d-dimensional Brownian motion.

Exercise 2

- (a)
- (b) It holds that

$$P(M_t > a) = P(M_t > a, B_t > a) + P(M_t > a, B_t \le a) = P(B_t > a) + P(M_t > a, B_t \le a),$$

since $B_t > a$ implies $M_t = \sup_{s \le t} B_s \ge B_t > a.$

(c) Since
$$\{M_t > a\} = \{T_a \le t\}$$
 and if $T_a \le t$ then $\tilde{B}_t = 2a - B_t$, then $P(M_t > a, B_t \le a) = P(T_a \le t, 2a - B_t \ge a) = P(T_a \le t, \tilde{B}_t \ge a) = P(\tilde{B}_t \ge a)$, since $\{T_a > t, \tilde{B}_t \ge a\} = \{T_a > t, B_t \ge a\} = \emptyset$.

(d) Thanks to part (a), (b) and (c) we have that

$$P(M_t > a) = P(B_t > a) + P(\tilde{B}_t \ge a) = 2\int_a^\infty \frac{1}{\sqrt{2\pi t}} e^{-x^2/2t} \, dx = \int_a^\infty \sqrt{\frac{2}{\pi t}} e^{-x^2/2t} \, dx.$$

Exercise 3

Exercise 4

(a) We showed in class that

$$Q_t^{\sigma}(W_t) \xrightarrow{L^2} t \quad \text{as } |\sigma| \to 0.$$
 (1)

Hence it is sufficient to notice that

$$Q_t^{\sigma}(aW_t + bt) = \sum_{i=0}^{n-1} |aW_{t_{i+1}} + bt_{i+1} - aW_{t_i} - bt_i|^2 = \sum_{i=0}^{n-1} |a(W_{t_{i+1}} - W_{t_i}) + b(t_{i+1} - t_i)|^2$$
$$= a^2 Q_t^{\sigma}(W_t) + ab \sum_{i=0}^{n-1} (W_{t_{i+1}} - W_{t_i})(t_{i+1} - t_i) + b^2 \sum_{i=0}^{n-1} (t_{i+1} - t_i)^2.$$

Now

$$\mathbb{E}\left[\left(\sum_{i=0}^{n-1}(W_{t_{i+1}}-W_{t_i})(t_{i+1}-t_i)\right)^2\right] = \sum_{i=0}^{n-1}\mathbb{E}\left[\left(W_{t_{i+1}}-W_{t_i}\right)^2\right](t_{i+1}-t_i)^2 = \sum_{i=0}^{n-1}(t_{i+1}-t_i)^4 \le |\sigma|^3t,$$

where the first equality holds since $\mathbb{E}[(W_{t_{i+1}} - W_{t_i})(W_{t_{j+1}} - W_{t_j})] = 0$ for every $i \neq j$, and so

$$ab \sum_{i=0}^{n-1} (W_{t_{i+1}} - W_{t_i})(t_{i+1} - t_i) \xrightarrow{L^2} 0$$
 as $|\sigma| \to 0$. (2)

Combining (1) and (2) and the fact that $\sum_{i=0}^{n-1} (t_{i+1} - t_i)^2 \leq |\sigma| t \xrightarrow{L^2} 0$ as $|\sigma| \to 0$, we get that

$$Q_t^{\sigma}(aW_t + bt) \xrightarrow{L^2} t$$
 as $|\sigma| \to 0$.

(b) Let's consider

$$Q_{t,4}^{\sigma}(W_t) = \sum_{i=0}^{n-1} (W_{t_{i+1}} - W_{t_i})^4.$$

We have

$$\mathbb{E}[(Q_{t,4}^{\sigma}(W_t))^2] = \sum_{i=0}^{n-1} \mathbb{E}[(W_{t_{i+1}} - W_{t_i})^8] + \sum_{\substack{i,j=0\\i\neq j}}^{n-1} \mathbb{E}[(W_{t_{i+1}} - W_{t_i})^4 (W_{t_{j+1}} - W_{t_j})^4]$$

Now

$$\sum_{i=0}^{n-1} \mathbb{E}[(W_{t_{i+1}} - W_{t_i})^8] = 105 \sum_{i=0}^{n-1} (t_{i+1} - t_i)^4 \le 105 |\sigma|^3 t \xrightarrow{L^2} 0 \quad \text{as } |\sigma| \to 0$$
 (3)

and

$$\sum_{\substack{i,j=0\\i\neq j}}^{n-1} \mathbb{E}[(W_{t_{i+1}} - W_{t_i})^4 (W_{t_{j+1}} - W_{t_j})^4] = \sum_{\substack{i,j=0\\i\neq j}}^{n-1} \mathbb{E}[(W_{t_{i+1}} - W_{t_i})^4] \mathbb{E}[(W_{t_{j+1}} - W_{t_j})^4]$$

$$= 225 \sum_{i=0}^{n-1} (t_{i+1} - t_i)^2 \sum_{\substack{j=0\\j\neq i}}^{n-1} (t_{j+1} - t_j)^2$$

$$\leq 225 \sum_{i=0}^{n-1} (t_{i+1} - t_i)^2 |\sigma| t$$

$$\leq 225 |\sigma|^2 t^2 \xrightarrow{L^2} 0 \quad \text{as } |\sigma| \to 0. \tag{4}$$

Hence (3) and (4) imply that

$$Q_{t,4}^{\sigma}(W_t) \xrightarrow{L^2} 0$$
 as $|\sigma| \to 0$.

Exercise 5

Let us denote by X_t^x the solution to $\dot{X}_t = a(X_t)$, $X_0 = x$. If $f \in C_b^2(\mathbb{R})$, then

$$(\mathcal{L}f)(x) = \lim_{t \to 0^+} \frac{f(X_t^x) - f(x)}{t} = \frac{d}{dt} f(X_t^x) \Big|_{t=0} = f'(X_0^x) \frac{d}{dt} X_t^x \Big|_{t=0} = f'(x) a(X_0^x) = a(x) f'(x),$$

i.e. $\mathcal{L} = a \, \partial_x$.

Exercise 6

Given $f \in C_b^2$, we have, for $x \in K$, where $K \subset \mathbb{R}$ is a compact set such that supp $\{p(\cdot,t|\cdot,0)\} \subseteq K^2$,

$$(\mathcal{L}f)(x) = \lim_{t \to 0^+} \frac{\mathbb{E}_x[f(X_t)] - f(x)}{t} = \lim_{t \to 0^+} \frac{1}{t} \int_K (f(y) - f(x)) \, p(y, t | x, 0) \, dy. \tag{5}$$

If $\varepsilon > 0$ we can split the integral in (5) as

$$\begin{split} t^{-1} \int_K (f(y) - f(x)) \, p(y, t | x, 0) \, dy &= t^{-1} \int_{y \in K, |x - y| \ge \varepsilon} (f(y) - f(x)) \, p(y, t | x, 0) \, dy \\ &+ t^{-1} f'(x) \int_{y \in K, |x - y| < \varepsilon} (y - x) \, p(y, t | x, 0) \, dy \\ &+ t^{-1} / 2 \int_{y \in K, |x - y| < \varepsilon} f''(\xi_y) (y - x)^2 \, p(y, t | x, 0) \, dy, \end{split}$$

where ξ_y is a point between x and y. Now,

$$t^{-1} \int_{y \in K, |x-y| \ge \varepsilon} (f(y) - f(x)) \, p(y, t|x, 0) \, dy \xrightarrow[t \to 0^+]{} \int_{y \in K, |x-y| \ge \varepsilon} (f(y) - f(x)) \, W(y|x) \, dy + O(\varepsilon),$$

$$t^{-1} f'(x) \int_{y \in K, |x-y| \le \varepsilon} (y - x) \, p(y, t|x, 0) \, dy \xrightarrow[t \to 0^+]{} f'(x) O(\varepsilon),$$

$$t^{-1}/2 \int_{y \in K, |x-y| < \varepsilon} f''(\xi_y) (y-x)^2 p(y,t|x,0) \, dy \le$$

$$\le \|f''\|_{\infty} t^{-1}/2 \int_{y \in K, |x-y| < \varepsilon} (y-x)^2 p(y,t|x,0) \, dy \xrightarrow[t \to 0^+]{} \|f''\|_{\infty} O(\varepsilon)/2.$$

hence, if we send $\varepsilon \to 0^+$, we get

$$(\mathcal{L}f)(x) = \int_K (f(y) - f(x)) W(y|x) dy = \int_{\mathbb{R}} f(y) W(y|x) dy - f(x)\lambda(x).$$