Brownian Motion and Stochastic Calculus

Exercise sheet 9

 $\label{eq:Please} Please \ hand \ in \ your \ solutions \ during \ exercise \ class \ or \ in \ your \ assistant's \ box \ in \ HG \ E65 \ no \ latter \ than \\ May \ 5th$

Exercise 9.1 For $M \in \mathcal{M}_{0,loc}^c$, we denote by $L_{loc}^2(M)$ the space of all predictable processes for which there is a sequence of stopping times $\tau_n \uparrow \infty$ *P*-a.s. such that $E\left[\int_0^{\tau_n} H_s^2 d\langle M \rangle_s\right] < \infty$ for any *n*.

(a) Let H be predictable. Show that

$$H \in L^2_{loc}(M) \iff \int_0^t H^2_s \, d\langle M \rangle_s < \infty \quad P\text{-a.s. for each } t \ge 0.$$

(b) Show that for any continuous semimartingale X, any adapted RCLL process H and any sequence of partitions $(\Pi_n)_{n\in\mathbb{N}}$ of $[0,\infty)$ with $\lim_{n\to\infty} |\Pi_n| = 0$, we have

$$\int_0^t H_{s-} dX_s = \lim_{n \to \infty} \sum_{t_i \le t, t_i \in \Pi_n} H_{t_i} \left(X_{t_{i+1} \land t} - X_{t_i} \right) \quad \text{in probability.}$$

(c) Find an adapted process with RCLL paths which is not locally bounded.

Solution 9.1

(a) (\Rightarrow) Let $H \in L^2_{loc}(M)$ and let $(\tau_n)_{n \in \mathbb{N}}$ be the corresponding localizing sequence. By definition, we have for each n that

$$P\Big[\int_0^{\tau_n} H_s^2 \, d\langle M \rangle_s < \infty\Big] = 1$$

Fix any $t \ge 0$. We see that for each $n \in \mathbb{N}$, we have

$$P\left[\int_{0}^{t} H_{s}^{2} d\langle M \rangle_{s} = \infty\right]$$

$$= P\left[\left\{\int_{0}^{t} H_{s}^{2} d\langle M \rangle_{s} = \infty\right\} \cap \left\{\tau_{n} \leq t\right\}\right] + P\left[\left\{\int_{0}^{t} H_{s}^{2} d\langle M \rangle_{s} = \infty\right\} \cap \left\{\tau_{n} > t\right\}\right]$$

$$\leq P\left[\tau_{n} \leq t\right] + P\left[\left\{\int_{0}^{\tau_{n}} H_{s}^{2} d\langle M \rangle_{s} = \infty\right\} \cap \left\{\tau_{n} > t\right\}\right]$$

$$\leq P\left[\tau_{n} \leq t\right] + P\left[\int_{0}^{\tau_{n}} H_{s}^{2} d\langle M \rangle_{s} = \infty\right]$$

$$= P\left[\tau_{n} \leq t\right].$$

Thus, we conclude that

$$P\left[\int_0^t H_s^2 d\langle M \rangle_s = \infty\right] \le \lim_{n \to \infty} P\left[\tau_n \le t\right] = 0.$$

 (\Leftarrow) Let *H* be predictable such that

$$\int_0^t H_s^2 d\langle M \rangle_s < \infty \quad P\text{-a.s. for each } t \ge 0.$$
(1)

Updated: May 8, 2017

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Consider the sequence of stopping times $(\tau_n)_{n\in\mathbb{N}}$ defined by

$$\tau_n := \inf \left\{ t \ge 0 \, \Big| \, \int_0^t H_s^2 \, d\langle M \rangle_s > n \right\}.$$

Due to (1), we obtain that $\tau_n \uparrow \infty$ *P*-a.s. Moreover, due to the definition of τ_n and the (left)-continuity of $\int H d\langle M \rangle$, we have for each *n*

$$E\left[\int_0^{\tau_n} H_s^2 \, d\langle M \rangle_s\right] \le n < \infty.$$

(b) For each n, set

$$H^n := \sum_{t_i \in \Pi_n} H_{t_i} \, \mathbf{1}_{(t_i, t_{i+1}]}.$$

By definition, we obtain that for each $t \ge 0$,

$$(H^n \cdot X)_t := \int_0^t H^n_s \, dX_s = \sum_{t_i \le t, t_i \in \Pi_n} H_{t_i} \, (X_{t_{i+1} \wedge t} - X_{t_i}).$$

Set $\mathcal{H}^n := H^n - H_-$. Being left-continuous and adapted, each H^n and H_- are locally bounded and thus each \mathcal{H}^n is locally bounded, too. Moreover, $\mathcal{H}^n \to 0$ pointwise on $\Omega \times [0, \infty)$ as $n \to \infty$. Let $\varepsilon > 0$ and $N \in \mathbb{N}$ such that $|\mathcal{H}^n| \le \varepsilon$ for all $n \ge N$. Then, we have

$$|\mathcal{H}^n| \leq \varepsilon + \max_{n=1,\dots,N} |\mathcal{H}^n|,$$

which is locally bounded. Thus we can apply Theorem 4.2.19 of the script to derive that for each $t \ge 0$,

 $\lim_{n \to \infty} \sup_{0 \le s \le t} \left| (\mathcal{H}^n \cdot X)_s \right| = 0 \quad \text{ in probability.}$

Thus, we obtain the result directly from the definition of \mathcal{H}^n .

(c) Let (Ω, \mathcal{F}, P) be probability space such that there is a random variable $U \sim \mathcal{N}(0, 1)$ which is \mathcal{F} -measurable. Fix any u > 0 and consider the process

$$X_t := U \mathbf{1}_{[u,\infty)}(t), \quad t \ge 0.$$

Moreover, we let \mathbb{F} be the filtration generated by the process X. By construction, X is right-continuous and \mathbb{F} -adapted. Assume that X is locally bounded. Then, as $|\Delta X_u| \leq 2 \sup_{t \in [0,u]} |X_t|$, we conclude that $|\Delta X_u| \leq C$ P-a.s. for some constant C by the locally boundedness of X. But by definition of X, this means that $|U| \leq C$ P-a.s. which gives a contradiction as $U \sim \mathcal{N}(0, 1)$. **Exercise 9.2** Consider a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, P)$ satisfying the usual conditions and let $\sigma \leq \tau$ be two stopping times. Moreover, let Z be a bounded, \mathcal{F}_{σ} -measurable random variable. The goal of this exercise is to compute the stochastic integral process $\int Z \mathbb{1}_{[\sigma,\tau]} dM$ for an integrator $M \in \mathcal{M}^c_{0,\text{loc}}$.

- (a) For a (uniformly integrable) right-continuous martingale X = (X_t)_{t≥0}, show that the process Z(X^τ X^σ) is again a (uniformly integrable) right-continuous martingale.
 Hint: Use Lemma 4.1.19 from the lecture notes to show the assertion first for Z of the form Z = 1_A for some A ∈ 𝔅_σ. Then extend the result to general Z.
- (b) Let $M, N \in \mathcal{M}_{0, \text{loc}}^c$. Show that

$$\langle Z(M^{\tau} - M^{\sigma}), N \rangle = Z\langle M^{\tau} - M^{\sigma}, N \rangle = Z(\langle M, N \rangle^{\tau} - \langle M, N \rangle^{\sigma}).$$

(c) Let $M \in \mathcal{M}^c_{0,\mathrm{loc}}$ and set $H := Z1_{]\sigma,\tau]}$. Show that $H \in L^2_{\mathrm{loc}}(M)$ and

$$\int H \, dM = Z(M^{\tau} - M^{\sigma}).$$

Conclude that if M is a (uniformly integrable) martingale, then the stochastic integral $\int H \, dM$ is also a (uniformly integrable) martingale.

Remark: The last statement is **not** true for arbitrary bounded $H \in L^2_{loc}(M)$.

Solution 9.2

(a) Let $X = (X_t)_{t\geq 0}$ be a uniformly integrable, right-continuous martingale. Set $Y := Z(X^{\tau} - X^{\sigma})$ and fix a stopping time ρ . We will show that $E[|Y_{\rho}|] < \infty$ and $E[Y_{\rho}] = 0$. The assertion then follows from Lemma 4.1.19 in the lecture notes.

Since X is uniformly integrable, the stopping theorem yields $E[X_{\infty}|\mathcal{F}_{\gamma}] = X_{\gamma}$ for any stopping time γ . In particular, the family $\{X_{\gamma} : \gamma \text{ a stopping time}\}$ is uniformly integrable (i.e., X is of *class* (D)), hence bounded in L^1 . It follows that

$$E[|Y_{\rho}|] \le C(E[|X_{\tau \land \rho}|] + E[|X_{\sigma \land \rho}|]) < \infty$$

where C > 0 is any constant bounding Z.

Next, we show that $E[Y_{\rho}] = 0$. By a monotone class argument or simply measure-theoretic induction, we may assume that $Z = 1_A$ for some $A \in \mathcal{F}_{\sigma}$. Then $\tau_A := \tau 1_A + \infty 1_{A^c}$ and $\sigma_A := \sigma 1_A + \infty 1_{A^c}$ are stopping times and

$$E[Y_{\rho}] = E[1_A(X_{\rho \wedge \tau} - X_{\rho \wedge \sigma})] = E[X_{\rho \wedge \tau_A} - X_{\rho \wedge \sigma_A}] = 0,$$

where we use the stopping theorem in the last equality.

If X is not uniformly integrable, then assuming that ρ is bounded, almost the same proof yields that Y is a martingale (but not uniformly integrable in general), c.f. Remark 4.(1.20) in the lecture notes.

(b) The equality $B := Z \langle M^{\tau} - M^{\sigma}, N \rangle = Z(\langle M, N \rangle^{\tau} - \langle M, N \rangle^{\sigma})$ follows from bilinearity of $\langle \cdot, \cdot \rangle$ and from the fact that for any stopping time τ ,

$$\langle M^{\tau}, N \rangle = \langle M, N^{\tau} \rangle = \langle M, N \rangle^{\tau}.$$

Next, we note that $Y := Z(M^{\tau} - M^{\sigma}) \in \mathcal{M}_{0,\text{loc}}^c$ by part **a**) and localisation. So $\langle Y, N \rangle$ is well-defined. We also note that the process B is continuous and of finite variation. Moreover, since B = 0 on $[\![0, \sigma]\!]$, we can write $B = (Z1_{]\![\sigma,\infty]\!]})(\langle M, N \rangle^{\tau} - \langle M, N \rangle^{\sigma})$ to see that B is also adapted.

Updated: May 8, 2017

Setting $X := (M^{\tau} - M^{\sigma})N - \langle M^{\tau} - M^{\sigma}, N \rangle \in \mathcal{M}_{0, \text{loc}}^c$ and noting that $X^{\sigma} = 0$, we have

$$YN - B = Z((M^{\tau} - M^{\sigma})N - \langle M^{\tau} - M^{\sigma}, N \rangle) = Z(X - X^{\sigma}).$$

By part **a**) and localisation, $Z(X - X^{\sigma}) \in \mathcal{M}_{0,\text{loc}}^c$. Thus, as $\langle Y, N \rangle$ is the unique process \widetilde{B} of cFV_0 such that $MN - \widetilde{B} \in \mathcal{M}_{0,\text{loc}}^c$, we conclude by uniqueness that $\langle Y, N \rangle = B$.

(c) Clearly, $H := Z1_{[\sigma,\tau]}$ is left-continuous. Moreover for $t \ge 0$, the second factor in $H_t = (Z1_{\{\sigma < t\}})1_{\{t \le \tau\}}$ is \mathcal{F}_t -measurable since τ is a stopping time, while the \mathcal{F}_t -measurability of the first factor follows from **4-3 c**) via measure-theoretic induction. Thus, H is adapted and hence predictable. Since H is also bounded, it follows that $H \in L^2_{loc}(M)$.

Now for any $N \in \mathcal{M}_{0,\text{loc}}^c$, we have

$$\langle Z(M^{\tau} - M^{\sigma}), N \rangle \stackrel{\mathrm{b})}{=} Z(\langle M, N \rangle^{\tau} - \langle M, N \rangle^{\sigma}) = \int Z \mathbf{1}_{]\!]\sigma,\tau]\!] d\langle M, N \rangle = \int H d\langle M, N \rangle.$$

Thus by the defining property of the stochastic integral, $\int H dM = Z(M^{\tau} - M^{\sigma})$.

Finally, from part **a**), we see that if M is a (uniformly integrable) martingale, then $\int H \, dM = Z(M^{\tau} - M^{\sigma})$ is a (uniformly integrable) martingale.

Exercise 9.3 Let $(B_t)_{t\geq 0}$ be a Brownian motion. Fix any $0 < T < \infty$ and let $f \in L^2([0,T])$ be a deterministic function. For any $0 \le a < b \le T$ we set

$$\mathcal{J}_{a,b} := \int_{a}^{b} f(s) \, dB_s.$$

Moreover, for any $t \in [0, T]$, we denote $\mathcal{J}_t := \mathcal{J}_{0,t}$.

- (a) Show that the process $\mathcal{J} := (\mathcal{J}_{a,b})_{0 \leq a \leq b \leq T}$ is a centered Gaussian process and calculate its covariance function.
- (b) Show that the process $(\mathcal{J}_t)_{t\in[0,T]}$ has the same law as the process $Y := (Y_t)_{t\in[0,T]}$ defined by

$$Y_t := B_{\int_0^t f^2(s) \, ds}.$$

Solution 9.3

(a) Note that $\cdot B$ is an isometry of \mathcal{L}^2 . Thus,

$$\mathbb{E}\left[\mathcal{J}_{a,b}\mathcal{J}_{a',b'}\right] = \mathbf{1}_{\{a \lor a' \le b \land b'\}} \int_{a \lor a'}^{b \land b'} f(s)^2 ds$$

Noting that \mathcal{J}_t is a local martingale such that $\mathbb{E}\left[\mathcal{J}_t^2\right] < \infty$ we have that $\mathbb{E}\left[\mathcal{J}_{a,b}\right] = 0$.

To see that it is a Gaussian process we start by taking f to be a continuous function. Using Exercise 9.1 (b) we know that if f is continuous, and if $(\Pi_n)_{n\in\mathbb{N}}$ is a partition with $\lim_{n\to\infty} |\Pi_n| = 0$ we have that

$$\mathcal{J}_{a,b} = \int_a^b f(s) dB_s = \lim_{n \to \infty} \sum_{t_i \le t, t_i \in \Pi_n n} f(t_i) (B_{t_{i+1}} - B_{t_i}).$$

Thus, thanks to Problem 3.3 if f is continuous $\sum_{i=1}^{N} \lambda_i \mathcal{J}_{a_i,b_i}$ a normal random variable. Due to the fact that $\cdot B$ is an isometry we have that if $f_n \stackrel{\mathcal{L}^2}{\to} f$, then $\mathcal{J}_{a,b}(f_n) \to \mathcal{J}_{a,b}(f)$ in $\mathcal{L}^2(\Omega)$. Thus, due to the fact that continuous function are dense in $\mathcal{L}^2([0,T])$, if $f \in \mathcal{L}^2([0,T])$, there exists f_n continuous functions such that $f_n \stackrel{\mathcal{L}^2}{\to} f$ thus $\sum_{i=1}^{N} \lambda_i \mathcal{J}_{a_i,b_i}(f_n) \stackrel{\mathcal{L}^2}{\to} \sum_{i=1}^{N} \lambda_i \mathcal{J}_{a_i,b_i}(f)$. Again by Problem 3.3, $\sum_{i=1}^{N} \lambda_i \mathcal{J}_{a_i,b_i}(f)$ is a normal random variable. Thus, $\mathcal{J}_{a,b}$ is a Gaussian process.

(b) By the previous exercise, we know that for any $t \ge 0$, $E[\mathcal{J}_t] = 0$. For $g(t) := \int_0^t f^2(s) \, ds$, it is clear that the process $Y := (Y_t)_{t \in [0,T]}$ defined by

$$Y_t := B_{q(t)}$$

is a Gaussian process with $E[Y_t] = 0$ for any $t \ge 0$ as Brownian motion is. Moreover, for any $s, t \in [0, T]$, due to the Covariance property of Brownian motion, we obtain that

$$\operatorname{Cov}(B_{g(s),g(t)}) = \min(g(s),g(t)) = \mathbb{E}[\mathcal{J}_s\mathcal{J}_t].$$

We conclude that the processes \mathcal{J} and Y are both Gaussian processes with same expectations and Covariance functions, thus have the same finite dimensional marginal distributions.