

Brownian Motion and Stochastic Calculus

Sketch of Solution Sheet 3

1. a) Fix any $t \in \mathbb{R}$. Since Brownian motion B is a Gaussian process, we get by definition that X_t is Gaussian distributed. It remains to check its mean and variance:

$$\begin{aligned} \mathbb{E}[X_t] &= 0, \\ \text{Var}(X_t) &= e^{-2t}e^{2t} = 1. \end{aligned}$$

- b) Fix any $n \in \mathbb{N}$ and any $t_1, t_2, \dots, t_n \geq 0$. It is enough to check that

$$(X_{-t_1}, X_{-t_2}, \dots, X_{-t_n}) \stackrel{Law}{=} (X_{t_1}, X_{t_2}, \dots, X_{t_n}).$$

From the invariance by time inversion property of Brownian motion (cf. Proposition 1.1 in Section 2.1)), we get that for any $\tilde{t}_1, \dots, \tilde{t}_n \geq 0$

$$(\tilde{t}_1 B_{1/\tilde{t}_1}, \tilde{t}_2 B_{1/\tilde{t}_2}, \dots, \tilde{t}_n B_{1/\tilde{t}_n}) \stackrel{Law}{=} (B_{\tilde{t}_1}, B_{\tilde{t}_2}, \dots, B_{\tilde{t}_n}).$$

Therefore, for $\tilde{t}_i := e^{-2t_i}$, $i := 1, \dots, n$, we get that

$$\begin{aligned} (X_{-t_1}, X_{-t_2}, \dots, X_{-t_n}) &= (e^{t_1} B_{e^{-2t_1}}, e^{t_2} B_{e^{-2t_2}}, \dots, e^{t_n} B_{e^{-2t_n}}) \\ &\stackrel{Law}{=} (e^{-t_1} B_{e^{2t_1}}, e^{-t_2} B_{e^{2t_2}}, \dots, e^{-t_n} B_{e^{2t_n}}) \\ &= (X_{t_1}, X_{t_2}, \dots, X_{t_n}). \end{aligned}$$

2. 1) \Rightarrow 4) This follows directly from the uniform integrability of the family $\{E[Y|\mathcal{G}] \mid \mathcal{G} \subseteq \mathcal{F}\}$.

- 4) \Rightarrow 2) As $(X_t)_{t \geq 0}$ is uniformly integrable, it is bounded in \mathcal{L}^1 , i.e. $\sup_{t \geq 0} E[|X_t|] < \infty$. Applying the supermartingale convergence theorem, we obtain that $X_\infty := \lim_{t \rightarrow \infty} X_t$ exists a.s., and $X_\infty \in \mathcal{L}^1$ by Fatou's lemma. By definition, as $(X_t)_{t \geq 0}$ is adapted, X_∞ is \mathcal{F}_∞ -measurable. Moreover, by the uniform integrability of $(X_t)_{t \geq 0}$, it converges also in \mathcal{L}^1 to X_∞ .

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2) \Rightarrow 3) From $X_t \rightarrow X_\infty$ in \mathcal{L}^1 , we conclude that also for any $t \geq 0$ and $A \in \mathcal{F}_t$ we have

$$X_t \mathbf{1}_A \rightarrow X_\infty \mathbf{1}_A \quad \text{in } \mathcal{L}^1 \text{ for } t \rightarrow \infty.$$

Therefore, as $(X_t)_{t \geq 0}$ is a martingale, we have for any $t \geq 0$ and $A \in \mathcal{F}_t$ that

$$E[X_\infty \mathbf{1}_A] = \lim_{s \rightarrow \infty} E[X_{t+s} \mathbf{1}_A] = \lim_{s \rightarrow \infty} E[X_t \mathbf{1}_A] = E[X_t \mathbf{1}_A],$$

which implies that $E[X_\infty | \mathcal{F}_t] = X_t$, and hence $(X_t)_{t \in [0, \infty]}$ is a martingale.

3) \Rightarrow 1) This is clear for $Y := X_\infty$.

Finally, if 1)–4) hold true, then we have like in the proof of 2) \Rightarrow 3) that for any $t \geq 0$ and $A \in \mathcal{F}_t$,

$$E[X_\infty \mathbf{1}_A] = E[X_t \mathbf{1}_A] = E[Y \mathbf{1}_A], \quad (1)$$

as $X_t = E[Y | \mathcal{F}_t]$. Therefore, (1) holds true for $A \in \bigcup_{t \geq 0} \mathcal{F}_t$. The collection of sets

$$\mathcal{D} := \left\{ A \in \mathcal{F} \mid E[X_\infty \mathbf{1}_A] = E[Y \mathbf{1}_A] \right\}$$

is a Dynkin system and contains $\bigcup_{t \geq 0} \mathcal{F}_t$, which is closed under finite intersections. By the Dynkin system theorem, we conclude that \mathcal{D} contains \mathcal{F}_∞ and thus $X_\infty = E[Y | \mathcal{F}_\infty]$.

3. We begin with the first equality: $\sigma(C(S)) = \mathcal{B}(S)$. If h is continuous, then $\{h > c\}$ is open for all $c \in \mathbb{R}$, therefore h is $\mathcal{B}(S)$ measurable and we have \subseteq . Conversely, let $A \subseteq S$ be closed, then $h(s) := \min(1, d(s, A))$ is in $C(S)$ and $A = \{h = 0\}$, therefore $A \in \sigma(C(S))$ and we have \supseteq .

For the second claim notice that for every $t \in [0, 1]$ the map $x \mapsto x(t)$ is a continuous map from S to \mathbb{R} . Therefore, $\sigma(\mathcal{Z}) \subseteq \sigma(C(S)) = \mathcal{B}(S)$.

Conversely, since the metric space S is separable, every open set in S can be written as a countable union of balls and because

$$U_\delta(x) = \bigcup_{n \in \mathbb{N}} \overline{U_{\delta-1/n}(x)}, \quad \text{with} \quad U_\varepsilon(x) := \{y \in S \mid d(y, x) < \varepsilon\},$$

it suffices to show that every closed ε -ball is in $\sigma(\mathcal{Z})$. Indeed,

$$\begin{aligned} \overline{U_\varepsilon(x)} &:= \{y \in S \mid d(y, x) \leq \varepsilon\} \\ &= \bigcap_{n \in \mathbb{N}} \{y \in S \mid |y(i/n) - x(i/n)| \leq \varepsilon, i = 0, 1, \dots, n\} \in \sigma(\mathcal{Z}). \end{aligned}$$

Therefore, $\mathcal{B}(S) \subseteq \sigma(\mathcal{Z})$. Finally, if X is measurable, then for every $t_i \in [0, 1]$ we have $X_{t_i} = F_{t_i} \circ X$ with $F_{t_i} : (S, \mathcal{B}(S)) \mapsto (\mathbb{R}, \mathcal{B}(\mathbb{R}))$ with $f \mapsto f(t_i)$. We see that

Siehe nächstes Blatt!

X_{t_i} is measurable, because X is measurable and F_{t_i} is continuous. Conversely, if all X_{t_i} are measurable then for $Z \in \mathcal{Z}$ we have

$$\begin{aligned} X^{-1}(Z) &= \{\omega \in \Omega \mid X_{t_i}(\omega) \in A_i, \quad i = 1, \dots, n\} \\ &= \bigcap_{i=1}^n X_{t_i}^{-1}(A_i) \in \mathcal{F}. \end{aligned}$$

Hence, X is measurable.

4. Matlab Files

```

1 function bmscex34
2 % In this exercise we simulate Brownian motion using the
   Wiener–Levy
3 % Representation (see Corollary I.(5.16) in the lecture
   notes)
4
5 % upper bound on n
6 nmax=12;
7 % number of iid normal variables
8 N=sum(2.^[1:nmax]);
9 % number of sample paths
10 M=10;
11 % final time
12 T=1;
13 % number of grid points
14 gridpoi=2000;
15 % time grid
16 grid=0:T/gridpoi:T;
17 % iid std normal random variables
18 Y=randn(N,M);
19 % output matrix (N,M)=(N*1)*(1*M) matrix, initialize for
   n=0: Y_0*phi_0(t)
20 out=grid'*randn(1,M);
21
22 % use the definition of W^N
23 for n=1:nmax
24     for k=1:(2^n)
25         % formula I.(5.8)
26         out=out+(schauderba(n,k,grid))*Y(2^(n-1)+k,:);
27     end
28 end

```

Bitte wenden!

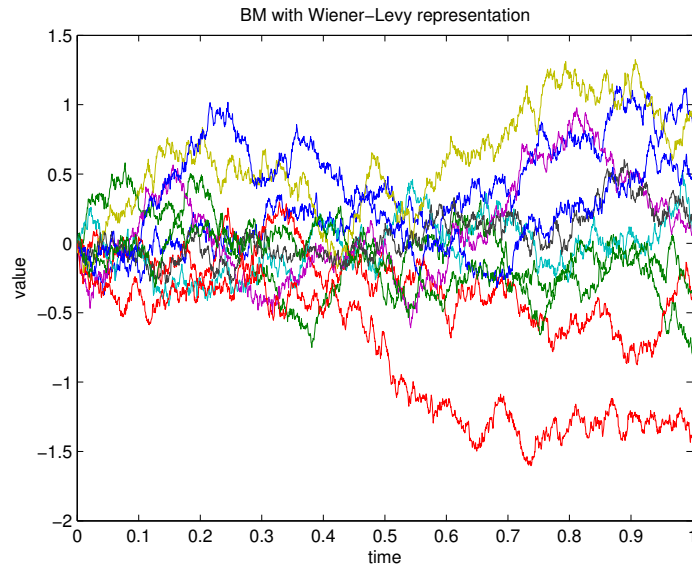


Abbildung 1: 10 sample paths of a BM

```

29 plot(grid , out)
30 title( 'BM with Wiener-Levy representation' );
31 xlabel( 'time' );
32 ylabel( 'value' );
33 end
34
35
36 function [ value ]=schauderba(n,k,t)
37 % the function implements the schauderbasis function see
   definition I (5.7)
38 ind1=t> (2*k-2)*2^(-(n+1));
39 ind2=t<= (2*k-1)*2^(-(n+1));
40
41 ind3=1-ind2;
42 ind4=t<=2*k*2^(-(n+1));
43
44 % Definition of the Schauder basis function definition I
   (5.7)
45 value=(ind1.*ind2).*2^(n/2).*(t-(k-1)*2^(-n))...
46      -(ind3.*ind4).*2^(n/2).*(t-k*2^(-n));
47 end

```