

Chapter 2: Brownian motion as a Markov process

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From now on, a BM is a Gaussian process $(B_t)_{t \geq 0}$ with continuous paths and independent Gaussian homogenous increments; in particular

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

are independent Gaussian r.v., centred, with variance $t_i - t_{i-1}$.

1 The Markov property

Informally, $\mathcal{F}_t^- = \sigma(B_s, s \leq t)$, $\mathcal{F}_t^+ = \sigma(B_s, s \geq t)$. The law of a $\mathcal{F}_t^+$ -measurable r.v., conditional on $\mathcal{F}_t^-$, only depends on the r.v. B_t .

Let us make this statement more precise. For any $t < t_1 < \dots < t_n$, we have

$$\begin{aligned} & \mathbb{E}[f(B_{t_1}, B_{t_2}, \dots, B_{t_n}) \mid \mathcal{F}_t^-] \\ &= \mathbb{E}[f(B_t + (B_{t_1} - B_t), (B_{t_2} - B_t) + B_t, \dots, (B_{t_n} - B_t) + B_t) \mid \mathcal{F}_t^-]. \end{aligned}$$

Observe first that $(B_{t_i} - B_t)_{i \leq n}$ is independent of $\mathcal{F}_t^-$. This follows from the fact that, for every $0 \leq s_1 \leq \dots \leq s_m \leq t$,

$$(B_{s_1}, B_{s_2}, \dots, B_{s_m}) \text{ is independent of } (B_{t_1} - B_t, B_{t_2} - B_t, \dots, B_{t_n} - B_t),$$

as a consequence of the basic property $\mathbb{E}[B_{s_i} \cdot (B_{t_j} - B_t)] = 0$, that carries over to the concatenated vector is Gaussian, so that uncorrelation implies independence in a Gaussian space. As a consequence

$$\mathbb{E}[f(B_{t_1}, B_{t_2}, \dots, B_{t_n}) \mid \mathcal{F}_t^-] = \varphi(B_t) \text{ a.s.},$$

where

$$\begin{aligned} \varphi(x) &= \mathbb{E}[f(x + B_{t_1} - B_t, x + B_{t_2} - B_t, \dots, x + B_{t_n} - B_t)] \\ &= \mathbb{E}[f(x + B_{t_1-t}, x + B_{t_2-t}, \dots, x + B_{t_n-t})], \end{aligned}$$

the last equality using the stationarity of the increments. We end the proof by a monotone-class argument: the family of bounded $\mathcal{F}_t^+$ -measurable Z such that $\mathbb{E}[Z \mid \mathcal{F}_t^+] = \mathbb{E}[Z \mid \sigma(B_t)]$ is a vector space, stable under increasing limits, and contains all bounded $f(B_{t_1}, \dots, B_{t_n})$; this proves the general statement.

We say Brownian motion is thus a homogeneous Markov process. More generally:

$$\mathbb{E}[F(B_{t+u}, u \geq 0) \mid \mathcal{F}_t^-] = \mathbb{E}_{\mathbb{W}_{B_t}}[F(B_u, u \geq 0)],$$

where W_x denotes the law of a Brownian motion started at x , i.e. the law of $\tilde{B}_t = x + B_t$ for B a standard BM. As a probability measure on $(\mathcal{C}(\mathbb{R}_+, \mathbb{R}), \mathfrak{C})$, we can see W_x as the push-forward of the Wiener measure $\mathbb{W}$ under the shift map

$$\tau_x : \mathcal{C}(\mathbb{R}_+, \mathbb{R}) \rightarrow \mathcal{C}(\mathbb{R}_+, \mathbb{R}), \quad \omega \mapsto x + \omega :$$

$$\mathbb{W}_x = \tau_x \# \mathbb{W}.$$

We wrap-up this discussion with the following

Proposition 1 (Simple Markov property). *For $s \geq 0$, the process $(\tilde{B}_t = B_{t+s} - B_s)_{t \geq 0}$ is a Brownian motion, independent of $\mathcal{F}_s$.*

Proof. $\tilde{B}$ is Gaussian, centered, with continuous paths; $\tilde{B}_0 = 0$ and $\mathbb{E}[\tilde{B}_t \tilde{B}_{t'}] = t \wedge t'$. Hence $\tilde{B}$ is a BM. It remains to check independence: for this; it suffices to show that, for $0 \leq t_1 \leq \dots \leq t_n$ and $0 \leq s_1 \leq \dots \leq s_m \leq s$,

$$(\tilde{B}_{t_1}, \dots, \tilde{B}_{t_n}) \text{ independent of } (B_{s_1}, B_{s_2}, \dots, B_{s_m}),$$

which holds since $\mathbb{E}[(B_{s+t_i} - B_s)B_{s_j}] = 0$ for $s \geq s_j$ (the concatenated Gaussian vector being uncorrelated is thus independent, componentwise). $\square$

2 The semigroup of Brownian motion

We address the following problem: how can we compute $\mathbb{W}_x(\Gamma)$ for Γ as general as possible. We abbreviate $\mathbb{E}_{\mathbb{W}_x}$ by $\mathbb{E}_x$ and start with

$$\mathbb{E}_x[f(X_{t_1}, \dots, X_{t_n})],$$

(with f bounded for instance) and $(X_t)_{t \geq 0}$ denotes the canonical process on the Wiener space.

Start with $n = 1$.

$$\begin{aligned} \mathbb{E}_x[f(X_t)] &= \mathbb{E}_0[f(x + X_t)] \\ &= \frac{1}{\sqrt{2\pi t}} \int_{\mathbb{R}} dy e^{-\frac{1}{2}y^2/t} f(x + y) \\ &= \frac{1}{\sqrt{2\pi t}} \int_{\mathbb{R}} dy e^{-(y-x)^2/(2t)} f(y) \\ &= \int_{\mathbb{R}} p_t(x, dy) f(y) = P_t f(x), \end{aligned}$$

say, where

$$p_t(x, dy) = \frac{1}{\sqrt{2\pi t}} \exp\left(-\frac{1}{2t}(y-x)^2\right) dy$$

is the kernel of the linear operator P_t that acts on bounded functions f (at least).

The case $n = 2$. For $s < t$,

$$\begin{aligned} \mathbb{E}_x[f(X_s)g(X_t)] &= \mathbb{E}_x[f(X_s)g(X_s + (X_t - X_s))] \\ &\stackrel{\text{Markov property}}{=} \mathbb{E}_x[f(X_s) \mathbb{E}_{X_s}[g(X_{t-s})]] \\ &= \mathbb{E}_x[f(X_s) P_{t-s}g(X_s)] \\ &= \int_{\mathbb{R}} P_s(x, dy) f(y) \int_{\mathbb{R}} P_{t-s}(y, dz) g(z) \\ &= \int_{\mathbb{R}} \frac{dy}{\sqrt{2\pi s}} e^{-(y-x)^2/(2s)} f(y) \int_{\mathbb{R}} \frac{dz}{\sqrt{2\pi(t-s)}} e^{-(z-y)^2/(2(t-s))} g(z). \end{aligned}$$

The general case. We can iterate the above computation, applying repeatedly the Markov property to obtain

$$\mathbb{E}_x[f_1(X_{t_1}) \cdots f_n(X_{t_n})] = \mathbb{E}_x \left[f_1(X_{t_1}) \cdots f_{n-1}(X_{t_{n-1}}) \underbrace{\int_{\mathbb{R}} P_{t_n - t_{n-1}}(X_{t_{n-1}}, dy_n) f_n(y_n)}_{= \mathbb{E}_{X_{t_{n-1}}}[f_n(X_{t_n - t_{n-1}})]} \right]$$

to finally obtain the formula

$$\begin{aligned} & \mathbb{E}_x[f_1(X_{t_1}) \cdots f_n(X_{t_n})] \\ &= \int_{\mathbb{R}} P_{t_1}(x, dy_1) f_1(y_1) \int_{\mathbb{R}} P_{t_2-t_1}(y_1, dy_2) f_2(y_2) \cdots \int_{\mathbb{R}} P_{t_n-t_{n-1}}(y_{n-1}, dy_n) f_n(y_n). \end{aligned}$$

The formula is actually valid in a general Markovian context and is related to the so-called

Lemma 2 (The Chapman–Kolmogorov equation). *We have, for any $s, t > 0$.*

$$p_{t+s}(x, dy) = \int_{\mathbb{R}} p_s(x, dz) p_t(z, dy).$$

At the operator level, this expresses the semigroup property

$$P_{t+s} = P_t P_s = P_s P_t.$$

Proof. For a bounded function f , we have, from the preceding computations

$$\begin{aligned} P_{t+s}f(x) &= \int P_{t+s}(x, dy) f(y) = \mathbb{E}_x[f(X_{t+s})] = \mathbb{E}_x[f(X_s + (X_{t+s} - X_s))] \\ &= \mathbb{E}_x[\mathbb{E}_{X_s}[f(X_t)]] = \mathbb{E}_x[P_t f(X_s)] = P_s(P_t f)(x). \end{aligned}$$

□

We end this section by gathering some useful (and deep) results about the Brownian semigroup P_t , that are quite easy to obtain in our setting. Introduce the functions spaces

$$\begin{aligned} C_b(\mathbb{R}) &= \{f : \mathbb{R} \rightarrow \mathbb{R}, f \text{ continuous and bounded}\}, \\ C_0(\mathbb{R}) &= \left\{f \in C_b(\mathbb{R}) : \lim_{|x| \rightarrow \infty} f(x) = 0\right\}, \\ C_c(\mathbb{R}) &= \{f \in C^2(\mathbb{R}) : f \text{ has compact support}\}, \end{aligned}$$

where for integer $k \geq 0$, $C^k(\mathbb{R})$ denotes the space of functions that are k -fold continuously differentiable. As usual we set¹ as usual $\|f\|_{\infty} = \sup_{x \in \mathbb{R}} |f(x)|$.

¹No need to take essential supremum if we work with continuous functions, we still have a valid norm on $C^k(\mathbb{R})$ (possibly taking the value ∞).

Proposition 3. (i) For every $f \in C_0(\mathbb{R})$, $P_t f \in C_0(\mathbb{R})$, $\|P_t f\|_\infty \leq \|f\|_\infty$, and $P_t(P_s f) = P_{t+s} f$.

(ii) **(Feller property)** $f \in C_0(\mathbb{R}) \implies P_t f \in C_0(\mathbb{R})$, and $\lim_{t \rightarrow 0} \|P_t f - f\|_\infty = 0$.

(iii) **(Infinitesimal generator)** If $f \in C_c^2$, then

$$\lim_{t \rightarrow 0} \frac{P_t f(x) - f(x)}{t} = \frac{1}{2} f''(x).$$

(iv) **(Heat equation)** If $f \in C_b(\mathbb{R})$, then $u(t, x) = P_t f(x)$ is continuous on $[0, \infty) \times \mathbb{R}$ and C^∞ on $(0, \infty) \times \mathbb{R}$; moreover $u(0, x) = f(x)$ and

$$\partial_t u = \frac{1}{2} \partial_x^2 u, \quad t > 0.$$

Proof. (i) From $P_t f(x) = \mathbb{E}_x[f(x + B_t)]$, we obtain continuity by Lebesgue's dominated convergence theorem.

(ii) For $f \in C_0(\mathbb{R})$, $P_t f \in C_0(\mathbb{R})$: indeed $\lim_{|x| \rightarrow \infty} \mathbb{E}[f(x + B_t)] = 0$ by dominated convergence. Moreover, $f \in C_0(\mathbb{R}) \implies f$ is uniformly continuous on $\mathbb{R}$, hence

$$\|P_t f - f\|_\infty \leq \mathbb{E} \left[\sup_x |f(x + B_t) - f(x)| \right] \xrightarrow{t \rightarrow 0} 0$$

by dominated convergence (using uniform continuity of f and $B_t \rightarrow 0$ a.s. along a suitable sequence, or directly since the modulus of continuity of f evaluated at $|B_t|$ tends to 0 a.s. and is bounded).

(iii) Let $f \in C_c^2(\mathbb{R})$; since f'' is bounded, say by $K > 0$, Taylor's formula with Lagrange remainder gives, for $x, z \in \mathbb{R}$,

$$f(x + z) = f(x) + z f'(x) + \frac{z^2}{2} f''(\xi) \quad \text{for some } \xi \text{ between } x \text{ and } x + z,$$

so that $|f(x + z) - f(x) - z f'(x)| \leq \frac{K}{2} z^2$. Using $\mathbb{E}[B_t] = 0$, it follows that

$$\begin{aligned} \frac{P_t f(x) - f(x)}{t} &= \frac{1}{t} \mathbb{E}[f(x + B_t) - f(x)] = \frac{1}{t} \mathbb{E}[f(x + B_t) - f(x) - f'(x) B_t] \\ &= \mathbb{E} \left[\underbrace{\frac{f(x + \sqrt{t} B_1) - f(x) - f'(x) \sqrt{t} B_1}{t}}_{|\cdot| \leq \frac{K}{2} B_1^2 \in L^1(\mathbb{R})} \right], \end{aligned}$$

using $B_t \stackrel{d}{=} \sqrt{t} B_1$. By dominated convergence (the integrand converging pointwise to $\frac{1}{2}f''(x)$ by Taylor's formula, and being dominated by the integrable $\frac{K}{2}B_1^2$), this tends to $\frac{1}{2}f''(x)$ as $t \rightarrow 0$.

(iv) $u(t, x) = \mathbb{E}[f(x + B_t)]$ is continuous on $[0, \infty) \times \mathbb{R}$, since $(t, x) \mapsto f(x + B_t)$ is continuous and bounded on $[0, \infty) \times \mathbb{R}$ (dominated convergence). The rest of the proof is a direct, if tedious, computation: writing

$$u(t, x) = \frac{1}{\sqrt{2\pi t}} \int_{\mathbb{R}} f(y) \exp\left(-\frac{1}{2t}(y-x)^2\right) dy,$$

one checks that u is C^∞ on $(0, \infty) \times \mathbb{R}$, and that differentiation under the integral sign (justified since f is bounded) gives

$$\partial_t u(t, x) = \frac{1}{\sqrt{2\pi t}} \int_{\mathbb{R}} f(y) \left(-\frac{1}{2t^{3/2}} + \frac{(y-x)^2}{2t^{5/2}}\right) \exp\left(-\frac{(y-x)^2}{2t}\right) dy,$$

$$\partial_x^2 u(t, x) = \frac{1}{\sqrt{2\pi t}} \int_{\mathbb{R}} f(y) \frac{1}{t} \left(-1 + \frac{(y-x)^2}{t}\right) \exp\left(-\frac{(y-x)^2}{2t}\right) dy,$$

and the result $\partial_t u = \frac{1}{2}\partial_x^2 u$ follows by comparing the two expressions. $\square$

3 The 0–1 law of Blumenthal

Proposition 4. For $s \geq 0$, define $\mathcal{F}_{s+} = \bigcap_{u>s} \mathcal{F}_u$. Then the process $(\tilde{B}_t = B_{t+s} - B_s)_{t \geq 0}$ is independent of $\mathcal{F}_{s+}$.

Proof. It suffices to show that, for $A \in \mathcal{F}_{s+}$, $0 \leq t_1 < t_2 < \dots < t_n$, and $F : \mathbb{R}^n \rightarrow \mathbb{R}$ continuous and bounded,

$$\mathbb{E}[\mathbf{1}_A F(\tilde{B}_{t_1}, \dots, \tilde{B}_{t_n})] = \mathbb{P}(A) \mathbb{E}[F(\tilde{B}_{t_1}, \dots, \tilde{B}_{t_n})].$$

For $\varepsilon > 0$, the process $t \mapsto B_{t+s+\varepsilon} - B_{s+\varepsilon}$ is independent of $\mathcal{F}_{s+\varepsilon}$, by the (classical) simple Markov property, and hence in particular independent of $\mathcal{F}_{s+} \subset \mathcal{F}_{s+\varepsilon}$:

$$\begin{aligned} & \mathbb{E}[\mathbf{1}_A F(B_{t_1+s+\varepsilon} - B_{s+\varepsilon}, \dots, B_{t_n+s+\varepsilon} - B_{s+\varepsilon})] \\ &= \mathbb{P}(A) \mathbb{E}[F(B_{t_1+s+\varepsilon} - B_{s+\varepsilon}, \dots, B_{t_n+s+\varepsilon} - B_{s+\varepsilon})] = \mathbb{P}(A) \mathbb{E}[F(B_{t_1}, \dots, B_{t_n})]. \end{aligned}$$

We conclude the proof by letting $\varepsilon \rightarrow 0^+$, using continuity of the Brownian paths and F , and dominated convergence. $\square$

Theorem 5 (Blumenthal's 0–1 law). $\mathcal{F}_{0+}$ is trivial: for every $A \in \mathcal{F}_{0+}$, $\mathbb{P}(A) = 0$ or 1 .

This will be seen to be of later importance for general filtrations.

Proof. By the preceding Proposition, $\mathcal{F}_{0+}$ is independent of $\sigma(B_t, t \geq 0)$. Moreover $\mathcal{F}_{0+} \subset \sigma(B_t, t \geq 0)$, hence $\mathcal{F}_{0+}$ is independent of itself, and is therefore trivial. $\square$

An application. We almost-surely have

$$\begin{aligned} \limsup_{t \rightarrow 0} \frac{B_t}{\sqrt{t}} &= +\infty, & \liminf_{t \rightarrow 0} \frac{B_t}{\sqrt{t}} &= -\infty, \\ \limsup_{t \rightarrow \infty} \frac{B_t}{\sqrt{t}} &= +\infty, & \liminf_{t \rightarrow \infty} \frac{B_t}{\sqrt{t}} &= -\infty. \end{aligned}$$

Proof. By symmetry and time-inversion, only the first claim needs to be proved. For $k > 0$, define $A_n = \{\sqrt{n} B_{1/n} > k\}$. We claim that $\limsup_n A_n \in \mathcal{F}_{0+}$. Indeed, for every $k \geq 1$,

$$\limsup_n A_n = \bigcap_{n \geq 0} \bigcup_{\ell \geq n} A_\ell = \bigcap_{n \geq 0} \bigcup_{\ell \geq n} A_\ell \in \mathcal{F}_{1/k} \quad \left(\text{since } \bigcup_{\ell \geq n} A_\ell \downarrow \text{ in } n \right),$$

hence $\limsup_n A_n \in \bigcap_{k \geq 1} \mathcal{F}_{1/k} = \mathcal{F}_{0+}$. Moreover

$$\mathbb{P}(\limsup_n A_n) \geq \limsup_N \mathbb{P}(A_N) \geq \mathbb{P}(A_1) > 0,$$

hence, by the 0–1 law, $\mathbb{P}(\limsup_n A_n) = 1$. It follows that $\limsup_{t \rightarrow 0} B_t/\sqrt{t} \geq k$ a.s., for every k , which proves the first claim. $\square$

This entails the following interesting properties of Brownian paths:

- (i) a.s. $t \mapsto B_t$ is not $\frac{1}{2}$ -Hölder;
- (ii) a.s. there exist $t_n \downarrow 0$ such that $B_{t_n} > 0$ for infinitely many n , and $B_{t_n} < 0$ for infinitely many n ;
- (iii) a.s. $\forall a \in \mathbb{R}: \tau_a = \inf\{t \geq 0, B_t = a\} < \infty$;
- (iv) a.s. $\{t \geq 0, B_t = 0\}$ is unbounded.

4 The strong Markov property

In the following, $\mathcal{F}_t = \sigma(B_s, 0 \leq s \leq t)$ and $\mathcal{F}_\infty = \sigma(B_s, s \geq 0)$ and $(B_t)_{t \geq 0}$ is a BM.

Definition 6. A map $\tau : \Omega \rightarrow \mathbb{R}_+ \cup \{\infty\}$ is a stopping time if $\{\tau \leq t\} \in \mathcal{F}_t$ for every $t \geq 0$. One then defines

$$\mathcal{F}_\tau = \{A \in \mathcal{F}_\infty : \forall t \geq 0, A \cap \{\tau \leq t\} \in \mathcal{F}_t\}.$$

Example 7.

(i) $\tau \equiv t_0$ is a stopping time.

(ii) $\tau_a = \inf\{t > 0, B_t = a\}$ (with $\inf \emptyset = \infty$) is a stopping time. Indeed, for $a \geq 0$,

$$\{\tau_a \leq t\} = \left\{ \sup_{s \in [0, t]} B_s \geq a \right\} = \left\{ \sup_{s \in [0, t] \cap \mathbb{Q}} B_s \geq a \right\} \in \mathcal{F}_t,$$

using the continuity of B to replace the (uncountable) supremum over $[0, t]$ by a countable one.

(iii) $\tau = \sup\{s \leq 1, B_s = 0\}$ is not a stopping time (exercise; see later, in connection with the strong Markov property).

Exercise. $\mathcal{F}_\tau$ is a σ -field, and both τ and $B_\tau \mathbf{1}_{\tau < \infty}$ are $\mathcal{F}_\tau$ -measurable random variables.

Indeed, $\{\tau \leq u\} \cap \{\tau \leq t\} = \{\tau \leq u \wedge t\} \in \mathcal{F}_t$ for all $u, t \geq 0$, which shows τ is $\mathcal{F}_\tau$ -measurable; and

$$B_\tau \mathbf{1}_{\tau < \infty} = \lim_{n \rightarrow \infty} \sum_{i=0}^{\infty} \mathbf{1}_{\{i2^{-n} \leq \tau < (i+1)2^{-n}\}} B_{i2^{-n}} = \lim_{n \rightarrow \infty} \sum_{i=0}^{\infty} (\mathbf{1}_{\{i2^{-n} \leq \tau\}} - \mathbf{1}_{\{(i+1)2^{-n} \leq \tau\}}) B_{i2^{-n}},$$

each term being $\mathcal{F}_\tau$ -measurable since, for $u \leq s$, $\mathbf{1}_{\{s < \tau\}} B_u$ is $\mathcal{F}_\tau$ -measurable, as follows from

$$\{\mathbf{1}_{\{s < \tau\}} B_u \leq a\} \cap \{\tau \leq t\} = (\{B_u \leq a, s < \tau \leq t\}) \cup (\{0 \leq a, \tau \leq s \wedge t\}) \in \mathcal{F}_t.$$

We are ready to state the main result of the chapter:

Theorem 8 (Strong Markov property). Let τ be a stopping time. Conditionally on $\{\tau < \infty\}$, $(\tilde{B}_t = B_{t+\tau} - B_\tau)_{t \geq 0}$ is a Brownian motion, independent of $\mathcal{F}_\tau$.

Proof. It suffices to show that, for every $A \in \mathcal{F}_\tau$, $0 \leq t_1 < \dots < t_n$, and $F : \mathbb{R}^n \rightarrow \mathbb{R}$ continuous and bounded,

$$\mathbb{E}[\mathbf{1}_{A \cap \{\tau < \infty\}} F(\tilde{B}_{t_1}, \dots, \tilde{B}_{t_n})] = \mathbb{P}(A \cap \{\tau < \infty\}) \mathbb{E}[F(B_{t_1}, \dots, B_{t_n})].$$

Set $\tau_m = \lceil \tau 2^m \rceil / 2^m$ on $\{\tau < \infty\}$ (where $\lceil x \rceil = \min\{k \in \mathbb{Z}, k \geq x\}$). By continuity of the paths and dominated convergence, the left-hand side equals $\lim_m \text{LHS}_m$, where

$$\begin{aligned} \text{LHS}_m &= \mathbb{E}[\mathbf{1}_{A \cap \{\tau < \infty\}} F(B_{\tau_m+t_1} - B_{\tau_m}, \dots, B_{\tau_m+t_n} - B_{\tau_m})] \\ &= \mathbb{E}\left[\sum_{k=0}^{\infty} \mathbf{1}_{A \cap \{(k-1)2^{-m} < \tau \leq k2^{-m}\}} F(B_{k2^{-m}+t_1} - B_{k2^{-m}}, \dots, B_{k2^{-m}+t_n} - B_{k2^{-m}})\right]. \end{aligned}$$

For each k , $A \cap \{(k-1)2^{-m} < \tau \leq k2^{-m}\} \in \mathcal{F}_{k2^{-m}}$. By the simple Markov property,

$$\begin{aligned} &\mathbb{E}[\mathbf{1}_{A \cap \{(k-1)2^{-m} < \tau \leq k2^{-m}\}} F(B_{k2^{-m}+t_1} - B_{k2^{-m}}, \dots)] \\ &= \mathbb{E}[\mathbf{1}_{A \cap \{(k-1)2^{-m} < \tau \leq k2^{-m}\}}] \mathbb{E}[F(B_{t_1}, \dots, B_{t_n})]. \end{aligned}$$

Summing over k gives

$$\begin{aligned} \text{LHS}_m &= \sum_{k=0}^{\infty} \mathbb{E}[\mathbf{1}_{A \cap \{(k-1)2^{-m} < \tau \leq k2^{-m}\}}] \mathbb{E}[F(B_{t_1}, \dots, B_{t_n})] \\ &= \mathbb{P}(A \cap \{\tau < \infty\}) \mathbb{E}[F(B_{t_1}, \dots, B_{t_n})], \end{aligned}$$

say, for every m ; hence $\lim_m \text{LHS}_m = \mathbb{P}(A \cap \{\tau < \infty\}) \mathbb{E}[F(B_{t_1}, \dots, B_{t_n})]$ and this proves the claim. $\square$

Remark 9. It is essential that τ be a stopping time: if $\tau = \sup\{s \leq 1, B_s = 0\}$, then $(B_{\tau+t} - B_\tau)_{t \geq 0}$ is clearly not a Brownian motion, since it does not vanish on $(0, 1 - \tau)$ (because $\tau < 1$ a.s., as $B_1 \neq 0$ a.s. and B is continuous).

Proposition 10. Let $\tau_a = \inf\{t > 0, B_t = a\}$. By the strong Markov property, $(\tau_a)_{a \geq 0}$ has independent and stationary increments (it is a Lévy process).

Proof. For $0 < a < b$: $\tau_b - \tau_a \stackrel{d}{=} \tau_{b-a}$, since

$$\tau_b - \tau_a = \tilde{\tau}_{b-a}, \quad \tilde{\tau}_x = \inf\{s > 0, \tilde{B}_{\tau_a+s} - B_{\tau_a} = x\},$$

and $\tilde{\tau}_{b-a}$ is independent of $\mathcal{F}_{\tau_a}$ (using that, for $\alpha \in [0, a]$, τ_α is $\mathcal{F}_{\tau_a}$ -measurable, since τ_α is $\mathcal{F}_{\tau_\alpha}$ -measurable and $\mathcal{F}_{\tau_\alpha} \subset \mathcal{F}_{\tau_a}$). $\square$

We also have that $(\tau_a)_{a \geq 0}$ has non-decreasing paths. Moreover

$$(c^{-2}\tau_{ca})_{a \geq 0} \stackrel{d}{=} (\tau_a)_{a \geq 0},$$

since

$$\begin{aligned} (c^{-2}\tau_{ca})_{a \geq 0} &= \left(\inf\{c^{-2}t > 0, B_t = ca\} \right)_{a \geq 0} \\ &= \left(\inf\{s > 0, c^{-1}B_{c^2s} = a\} \right)_{a \geq 0} \stackrel{d}{=} \left(\inf\{s > 0, B_s = a\} \right)_{a \geq 0} = (\tau_a)_{a \geq 0}. \end{aligned}$$

Terminology: $(\tau_a)_{a \geq 0}$ is a stable subordinator of index 1/2.

Theorem 11 (Reflection principle). *Let $S_t = \sup_{0 \leq s \leq t} B_s$, $t \geq 0$. Then, for $a \geq 0$ and $b \leq a$,*

$$\mathbb{P}(S_t \geq a, B_t \leq b) = \mathbb{P}(B_t \geq 2a - b).$$

In particular, for fixed $t > 0$, $S_t \stackrel{d}{=} |B_t|$. However $(S_t)_{t \geq 0}$ and $(|B_t|)_{t \geq 0}$ do not have the same law as processes: indeed (S_t) has non-decreasing paths, while $\mathbb{P}(|B_1| < |B_2|) < 1 = \mathbb{P}(S_1 < S_2)$.

Proof. We apply the strong Markov property to the stopping time

$$T_a = \inf\{t \geq 0, B_t = a\}.$$

Conditional on $\{T_a \leq t\}$, the probability that the (unreflected) Brownian path remains below b after time T_a equals the probability that the reflected path is beyond $2a - b$ at time t .

We have already seen that $T_a < \infty$ a.s. We compute:

$$\mathbb{P}(S_t \geq a, B_t \leq b) = \mathbb{P}(T_a \leq t, B_t \leq b) = \mathbb{P}\left(T_a \leq t, \underbrace{B_{(t-T_a)+T_a} - B_{T_a}}_{=: \tilde{B}_{t-T_a}} \leq b - a\right).$$

Here $\tilde{B}$ is a BM, independent of $\mathcal{F}_{T_a}$, by the strong Markov property, with $\tilde{B}_s = B_{s+T_a} - B_{T_a}$; in particular T_a is independent of $\tilde{B}$. Since $-\tilde{B} \stackrel{d}{=} \tilde{B}$, we get $(T_a, -\tilde{B}) \stackrel{d}{=} (T_a, \tilde{B})$.

Now, consider the map $\psi : \mathbb{R}_+ \times \mathcal{C}(\mathbb{R}_+, \mathbb{R}) \rightarrow \mathbb{R}_+ \times \mathbb{R}$, $(s, \omega) \mapsto (s, \omega(t-s)\mathbf{1}_{t>s})$: since ψ is measurable, it preserves the equality in distribution, so that

$$(T_a, \tilde{B}_{t-T_a}\mathbf{1}_{t>T_a}) \stackrel{d}{=} (T_a, -\tilde{B}_{t-T_a}\mathbf{1}_{t>T_a}).$$

It follows that

$$\begin{aligned}\mathbb{P}(T_a \leq t, \tilde{B}_{t-T_a} \leq b-a) &= \mathbb{P}(T_a \leq t, -\tilde{B}_{t-T_a} \leq b-a) = \mathbb{P}(T_a \leq t, -B_t + a \leq b-a) \\ &= \mathbb{P}(T_a \leq t, B_t \geq 2a-b) = \mathbb{P}(B_t \geq 2a-b),\end{aligned}$$

the last equality because $B_t \geq 2a-b \geq a$ (as $b \leq a$) already implies $T_a \leq t$. To complete the proof, note that

$$\begin{aligned}\mathbb{P}(S_t \geq a) &= \mathbb{P}(S_t \geq a, B_t \geq a) + \mathbb{P}(S_t \geq a, B_t \leq a) \\ &= \mathbb{P}(B_t \geq a) + \mathbb{P}(B_t \geq a) = 2\mathbb{P}(B_t \geq a) = \mathbb{P}(|B_t| \geq a),\end{aligned}$$

using the identity just proved with $b = a$ for the first term (where $\{S_t \geq a, B_t \geq a\} = \{B_t \geq a\}$ since $B_t \geq a \Rightarrow S_t \geq a$), and again with $b = a$ for the second. $\square$

Exercise. The r.v. τ_a has a density given by

$$f_{\tau_a}(t) = \frac{a}{\sqrt{2\pi t^3}} \exp\left(-\frac{a^2}{2t}\right) \mathbf{1}_{t>0}.$$

Proof. From the reflection principle, the joint density of (S_t, B_t) is

$$f_{(S_t, B_t)}(a, b) = \frac{2(2a-b)}{\sqrt{2\pi t^3}} \exp\left(-\frac{(2a-b)^2}{2t}\right) \mathbf{1}_{\{a>0, b<a\}}.$$

Now

$$\mathbb{P}(\tau_a \leq t) = \mathbb{P}(S_t \geq a) = \mathbb{P}(|B_t| \geq a) = \mathbb{P}(\sqrt{t} |B_1| \geq a) = \mathbb{P}\left(\frac{a^2}{B_1^2} \leq t\right),$$

i.e. $\tau_a \stackrel{d}{=} a^2/B_1^2$, and the stated density follows by a standard computation. In particular $\mathbb{E}[\tau_a] = \infty$ (and, if $a < 0$, $\tau_{-a} = \tau_{|a|}$ by symmetry). $\square$

5 The quadratic variation of Brownian motion

Proposition 12. Fix $t \geq 0$. For $n \geq 1$, let $\Delta_n = \{0 = t_0^n < t_1^n < \dots < t_{k_n}^n = t\}$ be a subdivision of $[0, t]$. Assume $|\Delta_n| = \max_{1 \leq i \leq k_n} (t_i^n - t_{i-1}^n) \rightarrow 0$ as $n \rightarrow \infty$. Then

$$\sum_{i=1}^{k_n} (B_{t_i^n} - B_{t_{i-1}^n})^2 \xrightarrow[n \rightarrow \infty]{} t \quad \text{in } L^2(\mathbb{P}).$$

If moreover $t_i^n = i2^{-n}$ (and $k_n = 2^n$), the convergence holds almost surely.

Proof. Set $Y_i^n = (B_{t_i^n} - B_{t_{i-1}^n})^2 - (t_i^n - t_{i-1}^n)$; the $(Y_i^n)_i$ are i.i.d. (for fixed n , across i), with mean 0 and variance $2(t_i^n - t_{i-1}^n)^2$. It follows that

$$\begin{aligned} \mathbb{E}\left[\left(\sum_{i=1}^{k_n} (B_{t_i^n} - B_{t_{i-1}^n})^2 - t\right)^2\right] &= \mathbb{E}\left[\left(\sum_{i=1}^{k_n} Y_i^n\right)^2\right] = \sum_{i=1}^{k_n} \mathbb{E}[(Y_i^n)^2] = 2 \sum_{i=1}^{k_n} (t_i^n - t_{i-1}^n)^2 \\ &\leq 2t \sup_{i \leq k_n} (t_i^n - t_{i-1}^n) \xrightarrow{n \rightarrow \infty} 0 \end{aligned}$$

(and equal to $2t^2 2^{-n}$ in the dyadic case). This proves the L^2 convergence. In the dyadic case, by Markov's inequality,

$$\mathbb{P}\left(\left|\sum_{i=1}^{2^n} Y_i^n\right| > \frac{1}{n}\right) \leq n^2 t^2 2^{-n},$$

a summable sequence in n ; by Borel–Cantelli, there exists (a.s.) $n_0 \geq 1$ such that $|\sum_{i=1}^{2^n} Y_i^n| \leq \frac{1}{n}$ for all $n \geq n_0$, whence the almost sure convergence. $\square$

Corollary 13 (Important). *Brownian motion has, almost surely, infinite variation on every interval: a.s., for every $0 \leq a < b$,*

$$|B|([a, b]) = \sup \left\{ \sum_i |B_{t_i} - B_{t_{i-1}}| \right\} = \infty,$$

the supremum being taken over all subdivisions $a = t_0 < \dots < t_n = b$ of $[a, b]$.

Proof. Take $a = 0, b = 1$. We have, almost surely,

$$1 = \lim_{n \rightarrow \infty} \sum_{i=1}^{2^n} (B_{i2^{-n}} - B_{(i-1)2^{-n}})^2 \leq |B|([0, 1]) \times \sup_{i=1, \dots, 2^n} |B_{i2^{-n}} - B_{(i-1)2^{-n}}|.$$

Since B is continuous, hence uniformly continuous, on $[0, 1]$, we have

$$\sup_{i=1, \dots, 2^n} |B_{i2^{-n}} - B_{(i-1)2^{-n}}| \rightarrow 0 \text{ almost surely.}$$

Hence

$$\{|B|([0, 1]) < \infty\} \subset \left\{ \lim_n \sum_{i=1}^{2^n} (B_{i2^{-n}} - B_{(i-1)2^{-n}})^2 = 0 \right\},$$

an event of probability 0 since the left-hand side of the display above converges a.s. to $1 \neq 0$; hence $|B|([0, 1]) = \infty$ a.s.

Consequently, a.s. $\forall 0 \leq a < b$ with $a, b \in \mathbb{Q}$, $|B|([a, b]) = \infty$ (by the same argument, rescaled); hence a.s. $\forall 0 \leq a < b$ (not necessarily rational), $|B|([a, b]) = \infty$, since $|B|([a, b]) \geq |B|([a', b'])$ whenever $a < a' < b' < b$ with $a', b' \in \mathbb{Q}$. $\square$