The modeling of random assets in finance is based on stochastic processes, which are families \((X_t)_{t \in I}\) of random variables indexed by a time interval \(I\). In this chapter we present a description of Brownian motion and a construction of the associated Itô stochastic integral.

### 4.1 Brownian Motion

We start by recalling the definition of Brownian motion, which is a fundamental example of a stochastic process. The underlying probability space \((\Omega, \mathcal{F}, \mathbb{P})\) of Brownian motion can be constructed on the space \(\Omega = \mathcal{C}_0(\mathbb{R}_+)\) of continuous real-valued functions on \(\mathbb{R}_+\) started at 0.

**Definition 4.1.** The standard Brownian motion is a stochastic process \((B_t)_{t \in \mathbb{R}_+}\) such that

1. \(B_0 = 0\) almost surely,

2. The sample trajectories \(t \mapsto B_t\) are continuous, with probability 1.

3. For any finite sequence of times \(t_0 < t_1 < \cdots < t_n\), the increments

\[
B_{t_1} - B_{t_0}, B_{t_2} - B_{t_1}, \ldots, B_{t_n} - B_{t_{n-1}}
\]
are mutually independent random variables.

4. For any given times $0 \leq s < t$, $B_t - B_s$ has the Gaussian distribution $\mathcal{N}(0, t - s)$ with mean zero and variance $t - s$.

In particular, for $t \in \mathbb{R}_+$, the random variable $B_t \sim \mathcal{N}(0, t)$ has a Gaussian distribution with mean zero and variance $t > 0$. Existence of a stochastic process satisfying the conditions of Definition 4.1 will be covered in Section 4.2.

In Figure 4.1 we draw three sample paths of a standard Brownian motion obtained by computer simulation using (4.3). Note that there is no point in “computing” the value of $B_t$ as it is a random variable for all $t > 0$. However, we can generate samples of $B_t$, which are distributed according to the centered Gaussian distribution with variance $t$.

![Figure 4.1: Sample paths of a one-dimensional Brownian motion.](image)

In particular, Property 4 in Definition 4.1 implies

$$
\mathbb{E}[B_t - B_s] = 0 \quad \text{and} \quad \operatorname{Var}[B_t - B_s] = t - s, \quad 0 \leq s \leq t,
$$

and we have

$$
\begin{align*}
\operatorname{Cov}(B_s, B_t) &= \mathbb{E}[B_s B_t] \\
&= \mathbb{E}[B_s (B_t - B_s + B_s)] \\
&= \mathbb{E}[B_s (B_t - B_s) + (B_s)^2] \\
&= \mathbb{E}[B_s (B_t - B_s)] + \mathbb{E}[(B_s)^2] \\
&= \mathbb{E}[B_s] \mathbb{E}[B_t - B_s] + \mathbb{E}[(B_s)^2] \\
&= \operatorname{Var}[B_s] \\
&= s, \quad 0 \leq s \leq t,
\end{align*}
$$
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hence
\[ \text{Cov}(B_s, B_t) = \mathbb{E}[B_s B_t] = \min(s, t), \quad s, t \in \mathbb{R}_+, \quad (4.1) \]
cf. also Exercise 4.1-(d). The following graphs present two examples of possible modeling of random data using Brownian motion.

Fig. 4.2: Evolution of the fortune of a poker player vs number of games played.

Fig. 4.3: Web traffic ranking.

In the sequel, we denote by \((\mathcal{F}_t)_{t \in \mathbb{R}_+}\) the filtration generated by the Brownian paths up to time \(t\). In other words, we write
\[ \mathcal{F}_t := \sigma(B_s : 0 \leq s \leq t), \quad t \geq 0. \quad (4.2) \]

Property 3 in Definition 4.1 shows that \(B_t - B_s\) is independent of all Brownian increments taken before time \(s\), i.e.
\[ (B_t - B_s) \perp \perp (B_{t_1} - B_{t_0}, B_{t_2} - B_{t_1}, \ldots, B_{t_n} - B_{t_{n-1}}), \]

\(0 \leq t_0 \leq t_1 \leq \cdots \leq t_n \leq s \leq t\), hence \(B_t - B_s\) is also independent of the whole Brownian history up to time \(s\), hence \(B_t - B_s\) is in fact independent of \(\mathcal{F}_s, s \geq 0\). As in Example 2 page 2 we have the following result.
Proposition 4.2. Brownian motion \((B_t)_{t \in \mathbb{R}^+}\) is a continuous-time martingale

Proof. We have
\[
\mathbb{E}[B_t \mid \mathcal{F}_s] = \mathbb{E}[B_t - B_s \mid \mathcal{F}_s] + \mathbb{E}[B_s \mid \mathcal{F}_s]
\]
\[
= \mathbb{E}[B_t - B_s] + B_s
\]
\[
= B_s, \quad 0 \leq s \leq t,
\]
because it has centered and independent increments, cf. Section 7.1. □

The \(n\)-dimensional Brownian motion can be constructed as \((B^1_t, B^2_t, \ldots, B^n_t)_{t \in \mathbb{R}^+}\)
where \((B^1_t)_{t \in \mathbb{R}^+}, (B^2_t)_{t \in \mathbb{R}^+}, \ldots, (B^n_t)_{t \in \mathbb{R}^+}\) are independent copies of \((B_t)_{t \in \mathbb{R}^+}\).

Next, we turn to simulations of 2 dimensional and 3 dimensional Brownian motions in Figures 4.4 and 4.5. Recall that the movement of pollen particles originally observed by R. Brown in 1827 was indeed 2-dimensional.

Fig. 4.4: Two sample paths of a two-dimensional Brownian motion.

Fig. 4.5: Sample path of a three-dimensional Brownian motion.

Figure 4.6 presents an illustration of the scaling property of Brownian motion.

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https://www.ntu.edu.sg/home/nprivault/indext.html
4.2 Three Constructions of Brownian Motion

We refer to Chapter 1 of Revuz and Yor (1994) and to Theorem 10.28 in Folland (1999) for the proof of existence of Brownian motion as a stochastic process \((B_t)_{t \in \mathbb{R}_+}\) satisfying the above Conditions 1-4.

Brownian motion as a random walk

For convenience we will informally regard Brownian motion as a random walk over infinitesimal time intervals of length \(\Delta t\), whose increments

\[ \Delta B_t := B_{t+\Delta t} - B_t \sim \mathcal{N}(0, \Delta t) \]

over the time interval \([t, t + \Delta t]\) will be approximated by the Bernoulli random variable

\[ \Delta B_t = \pm \sqrt{\Delta t} \] (4.3)

with equal probabilities \((1/2, 1/2)\). Figure 4.7 presents a simulation of Brownian motion as a random walk with \(\Delta t = 0.1\).

* The animation works in Acrobat Reader on the entire pdf file.
The choice of the square root in (4.3) is in fact not fortuitous. Indeed, any choice of $\pm (\Delta t)^\alpha$ with a power $\alpha > 1/2$ would lead to explosion of the process as $\Delta t$ tends to zero, whereas a power $\alpha \in (0, 1/2)$ would lead to a vanishing process. Note that we have

\[
\mathbb{E}[\Delta B_t] = \frac{1}{2} \sqrt{\Delta t} - \frac{1}{2} \sqrt{\Delta t} = 0,
\]

and

\[
\text{Var}[\Delta B_t] = \mathbb{E} \left[ (\Delta B_t)^2 \right] = \frac{1}{2} \Delta t + \frac{1}{2} \Delta t = \Delta t.
\]

According to this representation, the paths of Brownian motion are not differentiable, although they are continuous by Property 2, as we have

* The animation works in Acrobat Reader on the entire pdf file.
\[ \frac{dB_t}{dt} \simeq \pm \sqrt{dt} = \pm \frac{1}{\sqrt{dt}} \simeq \pm \infty. \quad (4.4) \]

In order to recover the Gaussian distribution property of the random variable \( B_T \), we can split the time interval \([0, T]\) into \( N\) subintervals

\[ \left( \frac{k - 1}{N} T, \frac{k}{N} T \right], \quad k = 1, 2, \ldots, N, \]

of same length \( \Delta t = T/N \), with \( N \) “large”.

Defining the Bernoulli random variable \( X_k \) as

\[ X_k := \pm \sqrt{T} \]

with equal probabilities \((1/2, 1/2)\), we have \( \text{Var}(X_k) = T \) and

\[ \Delta B_t := \frac{X_k}{\sqrt{N}} = \pm \sqrt{\Delta t} \]

is the increment of \( B_t \) over \( ((k - 1)\Delta t, k\Delta t] \), and we get

\[ B_T \simeq \sum_{0 < t < T} \Delta B_t \simeq \frac{X_1 + X_2 + \cdots + X_N}{\sqrt{N}}. \]

Hence by the central limit theorem we recover the fact that \( B_T \) has the centered Gaussian distribution with variance \( T \), cf. point 4 of the above Definition 4.1 of Brownian motion, and the illustration given in Figure 4.1.

Indeed, the central limit theorem states that given any sequence \((X_k)_{k \geq 1}\) of independent identically distributed centered random variables with variance \( \sigma^2 = \text{Var}[X_k] = T \), the normalized sum

\[ \frac{X_1 + X_2 + \cdots + X_N}{\sqrt{N}} \]

converges (in distribution) to the centered Gaussian random variable \( \mathcal{N}(0, \sigma^2) \) with variance \( \sigma^2 \) as \( N \) goes to infinity. As a consequence, \( \Delta B_t \) could in fact be replaced by any centered random variable with variance \( \Delta t \) in the above description.
Lévy’s construction of Brownian motion

Figure 4.8 represents the construction of Brownian motion by successive linear interpolations, see Problem 4.15 for a proof of existence of Brownian motion based on this construction.

Fig. 4.8: Lévy’s construction of Brownian motion.*

The following R code is used to generate Figure 4.8.†

```r
1 alpha=1/2; t <- 0:1; dt <- 1; z <- rnorm(1, mean=0, sd=dt^alpha)
2 plot(t*dt, c(0, z), xlab = "t", ylab = "", main = "", type = "l", xaxs="i")
3 k=0; while (k<10) {readline("Press <return> to continue")
4 m <- (z+c(0,head(z,-1)))/2; y <- rnorm(length(t)-1, mean=0, sd=(dt/4)^alpha)
5 x <- m+y; x <- c(matrix(c(x,z), 2, byrow = T)); n=2*length(t)-2; t <- 0:n
6 plot(t*dt/2, c(0, x), xlab = "t", ylab = "", main = "", type = "l", xaxs="i"); z=x; dt=dt/2}
```

Construction by series expansions

Brownian motion on $[0, T]$ can also be constructed by Fourier synthesis via the Paley-Wiener series expansion

$$B_t = \sum_{n \geq 1} X_n f_n(t) = \frac{\sqrt{2T}}{\pi} \sum_{n \geq 1} X_n \sin \left( \frac{(n - 1/2) \pi t}{T} \right), \quad t \in [0, T],$$

* The animation works in Acrobat Reader on the entire pdf file.
† Download the corresponding R code or the IPython notebook that can be run here.
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where \((X_n)_{n \geq 1}\) is a sequence of independent \(\mathcal{N}(0, 1)\) standard Gaussian random variables, as illustrated in Figure 4.9.

\[\text{Fig. 4.9: Construction of Brownian motion by series expansions.} \]

4.3 Wiener Stochastic Integral

In this section we construct the Wiener stochastic integral of square-integrable deterministic functions of time with respect to Brownian motion.

Recall that the price \(S_t\) of risky assets has been originally modeled by Bachelier (1900) as \(S_t := \sigma B_t\), where \(\sigma\) is a volatility parameter. The stochastic integral

\[
\int_0^T f(t) dS_t = \sigma \int_0^T f(t) dB_t
\]

can be used to represent the value of a portfolio as a sum of profits and losses \(f(t) dS_t\) where \(dS_t\) represents the stock price variation and \(f(t)\) is the quantity invested in the asset \(S_t\) over the short time interval \([t, t + dt]\).

A naive definition of the stochastic integral with respect to Brownian motion would consist in letting

\[
\int_0^T f(t) dB_t := \int_0^T f(t) \frac{dB_t}{dt} dt,
\]

and evaluating the above integral with respect to \(dt\). However this definition fails because the paths of Brownian motion are not differentiable, cf. (4.4). Next we present Itô’s construction of the stochastic integral with respect to

* Download the corresponding IPython notebook that can be run here.
† The animation works in Acrobat Reader on the entire pdf file.
Brownian motion. Stochastic integrals will be first constructed as integrals of simple step functions of the form

\[ f(t) = \sum_{i=1}^{n} a_i \mathbb{I}_{(t_{i-1}, t_i]}(t), \quad t \in [0, T], \] (4.5)

i.e. the function \( f \) takes the value \( a_i \) on the interval \((t_{i-1}, t_i], i = 1, 2, \ldots, n, \) with \( 0 \leq t_0 < \cdots < t_n \leq T \), as illustrated in Figure 4.10.

Recall that the classical integral of \( f \) given in (4.5) is interpreted as the area under the curve \( f \), and computed as

\[ \int_0^T f(t) dt = \sum_{i=1}^{n} a_i (t_i - t_{i-1}). \]

In the next Definition 4.3 we use such step functions for the construction of the stochastic integral with respect to Brownian motion. The stochastic integral (4.6) for step functions will be interpreted as the sum of profits and losses \( a_i (B_{t_i} - B_{t_{i-1}}), i = 1, 2, \ldots, n, \) in a portfolio holding a quantity \( a_i \) of a risky asset whose price variation is \( B_{t_i} - B_{t_{i-1}} \) at time \( i = 1, 2, \ldots, n. \)
Definition 4.3. The stochastic integral with respect to Brownian motion $(B_t)_{t \in [0,T]}$ of the simple step function $f$ of the form (4.5) is defined by

$$\int_0^T f(t)dB_t := \sum_{i=1}^{n} a_i(B_{t_i} - B_{t_{i-1}}).$$  \hspace{1cm} (4.6)

In the next Lemma 4.4 we determine the probability distribution of $\int_0^T f(t)dB_t$ and we show that it is independent of the particular representation (4.5) chosen for $f(t)$.

Lemma 4.4. Let $f$ be a simple step function $f$ of the form (4.5). The stochastic integral $\int_0^T f(t)dB_t$ defined in (4.6) has the centered Gaussian distribution

$$\int_0^T f(t)dB_t \sim N\left(0, \int_0^T |f(t)|^2dt\right)$$

with mean $\mathbb{E}\left[\int_0^T f(t)dB_t\right] = 0$ and variance given by the Itô isometry

$$\text{Var}\left[\int_0^T f(t)dB_t\right] = \mathbb{E}\left[\left(\int_0^T f(t)dB_t\right)^2\right] = \int_0^T |f(t)|^2dt. \hspace{1cm} (4.7)$$

Proof. Recall that if $X_1, X_2, \ldots, X_n$ are independent Gaussian random variables with probability distributions $\mathcal{N}(m_1, \sigma_1^2), \ldots, \mathcal{N}(m_n, \sigma_n^2)$ then the sum $X_1 + \cdots + X_n$ is a Gaussian random variable with distribution

$$\mathcal{N}(m_1 + \cdots + m_n, \sigma_1^2 + \cdots + \sigma_n^2).$$

As a consequence, the stochastic integral

$$\int_0^T f(t)dB_t = \sum_{k=1}^{n} a_k(B_{t_k} - B_{t_{k-1}})$$

of the step function

$$f(t) = \sum_{k=1}^{n} a_k \mathbb{1}_{(t_{k-1}, t_k]}(t), \hspace{1cm} t \in [0,T],$$

has the centered Gaussian distribution with mean 0 and variance

$$\text{Var}\left[\int_0^T f(t)dB_t\right] = \text{Var}\left[\sum_{k=1}^{n} a_k(B_{t_k} - B_{t_{k-1}})\right]$$

$$= \sum_{k=1}^{n} \text{Var}[a_k(B_{t_k} - B_{t_{k-1}})]$$
\[ = \sum_{k=1}^{n} |a_k|^2 \text{Var}[B_{t_k} - B_{t_{k-1}}] \]

\[ = \sum_{k=1}^{n} (t_k - t_{k-1}) |a_k|^2 \]

\[ = \sum_{k=1}^{n} |a_k|^2 \int_{t_{k-1}}^{t_k} dt \]

\[ = \int_0^T \sum_{k=1}^{n} |a_k|^2 \mathbb{1}_{(t_{k-1}, t_k)}(t) dt \]

\[ = \int_0^T |f(t)|^2 dt, \]

since the simple function

\[ f^2(t) = \sum_{i=1}^{n} a_i^2 \mathbb{1}_{(t_{i-1}, t_i)}(t), \quad t \in [0, T], \]

takes the value \( a_i^2 \) on the interval \( (t_{i-1}, t_i) \), \( i = 1, 2, \ldots, n \), as can be checked from the following Figure 4.12.

![Squared step function](image)

Fig. 4.12: Squared step function \( t \mapsto f^2(t) \).

In the sequel we will make a repeated use of the space \( L^2([0, T]) \) of square-integrable functions.

**Definition 4.5.** Let \( L^2([0, T]) \) denote the space of (measurable) functions \( f : [0, T] \to \mathbb{R} \) such that

\[ \|f\|_{L^2([0, T])} := \sqrt{\int_0^T |f(t)|^2 dt} < \infty, \quad f \in L^2([0, T]). \]  

(4.8)

For example, the function \( f(t) := t^\alpha, \ t \in (0, T] \), belongs to \( L^2([0, T]) \) if and only if \( \alpha > -1/2 \), as we have
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\[
\int_0^T f^2(t) dt = \int_0^T t^{2\alpha} dt = \begin{cases} 
+\infty & \text{if } \alpha \leq -1/2, \\
\left[ \frac{t^{1+2\alpha}}{1+2\alpha} \right]_0^t = \frac{T^{1+2\alpha}}{1+2\alpha} < \infty & \text{if } \alpha > -1/2.
\end{cases}
\]

The norm \( \| \cdot \|_{L^2([0,T])} \) on \( L^2([0,T]) \) induces a distance between two functions \( f \) and \( g \) in \( L^2([0,T]) \), defined as

\[
\| f - g \|_{L^2([0,T])} := \sqrt{\int_0^T |f(t) - g(t)|^2 dt < \infty},
\]

cf. e.g. Chapter 3 of Rudin (1974) for details.

**Definition 4.6.** Convergence in \( L^2([0,T]) \). We say that a sequence \( (f_n)_{n \in \mathbb{N}} \) of functions in \( L^2([0,T]) \) converges in \( L^2([0,T]) \) to another function \( f \in L^2([0,T]) \) if

\[
\lim_{n \to \infty} \| f - f_n \|_{L^2([0,T])} = \lim_{n \to \infty} \sqrt{\int_0^T |f(t) - f_n(t)|^2 dt} = 0.
\]

---

1. \( f = \text{function}(x)\{(\exp(\sin(x*1.8*pi)))\}
2. \( \text{for } (i \text{ in } 3:9) \{ n = 2^i; x = \text{cumsum}(c(0,\text{rep}(1,n)))/n; \}
3. \( z = c(\text{NA},\text{head}(x,1)) \)
4. \( y = c(f(x)-\text{pmax}(f(x)-f(z),0),f(1)) \)
5. \( t = \text{seq}(0,1,0.01); \)
6. \( \text{plot}(f, \text{from}=0, \text{to}=1, \text{ylim}=c(0.3,2.9), \text{type}="l", \text{lwd}=3, \text{col}="\text{red}", \text{main}="", \text{xaxs}="i", \text{yaxs}="i") \)
7. \( \text{lines} (\text{stepfun}(x,y), \text{do.points}=\text{F}, \text{lwd}=2, \text{col}="\text{blue}", \text{main}=""); \text{Sys.sleep}(1) \)

---

Fig. 4.13: Step function approximation.*

* The animation works in Acrobat Reader on the entire pdf file.
By *e.g.* Theorem 3.13 in *Rudin (1974)* or Proposition 2.4 page 63 of *Hirsch and Lacombe (1999)*, we have the following result which states that the set of simple step functions $f$ of the form (4.5) is a linear space which is dense in $L^2([0,T])$ for the norm (4.8), as stated in the next proposition.

**Proposition 4.7.** For any function $f \in L^2([0,T])$ satisfying (4.8) there exists a sequence $(f_n)_{n \in \mathbb{N}}$ of simple functions converging to $f$ in $L^2([0,T])$ in the sense that

$$\lim_{n \to \infty} \| f - f_n \|_{L^2([0,T])} = \lim_{n \to \infty} \sqrt{\int_0^T |f(t) - f_n(t)|^2 dt} = 0.$$ 

In order to extend the definition (4.6) of the stochastic integral $\int_0^T f(t) dB_t$ to any function $f \in L^2([0,T])$, i.e. to $f : [0,T] \rightarrow \mathbb{R}$ measurable such that

$$\int_0^T |f(t)|^2 dt < \infty,$$

we will make use of the space $L^2(\Omega)$ of square-integrable random variables.

**Definition 4.8.** Let $L^2(\Omega)$ denote the space of random variables $F : \Omega \rightarrow \mathbb{R}$ such that

$$\| F \|_{L^2(\Omega \times [0,T])} := \sqrt{\mathbb{E}[F^2]} < \infty.$$ 

The norm $\| \cdot \|_{L^2(\Omega)}$ on $L^2(\Omega)$ induces the distance

$$\| F - G \|_{L^2(\Omega)} := \sqrt{\mathbb{E}[(F - G)^2]} < \infty,$$

between the square-integrable random variables $F$ and $G$ in $L^2(\Omega)$.

**Definition 4.9.** Convergence in $L^2(\Omega)$. We say that a sequence $(F_n)_{n \in \mathbb{N}}$ of random variables in $L^2(\Omega)$ converges in $L^2(\Omega)$ to another random variable $F \in L^2(\Omega)$ if

$$\lim_{n \to \infty} \| F - F_n \|_{L^2(\Omega)} = \lim_{n \to \infty} \sqrt{\mathbb{E}[(F - F_n)^2]} = 0.$$ 

The next proposition allows us to extend Lemma 4.4 from simple step functions to square-integrable functions in $L^2([0,T])$.

**Proposition 4.10.** The definition (4.6) of the stochastic integral $\int_0^T f(t) dB_t$ can be extended to any function $f \in L^2([0,T])$. In this case, $\int_0^T f(t) dB_t$ has the centered Gaussian distribution

$$\int_0^T f(t) dB_t \simeq \mathcal{N} \left( 0, \int_0^T |f(t)|^2 dt \right)$$
with mean \( \mathbb{E} \left[ \int_0^T f(t) dB_t \right] = 0 \) and variance given by the Itô isometry

\[
\text{Var} \left[ \int_0^T f(t) dB_t \right] = \mathbb{E} \left[ \left( \int_0^T f(t) dB_t \right)^2 \right] = \int_0^T |f(t)|^2 dt. \quad (4.10)
\]

**Proof.** The extension of the stochastic integral to all functions satisfying (4.9) is obtained by density and a Cauchy\(^\ast\) sequence argument, based on the isometry relation (4.10). Given \( f \) a function satisfying (4.9), consider a sequence \((f_n)_{n \in \mathbb{N}}\) of simple functions converging to \( f \) in \( L^2([0,T]) \), i.e.

\[
\lim_{n \to \infty} \|f - f_n\|_{L^2([0,T])} = \lim_{n \to \infty} \sqrt{\int_0^T |f(t) - f_n(t)|^2 dt} = 0
\]
as in Proposition 4.7. By the isometry (4.10) and the triangle inequality\(^\dagger\) we have

\[
\left\| \int_0^T f_k(t) dB_t - \int_0^T f_n(t) dB_t \right\|_{L^2(\Omega)} = \sqrt{\mathbb{E} \left[ \left( \int_0^T f_k(t) dB_t - \int_0^T f_n(t) dB_t \right)^2 \right]} = \sqrt{\mathbb{E} \left[ \left( \int_0^T (f_k(t) - f_n(t)) dB_t \right)^2 \right]} = \|f_k - f_n\|_{L^2([0,T])} \leq \|f_k - f\|_{L^2([0,T])} + \|f - f_n\|_{L^2([0,T])},
\]

which tends to 0 as \( k \) and \( n \) tend to infinity, hence \( \left( \int_0^T f_n(t) dB_t \right)_{n \in \mathbb{N}} \) is a Cauchy sequence in \( L^2(\Omega) \) by for the \( L^2(\Omega) \)-norm. Since the sequence \( \left( \int_0^T f_n(t) dB_t \right)_{n \in \mathbb{N}} \) is Cauchy and the space \( L^2(\Omega) \) is complete, cf. e.g. Theorem 3.11 in Rudin (1974) or Chapter 4 of Dudley (2002), we conclude that \( \left( \int_0^T f_n(t) dB_t \right)_{n \in \mathbb{N}} \) converges for the \( L^2 \)-norm to a limit in \( L^2(\Omega) \). In this case we let

\[
\int_0^T f(t) dB_t := \lim_{n \to \infty} \int_0^T f_n(t) dB_t,
\]

which also satisfies (4.10) from (4.7) From (4.10) we can check that the limit is independent of the approximating sequence \((f_n)_{n \in \mathbb{N}}\). Finally, from the

\(^\ast\) See MH3100 Real Analysis I.

\(^\dagger\) The triangle inequality \( \|f_k - f_n\|_{L^2([0,T])} \leq \|f_k - f\|_{L^2([0,T])} + \|f - f_n\|_{L^2([0,T])} \) follows from the Minkowski inequality.
convergence of Gaussian characteristic functions

\[
\mathbb{E}\left[\exp\left(i\alpha \int_0^T f(t)dB_t\right)\right] = \mathbb{E}\left[\lim_{n\to\infty} \exp\left(i\alpha \int_0^T f_n(t)dB_t\right)\right]
\]

\[
= \lim_{n\to\infty} \mathbb{E}\left[\exp\left(i\alpha \int_0^T f_n(t)dB_t\right)\right]
\]

\[
= \lim_{n\to\infty} \exp\left(-\frac{\alpha^2}{2}\int_0^T |f_n(t)|^2 dt\right)
\]

\[
= \exp\left(-\frac{\alpha^2}{2}\int_0^T |f(t)|^2 dt\right),
\]

\(f \in L^2([0,T]), \alpha \in \mathbb{R},\) we check that \(\int_0^T f(t)dB_t\) has the centered Gaussian distribution

\[
\int_0^T f(t)dB_t \simeq \mathcal{N}\left(0, \int_0^T |f(t)|^2 dt\right).
\]

\(\square\)

For example, \(\int_0^T e^{-t}dB_t\) has the centered Gaussian distribution with variance

\[
\int_0^T e^{-2t}dt = \left[-\frac{1}{2} e^{-2t}\right]_{t=0}^{t=T} = \frac{1}{2} \left(1 - e^{-2T}\right).
\]

**Remark 4.11.** The Wiener stochastic integral \(\int_0^T f(s)dB_s\) is a Gaussian random variable which cannot be “computed” in the way standard integral are computed via the use of primitives. However, when \(f \in L^2([0,T])\) is in \(C^1([0,T]),\)\(\ast\) we have the integration by parts relation

\[
\int_0^T f(t)dB_t = f(T)B_T - \int_0^T B_t f'(t)dt. \tag{4.11}
\]

When \(f \in L^2(\mathbb{R}_+)\) is in \(C^1(\mathbb{R}_+)\) we also have following formula

\[
\int_0^\infty f(t)dB_t = -\int_0^\infty f'(t)B_t dt, \tag{4.12}
\]

provided that \(\lim_{t\to\infty} t|f(t)|^2 = 0\) and \(f \in L^2(\mathbb{R}_+),\) cf. e.g. Remark 2.5.9 in Privault (2009).

### 4.4 Itô Stochastic Integral

In this section we extend the Wiener stochastic integral from deterministic functions in \(L^2([0,T])\) to random square-integrable (random) adapted pro-

\(\ast\) This means that \(f\) is continuously differentiable on \([0,T].\)
cesses. For this, we will need the notion of *measurability*.

The extension of the stochastic integral to adapted random processes is actually necessary in order to compute a portfolio value when the portfolio process is no longer deterministic. This happens in particular when one needs to update the portfolio allocation based on random events occurring on the market.

A random variable $F$ is said to be $\mathcal{F}_t$-measurable if the knowledge of $F$ depends only on the information known up to time $t$. As an example, if $t =$today,

- the date of the past course exam is $\mathcal{F}_t$-measurable, because it belongs to the past.
- the date of the next Chinese new year, although it refers to a future event, is also $\mathcal{F}_t$-measurable because it is known at time $t$.
- the date of the next typhoon is not $\mathcal{F}_t$-measurable since it is not known at time $t$.
- the maturity date $T$ of the European option is $\mathcal{F}_t$-measurable for all $t \in [0, T]$, because it has been determined at time 0.
- the exercise date $\tau$ of an American option after time $t$ (see Section 14.4) is not $\mathcal{F}_t$-measurable because it refers to a future random event.

A stochastic process $(X_t)_{t \in [0,T]}$ is said to be $(\mathcal{F}_t)_{t \in [0,T]}$-adapted if $X_t$ is $\mathcal{F}_t$-measurable for all $t \in [0, T]$, where $(\mathcal{F}_t)_{t \in [0,T]}$ is the information flow defined in (4.2), i.e.

\[
\mathcal{F}_t := \sigma(B_s : 0 \leq s \leq t), \quad t \geq 0.
\]

For example,

- $(B_t)_{t \in \mathbb{R}_+}$ is an $(\mathcal{F}_t)_{t \in \mathbb{R}_+}$-adapted process,
- $(B_{t+1})_{t \in \mathbb{R}_+}$ is not an $(\mathcal{F}_t)_{t \in \mathbb{R}_+}$-adapted process,
- $(B_{t/2})_{t \in \mathbb{R}_+}$ is an $(\mathcal{F}_t)_{t \in \mathbb{R}_+}$-adapted process,
- $(B_{\sqrt{t}})_{t \in \mathbb{R}_+}$ is not an $(\mathcal{F}_t)_{t \in \mathbb{R}_+}$-adapted process,
- $(\max_{s \in [0,t]} B_s)_{t \in \mathbb{R}_+}$ is an $(\mathcal{F}_t)_{t \in \mathbb{R}_+}$-adapted process,
- $(\int_0^t B_s ds)_{t \in \mathbb{R}_+}$ is an $(\mathcal{F}_t)_{t \in \mathbb{R}_+}$-adapted process,
\[-\left( \int_0^t f(s)dB_s \right)_{t \in [0,T]} \] is an \((\mathcal{F}_t)_{t \in [0,T]}\)-adapted process when \(f \in L^2([0,T])\).

In other words, a stochastic process \((X_t)_{t \in \mathbb{R}^+}\) is \((\mathcal{F}_t)_{t \in [0,T]}\)-adapted if the value of \(X_t\) at time \(t\) depends only on information known up to time \(t\). Note that the value of \(X_t\) may still depend on “known” future data, for example a fixed future date in the calendar, such as a maturity time \(T > t\), as long as its value is known at time \(t\).

The next Figure 4.14 shows an adapted portfolio strategy on two assets, constructed from a sign-switching signal based on spread data, see § 1.5 in Privault (2019) and this R code.

![Fig. 4.14: Adapted pair trading portfolio strategy.](image)

The stochastic integral of adapted processes will be first constructed as integrals of simple predictable processes \((u_t)_{t \in \mathbb{R}^+}\) of the form

\[
u_t := \sum_{i=1}^{n} F_i \mathbb{1}_{(t_{i-1}, t_i)}(t), \quad t \in \mathbb{R}^+, \tag{4.13}
\]

where \(F_i\) is an \(\mathcal{F}_{t_{i-1}}\)-measurable random variable for \(i = 1, 2, \ldots, n\), and \(0 = t_0 < t_1 < \cdots < t_{n-1} < t_n = T\).

For example, a natural approximation of \((B_t)_{t \in \mathbb{R}^+}\) by a simple predictable process can be constructed as

\[
u_t = \sum_{i=1}^{n} F_i \mathbb{1}_{(t_{i-1}, t_i)}(t) := \sum_{i=1}^{n} B_{t_{i-1}} \mathbb{1}_{(t_{i-1}, t_i)}(t), \quad t \in \mathbb{R}^+,
\]

since \(F_i := B_{t_{i-1}}\) is \(\mathcal{F}_{t_{i-1}}\)-measurable for \(i = 1, 2, \ldots, n\). The notion of simple predictable process makes full sense in the context of portfolio investment, in which \(F_i\) will represent an investment allocation decided at time \(t_{i-1}\) and to remain unchanged over the time interval \((t_{i-1}, t_i]\).
By convention, $u : \Omega \times \mathbb{R}_+ \rightarrow \mathbb{R}$ is denoted in the sequel by $u_t(\omega), t \in \mathbb{R}_+, \omega \in \Omega$, and the random outcome $\omega$ is often dropped for convenience of notation.

**Definition 4.12.** The stochastic integral with respect to Brownian motion $(B_t)_{t \in \mathbb{R}_+}$ of any simple predictable process $(u_t)_{t \in \mathbb{R}_+}$ of the form (4.13) is defined by

$$\int_0^T u_t dB_t := \sum_{i=1}^{n} F_i(B_{t_i} - B_{t_{i-1}}),$$

(4.14)

with $0 = t_0 < t_1 < \cdots < t_{n-1} < t_n = T$.

The use of predictability in the definition (4.14) is essential from a financial point of view, as $F_i$ will represent a portfolio allocation made at time $t_{i-1}$ and kept constant over the trading interval $[t_{i-1}, t_i]$, while $B_{t_i} - B_{t_{i-1}}$ represents a change in the underlying asset price over $[t_{i-1}, t_i]$. See also the related discussion on self-financing portfolios in Section 5.3 and Lemma 5.15 on the use of stochastic integrals to represent the value of a portfolio.

**Definition 4.13.** Let $L^2(\Omega \times [0, T])$ denote the space of stochastic processes

$$u : \Omega \times [0, T] \rightarrow \mathbb{R}$$

such that

$$\|u\|_{L^2(\Omega \times [0, T])} := \sqrt{\mathbb{E} \left[ \int_0^T |u_t|^2 dt \right]} < \infty, \quad u \in L^2(\Omega \times [0, T]).$$

The norm $\| \cdot \|_{L^2(\Omega \times [0, T])}$ on $L^2(\Omega \times [0, T])$ induces a distance between two stochastic processes $u$ and $v$ in $L^2(\Omega \times [0, T])$, defined as

$$\|u - v\|_{L^2(\Omega \times [0, T])} = \sqrt{\mathbb{E} \left[ \int_0^T |u_t - v_t|^2 dt \right]}.$$

**Definition 4.14.** Convergence in $L^2(\Omega \times [0, T])$. We say that a sequence $(u^{(n)})_{n \in \mathbb{N}}$ of processes in $L^2(\Omega [0, T])$ converges in $L^2(\Omega \times [0, T])$ to another process $u \in L^2(\Omega \times [0, T])$ if

$$\lim_{n \rightarrow \infty} \| u^{(n)} - u \|_{L^2(\Omega \times [0, T])} = \lim_{n \rightarrow \infty} \sqrt{\mathbb{E} \left[ \int_0^T |u_t - u_t^{(n)}|^2 dt \right]} = 0.$$

By Lemma 1.1 of Ikeda and Watanabe (1989), pages 22 and 46, or Proposition 2.5.3 in Privault (2009), the set of simple predictable processes forms a linear space which is dense in the subspace $L^2_{ad}(\Omega \times \mathbb{R}_+)$ made of square-
integrable adapted processes in $L^2(\Omega \times \mathbb{R}_+)$, as stated in the next proposition.

**Proposition 4.15.** Given $u$ a square-integrable adapted process there exists a sequence $(u^{(n)})_{n \in \mathbb{N}}$ of simple predictable processes converging to $u$ in $L^2(\Omega \times \mathbb{R}_+)$, i.e.

$$\lim_{n \to \infty} \|u - u^{(n)}\|_{L^2(\Omega \times [0,T])} = \lim_{n \to \infty} \sqrt{\mathbb{E} \left[ \int_0^T |u_t - u_t^{(n)}|^2 dt \right]} = 0.$$ 

The next Proposition 4.16 extends the construction of the stochastic integral from simple predictable processes to square-integrable $(\mathcal{F}_t)_{t \in [0,T]}$-adapted processes $(u_t)_{t \in \mathbb{R}_+}$ for which the value of $u_t$ at time $t$ can only depend on information contained in the Brownian path up to time $t$.

This restriction means that the Itô integrand $u_t$ cannot depend on future information, for example a portfolio strategy that would allow the trader to “buy at the lowest” and “sell at the highest” is excluded as it would require knowledge of future market data. Note that the difference between Relation (4.15) below and Relation (4.10) is the presence of an expectation on the right hand side.

**Proposition 4.16.** The stochastic integral with respect to Brownian motion $(B_t)_{t \in \mathbb{R}_+}$ extends to all adapted processes $(u_t)_{t \in \mathbb{R}_+}$ such that

$$\|u\|_{L^2(\Omega \times [0,T])}^2 := \mathbb{E} \left[ \int_0^T |u_t|^2 dt \right] < \infty,$$

with the Itô isometry

$$\left\| \int_0^T u_t dB_t \right\|_{L^2(\Omega)}^2 := \mathbb{E} \left[ \left( \int_0^T u_t dB_t \right)^2 \right] = \mathbb{E} \left[ \int_0^T |u_t|^2 dt \right]. \quad (4.15)$$

In addition, the Itô integral of an adapted process $(u_t)_{t \in \mathbb{R}_+}$ is always a centered random variable:

$$\mathbb{E} \left[ \int_0^T u_t dB_t \right] = 0. \quad (4.16)$$

**Proof.** We start by showing that the Itô isometry (4.15) holds for the simple predictable process $u$ of the form (4.13). We have

$$\mathbb{E} \left[ \left( \int_0^T u_t dB_t \right)^2 \right] = \mathbb{E} \left[ \left( \sum_{i=1}^n F_i(B_{t_i} - B_{t_{i-1}}) \right)^2 \right]$$

$$= \mathbb{E} \left[ \left( \sum_{i=1}^n F_i(B_{t_i} - B_{t_{i-1}}) \right) \left( \sum_{j=1}^n F_j(B_{t_j} - B_{t_{j-1}}) \right) \right].$$
\[= \mathbb{E} \left[ \sum_{i,j=1}^{n} F_i F_j (B_{t_i} - B_{t_{i-1}})(B_{t_j} - B_{t_{j-1}}) \right] \]

\[= \mathbb{E} \left[ \sum_{i=1}^{n} |F_i|^2 (B_{t_i} - B_{t_{i-1}})^2 \right] \]

\[+ 2 \mathbb{E} \left[ \sum_{1 \leq i < j \leq n} F_i F_j (B_{t_i} - B_{t_{i-1}})(B_{t_j} - B_{t_{j-1}}) \right] \]

\[= \mathbb{E} \left[ \sum_{i=1}^{n} |F_i|^2 (B_{t_i} - B_{t_{i-1}})^2 \right] \]

\[+ 2 \sum_{1 \leq i < j \leq n} \mathbb{E} \left[ F_i F_j (B_{t_i} - B_{t_{i-1}})(B_{t_j} - B_{t_{j-1}}) \right] \]

\[= \sum_{i=1}^{n} \mathbb{E} \left[ |F_i|^2 \mathbb{E} \left[ (B_{t_i} - B_{t_{i-1}})^2 | \mathcal{F}_{t_{i-1}} \right] \right] \]

\[+ 2 \sum_{1 \leq i < j \leq n} \mathbb{E} \left[ F_i F_j (B_{t_i} - B_{t_{i-1}}) \mathbb{E} \left[ (B_{t_j} - B_{t_{j-1}}) | \mathcal{F}_{t_{j-1}} \right] \right] \]

\[= \sum_{i=1}^{n} \mathbb{E} \left[ |F_i|^2 \mathbb{E} \left[ (B_{t_i} - B_{t_{i-1}})^2 \right] \right] \]

\[+ 2 \sum_{1 \leq i < j \leq n} \mathbb{E} \left[ F_i F_j (B_{t_i} - B_{t_{i-1}}) \mathbb{E} \left[ (B_{t_j} - B_{t_{j-1}}) \right] \right] \]

\[= \sum_{i=1}^{n} \mathbb{E} \left[ |F_i|^2 (t_i - t_{i-1}) \right] \]

\[= \mathbb{E} \left[ \sum_{i=1}^{n} |F_i|^2 (t_i - t_{i-1}) \right] \]

\[= \mathbb{E} \left[ \int_{0}^{T} |u_i|^2 dt \right], \]

where we applied the “tower property” (22.38) of conditional expectations and the facts that \(B_{t_i} - B_{t_{i-1}}\) is independent of \(\mathcal{F}_{t_{i-1}}\) with

\[\mathbb{E}[B_{t_i} - B_{t_{i-1}}] = 0, \quad \mathbb{E} \left[ (B_{t_i} - B_{t_{i-1}})^2 \right] = t_i - t_{i-1}, \quad i = 1, 2, \ldots, n.\]
The extension of the stochastic integral to square-integrable adapted processes \((u_t)_{t \in \mathbb{R}^+}\) is obtained by density and a Cauchy sequence argument using the isometry (4.15), in the same way as in the proof of Proposition 4.10. By Proposition 4.15 given \(u \in L^2(\Omega \times [0, T])\) a square-integrable adapted process there exists a sequence \((u^{(n)}_t)_{n \in \mathbb{N}}\) of simple predictable processes such that

\[
\lim_{n \to \infty} \|u - u^{(n)}_t\|_{L^2(\Omega \times [0, T])} = \lim_{n \to \infty} \sqrt{\mathbb{E} \left[ \int_0^T |u_t - u^{(n)}_t|^2 dt \right]} = 0.
\]

Since the sequence \((u^{(n)}_t)_{n \in \mathbb{N}}\) converges it is a Cauchy sequence in \(L^2(\Omega \times \mathbb{R}^+)\), hence by the Itô isometry (4.15), the sequence \((\int_0^T u^{(n)}_t dB_t)_{n \in \mathbb{N}}\) is a Cauchy sequence in \(L^2(\Omega)\), therefore it admits a limit in the complete space \(L^2(\Omega)\). In this case we let

\[
\int_0^T u_t dB_t := \lim_{n \to \infty} \int_0^T u^{(n)}_t dB_t
\]

and the limit is unique from (4.15) and satisfies (4.15). The fact that the random variable \(\int_0^T u_t dB_t\) is centered can be proved first on simple predictable process \(u\) of the form (4.13) as

\[
\mathbb{E} \left[ \int_0^T u_t dB_t \right] = \mathbb{E} \left[ \sum_{i=1}^n F_i (B_{t_i} - B_{t_{i-1}}) \right]
\]

\[
= \sum_{i=1}^n \mathbb{E} \left[ \mathbb{E} [F_i (B_{t_i} - B_{t_{i-1}}) \mid \mathcal{F}_{t_{i-1}}] \right]
\]

\[
= \sum_{i=1}^n \mathbb{E} [F_i \mathbb{E} [B_{t_i} - B_{t_{i-1}} \mid \mathcal{F}_{t_{i-1}}]]
\]

\[
= \sum_{i=1}^n \mathbb{E} [F_i \mathbb{E} [B_{t_i} - B_{t_{i-1}}]]
\]

\[
= 0,
\]

and this identity extends as above from simple predictable processes to adapted processes \((u_t)_{t \in \mathbb{R}^+}\) in \(L^2(\Omega \times \mathbb{R}^+)\).

As an application of the Itô isometry (4.15), we note in particular the identity

\[
\mathbb{E} \left[ \left( \int_0^T B_t dB_t \right)^2 \right] = \mathbb{E} \left[ \int_0^T |B_t|^2 dt \right] = \int_0^T \mathbb{E} [|B_t|^2] dt = \int_0^T t dt = T^2 / 2.
\]

The next proposition is obtained by bilinearity from the Itô isometry (4.15).
Corollary 4.17. The stochastic integral with respect to Brownian motion \((B_t)_{t \in \mathbb{R}^+}\) satisfies the isometry
\[
\mathbb{E} \left[ \int_0^T u_t dB_t \int_0^T v_t dB_t \right] = \mathbb{E} \left[ \int_0^T u_t v_t dt \right],
\]
for all square-integrable adapted processes \((u_t)_{t \in \mathbb{R}^+}, (v_t)_{t \in \mathbb{R}^+}\).

Proof. Applying the Itô isometry (4.15) to the processes \(u + v\) and \(u - v\) we have
\[
\mathbb{E} \left[ \int_0^T u_t dB_t \int_0^T v_t dB_t \right]
= \frac{1}{4} \left( \mathbb{E} \left[ \left( \int_0^T u_t dB_t + \int_0^T v_t dB_t \right)^2 \right] - \mathbb{E} \left[ \left( \int_0^T u_t dB_t \right)^2 \right] \right)
= \frac{1}{4} \left( \mathbb{E} \left[ \left( \int_0^T (u_t - v_t) dB_t \right)^2 \right] - \mathbb{E} \left[ \left( \int_0^T (u_t - v_t) dB_t \right)^2 \right] \right)
= \frac{1}{4} \left( \mathbb{E} \left[ \int_0^T (u_t + v_t)^2 dt \right] - \mathbb{E} \left[ \int_0^T (u_t - v_t)^2 dt \right] \right)
= \mathbb{E} \left[ \int_0^T u_t v_t dt \right].
\]

In addition, when the integrand \((u_t)_{t \in \mathbb{R}^+}\) is not a deterministic function of time, the random variable \(\int_0^T u_t dB_t\) no longer has a Gaussian distribution, except in some exceptional cases.

Definite stochastic integral

The definite stochastic integral of an adapted process \(u \in L^2(\Omega \times \mathbb{R}^+)\) over an interval \([a, b] \subset [0, T]\) is defined as
\[
\int_a^b u_t dB_t := \int_0^T \mathbb{1}_{[a,b]}(t) u_t dB_t,
\]
with in particular
\[
\int_a^b dB_t = \int_0^T \mathbb{1}_{[a,b]}(t) dB_t = B_b - B_a, \quad 0 \leq a \leq b,
\]
We also have the Chasles relation

\(\bigcirc\)

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\[
\int_a^c u_t dB_t = \int_a^b u_t dB_t + \int_b^c u_t dB_t, \quad 0 \leq a \leq b \leq c,
\]
and the stochastic integral has the following linearity property:
\[
\int_0^T (u_t + v_t) dB_t = \int_0^T u_t dB_t + \int_0^T v_t dB_t, \quad u, v \in L^2(\mathbb{R}_+).
\]

### 4.5 Stochastic Calculus

Fig. 4.15: NGram Viewer output for the term "stochastic calculus".

**Stochastic modeling of asset returns**

In the sequel we will define the return at time \( t \in \mathbb{R}_+ \) of the risky asset \((S_t)_{t \in \mathbb{R}_+}\) as

\[
dS_t = \mu S_t dt + \sigma S_t dB_t, \quad \text{or} \quad \frac{dS_t}{S_t} = \mu dt + \sigma dB_t. \quad (4.17)
\]

with \( \mu \in \mathbb{R} \) and \( \sigma > 0 \). Using the relation

\[
X_T = X_0 + \int_0^T dX_t, \quad T > 0,
\]

which holds for any process \((X_t)_{t \in \mathbb{R}_+}\), Equation (4.17) can be rewritten in integral form as

\[
S_T = S_0 + \int_0^T dS_t = S_0 + \mu \int_0^T S_t dt + \sigma \int_0^T S_t dB_t, \quad (4.18)
\]

hence the need to define an integral with respect to \( dB_t \), in addition to the usual integral with respect to \( dt \). Note that in view of the definition (4.14), this is a continuous-time extension of the notion portfolio value based on a predictable portfolio strategy.
In Proposition 4.16 we have defined the stochastic integral of square-integrable processes with respect to Brownian motion, thus we have made sense of the equation (4.18) where \((S_t)_{t \in \mathbb{R}_+}\) is an \((\mathcal{F}_t)_{t \in [0,T]}\)-adapted process, which can be rewritten in differential notation as in (4.17).

This model will be used to represent the random price \(S_t\) of a risky asset at time \(t\). Here the return \(dS_t/S_t\) of the asset is made of two components: a constant return \(\mu dt\) and a random return \(\sigma dB_t\) parametrized by the coefficient \(\sigma\), called the volatility.

Our goal is now to solve Equation (4.17) and for this we will need to introduce Itô’s calculus in Section 4.5 after a review of classical deterministic calculus.

**Deterministic calculus**

The *fundamental theorem of calculus* states that for any continuously differentiable (deterministic) function \(f\) we have the integral relation

\[
f(x) = f(0) + \int_0^x f'(y)dy.
\]

In differential notation this relation is written as the first order expansion

\[
df(x) = f'(x)dx,
\]

(4.19)

where \(dx\) is “infinitesimally small”. Higher-order expansions can be obtained from *Taylor’s formula*, which, letting

\[
\Delta f(B_t) := f(B_t + \Delta t) - f(B_t),
\]

states that

\[
\Delta f(x) = f'(x)\Delta x + \frac{1}{2} f''(x)(\Delta x)^2 + \frac{1}{3!} f'''(x)(\Delta x)^3 + \frac{1}{4!} f^{(4)}(x)(\Delta x)^4 + \cdots.
\]

Note that Relation (4.19), i.e. \(df(x) = f'(x)dx\), can be obtained by neglecting all terms of order higher than one in Taylor’s formula, since \((\Delta x)^n << \Delta x\), \(n \geq 2\), as \(\Delta x\) becomes “infinitesimally small”.

**Stochastic calculus**

Let us now apply Taylor’s formula to Brownian motion, taking

\[
\Delta B_t = B_{t+\Delta t} - B_t \simeq \pm \sqrt{\Delta t},
\]

and letting

\[
\Delta f(B_t) := f(B_{t+\Delta t}) - f(B_t),
\]
we have
\[ \Delta f(B_t) = f'(B_t) \Delta B_t + \frac{1}{2} f''(B_t) (\Delta B_t)^2 + \frac{1}{3!} f'''(B_t) (\Delta B_t)^3 + \frac{1}{4!} f^{(4)}(B_t) (\Delta B_t)^4 + \cdots. \]

From the construction of Brownian motion by its small increments \( \Delta B_t = \pm \sqrt{\Delta t} \), it turns out that the terms in \( (\Delta t)^2 \) and \( \Delta t \Delta B_t \simeq \pm (\Delta t)^{3/2} \) can be neglected in Taylor’s formula at the first order of approximation in \( \Delta t \). However, the term of order two
\[ (\Delta B_t)^2 = (\pm \sqrt{\Delta t})^2 = \Delta t \]
can no longer be neglected in front of \( \Delta t \) itself.

**Simple Itô formula**

For \( f \in C^2(\mathbb{R}) \), Taylor’s formula written at the second order for Brownian motion reads
\[ df(B_t) = f'(B_t) dB_t + \frac{1}{2} f''(B_t) dt, \tag{4.20} \]
for “infinitesimally small” \( dt \). Note that writing this formula as
\[ \frac{df(B_t)}{dt} = f'(B_t) \frac{dB_t}{dt} + \frac{1}{2} f''(B_t) \]
does not make sense because the pathwise derivative
\[ \frac{dB_t}{dt} \simeq \pm \sqrt{dt} \frac{dt}{dt} \simeq \pm \frac{1}{\sqrt{dt}} \simeq \pm \infty \]
of \( B_t \) with respect to \( t \) does not exist. Integrating (4.20) on both sides and using the relation
\[ f(B_t) - f(B_0) = \int_0^t df(B_s) \]
we get the integral form of Itô’s formula for Brownian motion, *i.e.*
\[ f(B_t) = f(B_0) + \int_0^t f'(B_s) dB_s + \frac{1}{2} \int_0^t f''(B_s) ds. \]

**Itô processes**

We now turn to the general expression of Itô’s formula, which is stated for Itô processes.
Definition 4.18. An Itô process is a stochastic process \((X_t)_{t \in \mathbb{R}_+}\) that can be written as
\[
X_t = X_0 + \int_0^t v_s ds + \int_0^t u_s dB_s, \quad t \in \mathbb{R}_+,
\]
(4.21)
or in differential notation
\[
dX_t = v_t dt + u_t dB_t,
\]
where \((u_t)_{t \in \mathbb{R}_+}\) and \((v_t)_{t \in \mathbb{R}_+}\) are square-integrable adapted processes.

Given \((t, x) \mapsto f(t, x)\) a smooth function of two variables on \(\mathbb{R}_+ \times \mathbb{R}\), from now on we let \(\frac{\partial f}{\partial t}\) denote partial differentiation with respect to the first (time) variable in \(f(t, x)\), while \(\frac{\partial f}{\partial x}\) denotes partial differentiation with respect to the second (price) variable in \(f(t, x)\).

Theorem 4.19. (Itô formula for Itô processes). For any Itô process \((X_t)_{t \in \mathbb{R}_+}\) of the form (4.21) and any \(f \in C_1,2(\mathbb{R}_+ \times \mathbb{R})\) we have
\[
f(t, X_t) = f(0, X_0) + \int_0^t \frac{\partial f}{\partial s}(s, X_s) ds + \int_0^t v_s \frac{\partial f}{\partial x}(s, X_s) ds + \int_0^t u_s \frac{\partial f}{\partial x}(s, X_s) dB_s
+ \frac{1}{2} \int_0^t |u_s|^2 \frac{\partial^2 f}{\partial x^2}(s, X_s) ds.
\]
(4.22)

Proof. The proof of the Itô formula can be outlined as follows in the case where \((X_t)_{t \in \mathbb{R}_+} = (B_t)_{t \in \mathbb{R}_+}\) is a standard Brownian motion. We refer to Theorem II-32, page 79 of Protter (2004) for the general case.

Let \(\{0 = t_0^n \leq t_1^n \leq \cdots \leq t_m^n = t\}, n \geq 1\), be a refining sequence of partitions of \([0, t]\) tending to the identity. We have the telescoping identity
\[
f(B_t) - f(B_0) = \sum_{k=1}^n \left( f(B_{t_i}^n) - f(B_{t_{i-1}}^n) \right),
\]
and from Taylor’s formula
\[
f(y) - f(x) = (y - x) \frac{\partial f}{\partial x}(x) + \frac{1}{2} (y - x)^2 \frac{\partial^2 f}{\partial x^2}(x) + R(x, y),
\]
where the remainder \(R(x, y)\) satisfies \(R(x, y) \leq o(|y - x|^2)\), we get
f(B_t) - f(B_0) = \sum_{k=1}^{n} (B^n_{i_k} - B^n_{i_k-1}) \frac{\partial f}{\partial x}(B^n_{i_k-1}) + 1/2 |B^n_{i_k} - B^n_{i_k-1}|^2 \frac{\partial^2 f}{\partial x^2}(B^n_{i_k-1}) + \sum_{k=1}^{n} R(B^n_{i_k}, B^n_{i_k-1}).

It remains to show that as n tends to infinity the above converges to

f(B_t) - f(B_0) = \int_0^t \frac{\partial f}{\partial x}(B_s) dB_s + 1/2 \int_0^t \frac{\partial^2 f}{\partial x^2}(B_s) ds.

□

From the relation

\int_0^t df(s, X_s) = f(t, X_t) - f(0, X_0),

we can rewrite (4.22) as

\int_0^t df(s, X_s) = \int_0^t v_s \frac{\partial f}{\partial x}(s, X_s) ds + \int_0^t u_s \frac{\partial f}{\partial x}(s, X_s) dB_s + \int_0^t \frac{\partial f}{\partial s}(s, X_s) ds + \frac{1}{2} \int_0^t |u_s|^2 \frac{\partial^2 f}{\partial x^2}(s, X_s) ds,

which allows us to rewrite (4.22) in differential notation, as

\begin{align}
\frac{df(t, X_t)}{dt} &= \frac{\partial f}{\partial t}(t, X_t) dt + v_t \frac{\partial f}{\partial x}(t, X_t) dt + u_t \frac{\partial f}{\partial x}(t, X_t) dB_t + \frac{1}{2} |u_t|^2 \frac{\partial^2 f}{\partial x^2}(t, X_t) dt.
\end{align}

(4.23)

In case the function x \mapsto f(x) does not depend on the time variable t we get

\begin{align}
df(X_t) &= u_t \frac{\partial f}{\partial x}(X_t) dB_t + v_t \frac{\partial f}{\partial x}(X_t) dt + \frac{1}{2} |u_t|^2 \frac{\partial^2 f}{\partial x^2}(X_t) dt.
\end{align}

Taking u_t = 1, v_t = 0 and X_0 = 0 in (4.21) yields X_t = B_t, in which case the Itô formula (4.22) reads

f(t, B_t) = f(0, B_0) + \int_0^t \frac{\partial f}{\partial s}(s, B_s) ds + \int_0^t \frac{\partial f}{\partial x}(s, B_s) dB_s + \frac{1}{2} \int_0^t \frac{\partial^2 f}{\partial x^2}(s, B_s) ds,

i.e. in differential notation:

\begin{align}
\frac{df(t, B_t)}{dt} &= \frac{\partial f}{\partial t}(t, B_t) dt + \frac{\partial f}{\partial x}(t, B_t) dB_t + \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(t, B_t) dt.
\end{align}

(4.24)

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Itô multiplication table

Next, consider two Itô processes \( (X_t)_{t \in \mathbb{R}_+} \) and \( (Y_t)_{t \in \mathbb{R}_+} \) written in integral form as

\[
X_t = X_0 + \int_0^t v_s ds + \int_0^t u_s dB_s, \quad t \in \mathbb{R}_+,
\]

and

\[
Y_t = Y_0 + \int_0^t b_s ds + \int_0^t a_s dB_s, \quad t \in \mathbb{R}_+,
\]

or in differential notation as

\[
dX_t = v_t dt + u_t dB_t, \quad \text{and} \quad dY_t = b_t dt + a_t dB_t, \quad t \in \mathbb{R}_+.
\]

The Itô formula can also be written for functions \( f \in C^{1,2,2}(\mathbb{R}_+ \times \mathbb{R}^2) \) we have of two state variables as

\[
df(t, X_t, Y_t) = \frac{\partial f}{\partial t}(t, X_t, Y_t) dt + \frac{\partial f}{\partial x}(t, X_t, Y_t) dX_t + \frac{1}{2} |u_t|^2 \frac{\partial^2 f}{\partial x^2}(t, X_t, Y_t) dt + \frac{\partial f}{\partial y}(t, X_t, Y_t) dY_t + u_t a_t \frac{\partial^2 f}{\partial x \partial y}(t, X_t, Y_t) dt,
\]

which can be used to show that

\[
d(X_t Y_t) = X_t dY_t + Y_t dX_t + dX_t \cdot dY_t
\]

where the product \( dX_t \cdot dY_t \) is computed according to the Itô rule

\[
dt \cdot dt = 0, \quad dt \cdot dB_t = 0, \quad dB_t \cdot dB_t = dt,
\]

which can be encoded in the Itô multiplication table:

\[
\begin{array}{c|cc}
\cdot & dt & dB_t \\
\hline
dt & 0 & 0 \\
DB_t & 0 & dt \\
\end{array}
\]

Table 4.1: Itô multiplication table.

From the Itô Table 4.1 it follows that

\[
dX_t \cdot dY_t = (v_t dt + u_t dB_t) \cdot (b_t dt + a_t dB_t) = b_t v_t (dt)^2 + b_t u_t dt dB_t + a_t v_t dt dB_t + a_t u_t (dB_t)^2 = a_t u_t dt.
\]
Hence we also have
\[
(dX_t)^2 = (v_t dt + u_t dB_t)^2
= (v_t)^2 dt^2 + (u_t)^2 (dB_t)^2 + 2u_t v_t (dt \cdot dB_t)
= (u_t)^2 dt,
\]
according to the Itô Table 4.1. Consequently, (4.23) can also be rewritten as
\[
df(t, X_t) = \frac{\partial f}{\partial t}(t, X_t) dt + \frac{\partial f}{\partial x}(t, X_t) dX_t + \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(t, X_t)(dX_t)^2,
\]
and the Itô formula for functions \( f \in C^{1,2,2}(\mathbb{R}_+ \times \mathbb{R}^2) \) of two state variables can be rewritten as
\[
df(t, X_t, Y_t) = \frac{\partial f}{\partial t}(t, X_t, Y_t) dt + \frac{\partial f}{\partial x}(t, X_t, Y_t) dX_t + \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(t, X_t, Y_t)(dX_t)^2
+ \frac{\partial f}{\partial y}(t, X_t, Y_t) dY_t + \frac{1}{2} \frac{\partial^2 f}{\partial y^2}(t, X_t, Y_t)(dY_t)^2
+ \frac{\partial^2 f}{\partial x\partial y}(t, X_t, Y_t)(dX_t \cdot dY_t).
\]

Examples

Applying Itô’s formula (4.24) to \( B_t^2 \) with
\[
B_t^2 = f(t, B_t) \quad \text{and} \quad f(t, x) = x^2,
\]
and
\[
\frac{\partial f}{\partial t}(t, x) = 0, \quad \frac{\partial f}{\partial x}(t, x) = 2x, \quad \text{and} \quad \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(t, x) = 1,
\]
we find
\[
d(B_t^2) = df(B_t)
= \frac{\partial f}{\partial t}(t, B_t) dt + \frac{\partial f}{\partial x}(t, B_t) dB_t + \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(t, B_t) dt
= 2B_t dB_t + dt,
\]
Note that from the Itô Table 4.1 we could also write directly
\[
d(B_t^2) = B_t dB_t + B_t dB_t + (dB_t)^2 = 2B_t dB_t + dt.
\]
Next, by integration in \( t \in [0, T] \) we find

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\[ B_T^2 = B_0 + 2 \int_0^T B_s dB_s + \int_0^T dt = 2 \int_0^T B_s dB_s + T, \]
and the relation
\[ \int_0^T B_s dB_s = \frac{1}{2} (B_T^2 - T). \]

Similarly, we have
\[
\begin{align*}
    d(B_t^3) &= 3B_t^2 dB_t + 3B_t dt, \\
    d(\sin B_t) &= \cos(B_t) dB_t - \frac{1}{2} \sin(B_t) dt, \\
    d e^{B_t} &= e^{B_t} dB_t + \frac{1}{2} e^{B_t} dt, \\
    d \log B_t &= \frac{1}{B_t} dB_t - \frac{1}{2B_t^2} dt, \\
    d e^{tB_t} &= B_t e^{tB_t} dt + \frac{t^2}{2} e^{tB_t} dt,
\end{align*}
\]

etc.

**Notation**

We close this section with some comments on the practice of Itô’s calculus. In certain finance textbooks, Itô’s formula for e.g. geometric Brownian motion \((S_t)_{t \in \mathbb{R}_+}\) given by
\[ dS_t = \mu S_t dt + \sigma S_t d\mathcal{W}_t \]
can be found written in the notation
\[
\begin{align*}
    f(T,S_T) &= f(0, X_0) + \int_0^T S_t \frac{\partial f}{\partial S_t}(t,S_t) dB_t + \mu \int_0^T S_t \frac{\partial f}{\partial S_t}(t,S_t) dt \\
    &\quad + \int_0^T \frac{\partial f}{\partial t}(t,S_t) dt + \frac{1}{2} \sigma^2 \int_0^T S_t^2 \frac{\partial^2 f}{\partial S_t^2}(t,S_t) dt,
\end{align*}
\]
or
\[
\begin{align*}
    df(S_t) &= \sigma S_t \frac{\partial f}{\partial S_t}(S_t) dB_t + \mu S_t \frac{\partial f}{\partial S_t}(S_t) dt + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 f}{\partial S_t^2}(S_t) dt.
\end{align*}
\]

The notation \(\frac{\partial f}{\partial S_t}(S_t)\) can in fact be easily misused in combination with the fundamental theorem of classical calculus, and potentially leads to the wrong identity
\[
\underline{df(S_t) = \frac{\partial f}{\partial S_t}(S_t) dS_t}. 
\]
Similarly, writing
\[ df(B_t) = \frac{\partial f}{\partial x}(B_t)dB_t + \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(B_t)dt \]
is consistent, while writing
\[ df(B_t) = \frac{\partial f(B_t)}{\partial B_t} dB_t + \frac{1}{2} \frac{\partial^2 f(B_t)}{\partial B_t^2} dt \]
is potentially a source of confusion. Note also that the right hand side of the Itô formula uses partial derivatives while its left hand side is a total derivative.

**Stochastic differential equations**

In addition to geometric Brownian motion there exists a large family of stochastic differential equations that can be studied, although most of the time they cannot be explicitly solved. Let now
\[ \sigma : \mathbb{R}_+ \times \mathbb{R}^n \to \mathbb{R}^d \otimes \mathbb{R}^n \]
where \( \mathbb{R}^d \otimes \mathbb{R}^n \) denotes the space of \( d \times n \) matrices, and
\[ b : \mathbb{R}_+ \times \mathbb{R}^n \to \mathbb{R} \]
satisfy the global Lipschitz condition
\[ \| \sigma(t,x) - \sigma(t,y) \|^2 + \| b(t,x) - b(t,y) \|^2 \leq K^2 \| x - y \|^2, \]
\( t \in \mathbb{R}_+ \), \( x, y \in \mathbb{R}^n \). Then there exists a unique strong solution to the stochastic differential equation
\[ X_t = X_0 + \int_0^t b(s,X_s)ds + \int_0^t \sigma(s,X_s)dB_s, \quad t \in \mathbb{R}_+, \quad (4.27) \]
where \((B_t)_{t \in \mathbb{R}_+}\) is a \( d \)-dimensional Brownian motion, see e.g. Protter (2004), Theorem V-7. In addition, the solution process \((X_t)_{t \in \mathbb{R}_+}\) of \((4.27)\) has the Markov property, see § V-6 of Protter (2004).

The term \( \sigma(s,X_s) \) in \((4.27)\) will be interpreted later on in Chapters 8-9 as a local volatility component.

Stochastic differential equations can be used to model the behaviour of a variety of quantities, such as
- stock prices,
- interest rates,
- exchange rates,
• weather factors,
• electricity/energy demand,
• commodity (e.g. oil) prices, etc.

Next, we consider several examples of stochastic differential equations that can be solved explicitly using Itô calculus, in addition to geometric Brownian motion. See e.g. § II-4.4 of Kloeden and Platen (1999) for more examples of explicitly solvable stochastic differential equations.

Examples of stochastic differential equations

1. Consider the stochastic differential equation

\[ dX_t = -\alpha X_t \, dt + \sigma dB_t, \quad X_0 = x_0, \]  

with \( \alpha > 0 \) and \( \sigma > 0 \).

Looking for a solution of the form

\[ X_t = a(t)Y_t = a(t) \left( x_0 + \int_0^t b(s) \, dB_s \right) \]

where \( a(\cdot) \) and \( b(\cdot) \) are deterministic functions of time, yields

\[ dX_t = d(a(t)Y_t) = Y_t a'(t) \, dt + a(t) \, dY_t = Y_t a'(t) \, dt + a(t)b(t) \, dB_t, \]

after applying Theorem 4.19 to the Itô process \( x_0 + \int_0^t b(s) \, dB_s \) of the form (4.21) with \( u(t) = b(t) \) and \( v(t) = 0 \), and to the function \( f(t, x) = a(t)x \). Hence, by identification with (4.28) we get

\[
\begin{cases}
  a'(t) = -\alpha a(t) \\
  a(t)b(t) = \sigma
\end{cases}
\]

hence \( a(t) = a(0)e^{-\alpha t} = e^{-\alpha t} \) and \( b(t) = \sigma/a(t) = \sigma e^{\alpha t} \), which shows that

\[ X_t = x_0 e^{-\alpha t} + \sigma \int_0^t e^{-(t-s)\alpha} \, dB_s, \quad t \in \mathbb{R}_+, \]  

Using integration by parts, we can also write

\[ X_t = x_0 e^{-\alpha t} + \sigma B_t - \sigma \alpha \int_0^t e^{-(t-s)\alpha} B_s \, ds, \quad t \in \mathbb{R}_+, \]  

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Remark: the solution of the equation (4.28) cannot be written as a function $f(t, B_t)$ of $t$ and $B_t$ as in the proof of Proposition 5.16.

Fig. 4.16: Simulated path of (4.28) with $\alpha = 10$ and $\sigma = 0.2$.

2. Consider the stochastic differential equation

$$dX_t = tX_t dt + e^{t^2/2} dB_t, \quad X_0 = x_0. \quad (4.31)$$

Looking for a solution of the form $X_t = a(t) \left( X_0 + \int_0^t b(s) dB_s \right)$, where $a(\cdot)$ and $b(\cdot)$ are deterministic functions of time, we get $a'(t)/a(t) = t$ and $a(t)b(t) = e^{t^2/2}$, hence $a(t) = e^{t^2/2}$ and $b(t) = 1$, which yields $X_t = e^{t^2/2}(X_0 + B_t), t \in \mathbb{R}_+.$

Fig. 4.17: Simulated path of (4.31).

3. Consider the stochastic differential equation

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Brownian Motion and Stochastic Calculus

\[ dY_t = (2\mu Y_t + \sigma^2)dt + 2\sigma\sqrt{Y_t}dB_t, \]  
(4.32)

where \( \mu \in \mathbb{R} \) and \( \sigma > 0 \).

```r
N=10000; t <- 0:(N-1); dt <- 1.0/N; mu=-5; sigma=1;
Z <- rnorm(N,mean=0,sd=sqrt(dt));Y <- c(1,N);Y[1]=0.5
for (j in 2:N){
  Y[j]=max(0,Y[j-1]+(2*mu*Y[j-1]+sigma*sigma)*dt+2*sigma*sqrt(Y[j-1])*Z[j])
}
plot(t, Y, xlab = "t", ylab = "", type = "l", ylim = c(-0.1,1), col = "blue")
abline(h=0)
```

Letting \( X_t = \sqrt{Y_t} \), we find that \( dX_t = \mu X_t dt + \sigma dB_t \), hence

\[ Y_t = (X_t)^2 = \left( e^{\mu t} \sqrt{Y_0} + \sigma \int_0^t e^{\mu(t-s)} dB_s \right)^2. \]

![Simulated path of (4.32) with \( \mu = 5 \) and \( \sigma = 1 \).](image)

**Exercises**

Exercise 4.1 Let \((B_t)_{t \in \mathbb{R}^+}\) denote a standard Brownian motion.

a) Let \( c > 0 \). Among the following processes, tell which is a standard Brownian motion and which is not. Justify your answer.

(i) \((X_t)_{t \in \mathbb{R}^+} := (B_{c+t} - B_c)_{t \in \mathbb{R}^+}\),
(ii) \((X_t)_{t \in \mathbb{R}^+} := (cB_{t/c^2})_{t \in \mathbb{R}^+}\),
(iii) \((X_t)_{t \in \mathbb{R}^+} := (B_{ct^2})_{t \in \mathbb{R}^+}\),
(iv) \((X_t)_{t \in \mathbb{R}^+} := (B_t + B_{t/2})_{t \in \mathbb{R}^+}\).

b) Compute the stochastic integrals

\[ \int_0^T 2dB_t \quad \text{and} \quad \int_0^T \left( 2 \times 1_{[0,T/2]}(t) + 1_{(T/2,T]}(t) \right) dB_t \]
and determine their probability distributions (including mean and variance).

c) Determine the probability distribution (including mean and variance) of the stochastic integral
\[ \int_0^{2\pi} \sin(t) dB_t. \]

d) Compute \( \mathbb{E}[B_s B_t] \) in terms of \( s, t \in \mathbb{R}_+ \).

e) Let \( T > 0 \). Show that for \( f : [0, T] \mapsto \mathbb{R} \) a differentiable function such that \( f(T) = 0 \), we have
\[ \int_0^T f(t) dB_t = - \int_0^T f'(t) B_t dt. \]

Hint: Apply Itô’s calculus to \( t \mapsto f(t) B_t \).

Exercise 4.2 Given \((B_t)_{t \in \mathbb{R}_+}\) a standard Brownian motion and \( n \geq 1 \), let the random variable \( X_n \) be defined as
\[ X_n := \int_0^{2\pi} \sin(nt) dB_t, \quad n \geq 1. \]

a) Give the probability distribution of \( X_n \) for all \( n \geq 1 \).

b) Show that \((X_n)_{n \geq 1}\) is a sequence of pairwise independent and identically distributed random variables.

Hint: We have \( \sin a \sin b = \frac{1}{2} (\cos(a - b) - \cos(a + b)) \), \( a, b \in \mathbb{R} \).

Exercise 4.3 Apply the Itô formula to the process \( X_t := \sin^2(B_t), t \in \mathbb{R}_+ \).

Exercise 4.4 Let \((B_t)_{t \in \mathbb{R}_+}\) denote a standard Brownian motion.

a) Using the Itô isometry and the known relations
\[ B_T = \int_0^T dB_t \quad \text{and} \quad B_T^2 = T + 2 \int_0^T B_t dB_t, \]
compute the third and fourth moments \( \mathbb{E}[B_T^3] \) and \( \mathbb{E}[B_T^4] \).

b) Give the third and fourth moments of the centered normal distribution with variance \( \sigma^2 \).

Exercise 4.5 Given \( T > 0 \), find a stochastic integral decomposition of the form
\[ (B_T)^3 = C + \int_0^T \zeta_{t,T} dB_t \quad (4.33) \]
for \((B_T)^3\), where \(C \in \mathbb{R}\) is a constant and \((\zeta_t, t \in [0, T])\) is an adapted process to be determined.

**Exercise 4.6** Let \(f \in L^2([0, T])\). Compute the conditional expectation

\[
\mathbb{E} \left[ e^{\int_0^T f(s)dB_s} | \mathcal{F}_t \right], \quad 0 \leq t \leq T,
\]

where \((\mathcal{F}_t)_{t \in [0, T]}\) denotes the filtration generated by \((B_t)_{t \in [0, T]}\).

**Exercise 4.7** Let \(f \in L^2([0, T])\) and consider a standard Brownian motion \((B_t)_{t \in [0, T]}\). Using the result of Exercises 4.6, show that the process

\[
t \mapsto -\exp \left( \int_0^t f(s)dB_s - \frac{1}{2} \int_0^t f^2(s)ds \right), \quad t \in [0, T],
\]

is an \((\mathcal{F}_t)\)-martingale, where \((\mathcal{F}_t)_{t \in [0, T]}\) denotes the filtration generated by \((B_t)_{t \in [0, T]}\).

**Exercise 4.8** Compute the expected value

\[
\mathbb{E} \left[ \exp \left( \beta \int_0^T B_t dB_t \right) \right]
\]

for all \(\beta < 1/T\). *Hint:* Expand \((B_T)^2\) using Itô’s formula.

**Exercise 4.9**

a) Solve the stochastic differential equation

\[
dX_t = -bX_t dt + \sigma e^{-bt} dB_t, \quad t \in \mathbb{R}_+,
\]

where \((B_t)_{t \in \mathbb{R}_+}\) is a standard Brownian motion and \(\sigma, b \in \mathbb{R}\).

b) Solve the stochastic differential equation

\[
dX_t = -bX_t dt + \sigma e^{-at} dB_t, \quad t \in \mathbb{R}_+,
\]

where \((B_t)_{t \in \mathbb{R}_+}\) is a standard Brownian motion and \(a, b, \sigma \in \mathbb{R}\) are positive constants.

**Exercise 4.10** Given \(T > 0\), let \((X^T_t)_{t \in [0, T]}\) denote the solution of the stochastic differential equation

\[
dX^T_t = \sigma dB_t - \frac{X^T_t}{T-t} dt, \quad t \in [0, T), \quad (4.34)
\]

\[\blacklozenge\]
under the initial condition $X_0^T = 0$ and $\sigma > 0$.

a) Show that

$$X_t^T = (T-t)\sigma \int_0^t \frac{1}{T-s} dB_s, \quad t \in [0,T).$$

Hint: Start by computing $d(X_t^T/(T-t))$ using Itô’s calculus.

b) Show that $\mathbb{E}[X_t^T] = 0$ for all $t \in [0,T)$.

c) Show that $\text{Var}[X_t^T] = \sigma^2 t (T-t)/T$ for all $t \in [0,T)$.

d) Show that $\lim_{t \to T} X_t^T = 0$ in $L^2(\Omega)$. The process $(X_t^T)_{t \in [0,T]}$ is called a Brownian bridge.

Exercise 4.11  Exponential Vasicek model (1). Consider a Vasicek process $(r_t)_{t \in \mathbb{R}_+}$ solution of the stochastic differential equation

$$dr_t = (a - br_t)dt + \sigma dB_t, \quad t \in \mathbb{R}_+,$$

where $(B_t)_{t \in \mathbb{R}_+}$ is a standard Brownian motion and $\sigma, a, b > 0$ are positive constants. Show that the exponential $X_t := e^{rt}$ satisfies a stochastic differential equation of the form

$$dX_t = X_t (\tilde{a} - \tilde{b} f(X_t)) dt + \sigma g(X_t) dB_t,$$

where the coefficients $\tilde{a}$ and $\tilde{b}$ and the functions $f(x)$ and $g(x)$ are to be determined.

Exercise 4.12  Exponential Vasicek model (2). Consider a short-term rate interest rate process $(r_t)_{t \in \mathbb{R}_+}$ in the exponential Vasicek model:

$$dr_t = r_t (\eta - a \log r_t) dt + \sigma r_t dB_t,$$  \hspace{1cm} (4.35)

where $\eta, a, \sigma$ are positive parameters and $(B_t)_{t \in \mathbb{R}_+}$ is a standard Brownian motion.

a) Find the solution $(Z_t)_{t \in \mathbb{R}_+}$ of the stochastic differential equation

$$dZ_t = -a Z_t dt + \sigma dB_t$$

as a function of the initial condition $Z_0$, where $a$ and $\sigma$ are positive parameters.

b) Find the solution $(Y_t)_{t \in \mathbb{R}_+}$ of the stochastic differential equation

$$dY_t = (\theta - aY_t) dt + \sigma dB_t$$  \hspace{1cm} (4.36)

as a function of the initial condition $Y_0$. Hint: Let $Z_t := Y_t - \theta/a$. 

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c) Let $X_t = e^{Y_t}$, $t \in \mathbb{R}_+$. Determine the stochastic differential equation satisfied by $(X_t)_{t \in \mathbb{R}_+}$.
d) Find the solution $(r_t)_{t \in \mathbb{R}_+}$ of (4.35) in terms of the initial condition $r_0$.
e) Compute the conditional mean $\mathbb{E}[r_t|\mathcal{F}_u]$.
f) Compute the conditional variance $\text{Var}[r_t|\mathcal{F}_u]$ of $r_t$, $0 \leq u \leq t$, where $(\mathcal{F}_u)_{u \in \mathbb{R}_+}$ denotes the filtration generated by the Brownian motion $(B_t)_{t \in \mathbb{R}_+}$.
g) Compute the asymptotic mean and variance $\lim_{t \to \infty} \mathbb{E}[r_t]$ and $\lim_{t \to \infty} \text{Var}[r_t]$.

Exercise 4.13 Cox-Ingersoll-Ross (CIR) model. Consider the equation

$$dr_t = (\alpha - \beta r_t)dt + \sigma \sqrt{r_t}dB_t$$

modeling the variations of a short-term interest rate process $r_t$, where $\alpha, \beta, \sigma$ and $r_0$ are positive parameters and $(B_t)_{t \in \mathbb{R}_+}$ is a standard Brownian motion.

a) Write down the equation (4.37) in integral form.
b) Let $u(t) = \mathbb{E}[r_t]$. Show, using the integral form of (4.37), that $u(t)$ satisfies the differential equation

$$u'(t) = \alpha - \beta u(t),$$

and compute $\mathbb{E}[r_t]$ for all $t \in \mathbb{R}_+$.
c) By an application of Itô’s formula to $r_t^2$, show that

$$dr_t^2 = r_t(2\alpha + \sigma^2 - 2\beta r_t)dt + 2\sigma r_t^{3/2}dB_t.$$  

(4.38)
d) Using the integral form of (4.38), find a differential equation satisfied by $v(t) := \mathbb{E}[r_t^2]$ and compute $\mathbb{E}[r_t^2]$ for all $t \in \mathbb{R}_+$.
e) Show that

$$\text{Var}[r_t^2] = r_0^2 \frac{\sigma^2}{\beta} (e^{-\beta t} - e^{-2\beta t}) + \frac{\alpha \sigma^2}{2\beta^2} (1 - e^{-\beta t})^2, \quad t \in \mathbb{R}_+.$$  

Problem 4.14 Tanaka formula. Let $(B_t)_{t \in \mathbb{R}_+}$ be a standard Brownian motion started at $B_0 \in \mathbb{R}$. All questions are interdependent.

a) Does the Itô formula apply to the European call option payoff function $f(x) := (x - K)^+$? Why?

* One may use the Gaussian moment generating function $\mathbb{E}[e^X] = e^{\alpha^2/2}$ for $X \sim \mathcal{N}(0, \alpha^2)$. 

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b) For every \( \varepsilon > 0 \), consider the approximation \( f_\varepsilon(x) \) of \( f(x) := (x - K)^+ \) defined by

\[
f_\varepsilon(x) := \begin{cases} 
    x - K & \text{if } x > K + \varepsilon, \\
    \frac{1}{4\varepsilon}(x - K + \varepsilon)^2 & \text{if } K - \varepsilon < x < K + \varepsilon, \\
    0 & \text{if } x < K - \varepsilon.
\end{cases}
\]

Plot the graph of the function \( x \mapsto f_\varepsilon(x) \) for \( \varepsilon = 1 \) and \( K = 10 \).

c) Using the Itô formula, show that we have

\[
f_\varepsilon(B_T) = f_\varepsilon(B_0) + \int_0^T f_\varepsilon'(B_t) dB_t + \frac{1}{4\varepsilon} \ell \left( \{ t \in [0, T] : K - \varepsilon < B_t < K + \varepsilon \} \right),
\]

where \( \ell \) denotes the measure of time length (Lebesgue measure) in \( \mathbb{R} \).

d) Show that \( \lim_{\varepsilon \to 0} \| \mathbb{1}_{[K, \infty)}(\cdot) - f_\varepsilon'(\cdot) \|_{L^2(\mathbb{R}^+)} = 0 \).

e) Show, using the Itô isometry,* that the limit

\[
\mathcal{L}_{[0,T]}^K := \lim_{\varepsilon \to 0} \frac{1}{2\varepsilon} \ell \left( \{ t \in [0, T] : K - \varepsilon < B_t < K + \varepsilon \} \right)
\]

exists in \( L^2(\Omega) \), and that we have

\[
(B_T - K)^+ = (B_0 - K)^+ + \int_0^T \mathbb{1}_{[K, \infty)}(B_t) dB_t + \frac{1}{2} \mathcal{L}_{[0,T]}^K. \tag{4.40}
\]

The quantity \( \mathcal{L}_{[0,T]}^K \) is called the local time spent by Brownian motion at the level \( K \).

Problem 4.15 Lévy’s construction of Brownian motion. The goal of this problem is to prove the existence of standard Brownian motion \((B_t)_{t \in [0,1]}\) as a stochastic process satisfying the four properties of Definition 4.1, i.e.:

1. \( B_0 = 0 \) almost surely;

2. The sample trajectories \( t \mapsto B_t \) are continuous, with probability 1.

3. For any finite sequence of times \( t_0 < t_1 < \cdots < t_n \), the increments

\[
B_{t_1} - B_{t_0}, B_{t_2} - B_{t_1}, \ldots, B_{t_n} - B_{t_{n-1}}
\]

are independent.

* Hint: Show that \( \lim_{\varepsilon \to 0} \mathbb{E} \left[ \int_0^T \left( \mathbb{1}_{[K, \infty)}(B_t) - f_\varepsilon'(B_t) \right)^2 dt \right] = 0. \)
4. For any given times $0 \leq s < t$, $B_t - B_s$ has the Gaussian distribution $\mathcal{N}(0, t-s)$ with mean zero and variance $t-s$.

The construction will proceed by the linear interpolation scheme illustrated in Figure 4.8. We work on the space $C_0([0, 1])$ of continuous functions on $[0, 1]$ started at 0, with the norm

$$
\|f\|_\infty := \max_{t \in [0, 1]} |f(t)|
$$

and the distance

$$
\|f - g\|_\infty := \max_{t \in [0, 1]} |f(t) - g(t)|.
$$

The following ten questions are interdependent.

a) Show that for any Gaussian random variable $X \sim \mathcal{N}(0, \sigma^2)$ we have

$$
P(|X| \geq \varepsilon) \leq \frac{\sigma}{\varepsilon \sqrt{\pi} / 2} e^{-\varepsilon^2/(2\sigma^2)}, \quad \varepsilon > 0.
$$

*Hint:* Start from the inequality $\mathbb{E}[(X - \varepsilon)^+] \geq 0$ and compute the left-hand side.

b) Let $X$ and $Y$ be two independent centered Gaussian random variables with variances $\alpha^2$ and $\beta^2$. Show that the conditional distribution

$$
P(X \in dx \mid X + Y = z)
$$

of $X$ given $X + Y = z$ is Gaussian with mean $\alpha^2 z / (\alpha^2 + \beta^2)$ and variance $\alpha^2 \beta^2 / (\alpha^2 + \beta^2)$.

*Hint:* Use the definition

$$
P(X \in dx \mid X + Y = z) := \frac{P(X \in dx \text{ and } X + Y \in dz)}{P(X + Y \in dz)}
$$

and the formulas

$$
dP(X \leq x) := \frac{1}{\sqrt{2\pi \alpha^2}} e^{-x^2/(2\alpha^2)} dx, \quad dP(Y \leq x) := \frac{1}{\sqrt{2\pi \beta^2}} e^{-x^2/(2\beta^2)} dx,
$$

where $dx$ (resp. $dy$) represents a “small” interval $[x, x + dx]$ (resp. $[y, y + dy]$).

c) Let $(B_t)_{t \in \mathbb{R}}$ denote a standard Brownian motion and let $0 < u < v$. Give the distribution of $B_{(u+v)/2}$ given that $B_u = x$ and $B_v = y$.

*Hint:* Note that given that $B_u = x$, the random variable $B_v$ can be written as

$$
B_v = (B_v - B_{(u+v)/2}) + (B_{(u+v)/2} - B_u) + x, \quad (4.41)
$$
and apply the result of Question (b) after identifying $X$ and $Y$ in the above decomposition (4.41).

d) Consider the random sequences

\[
\begin{align*}
Z^{(0)} &= (0, Z_1^{(0)}) \\
Z^{(1)} &= (0, Z_{1/2}^{(1)}, Z_1^{(0)}) \\
Z^{(2)} &= (0, Z_{1/4}^{(2)}, Z_{1/2}^{(1)}, Z_{3/4}^{(2)}, Z_1^{(0)}) \\
Z^{(3)} &= (0, Z_{1/8}^{(3)}, Z_{1/4}^{(2)}, Z_{3/8}^{(3)}, Z_{1/2}^{(1)}, Z_{5/8}^{(3)}, Z_{3/4}^{(2)}, Z_{7/8}^{(3)}, Z_1^{(0)}) \\
\vdots & \vdots \\
Z^{(n)} &= (0, Z_{1/2^n}^{(n)}, Z_{2/2^n}^{(n)}, Z_{3/2^n}^{(n)}, Z_{4/2^n}^{(n)}, \ldots, Z_{1}^{(n)}) \\
Z^{(n+1)} &= (0, Z_{1/2^{n+1}}^{(n+1)}, Z_{1/2^n}^{(n)}, Z_{3/2^n}^{(n+1)}, Z_{5/2^n}^{(n+1)}, Z_{3/2^n}^{(n+1)}, \ldots, Z_{1}^{(n+1)})
\end{align*}
\]

with $Z_0^{(n)} = 0$, $n \geq 0$, defined recursively as

\[
\begin{align*}
i) & \quad Z_1^{(0)} \sim \mathcal{N}(0,1), \\
ii) & \quad Z_{1/2}^{(1)} \sim \frac{Z_0^{(0)} + Z_1^{(0)}}{2} + \mathcal{N}(0,1/4), \\
iii) & \quad Z_{1/4}^{(2)} \sim \frac{Z_0^{(1)} + Z_{1/2}^{(1)}}{2} + \mathcal{N}(0,1/8), \quad Z_{3/4}^{(2)} \sim \frac{Z_{1/2}^{(1)} + Z_1^{(0)}}{2} + \mathcal{N}(0,1/8),
\end{align*}
\]

and more generally

\[
Z_{(2k+1)/2^n}^{(n+1)} = \frac{Z_{k/2^n}^{(n)} + Z_{(k+1)/2^n}^{(n)}}{2} + \mathcal{N}(0,1/2^{n+2}), \quad k = 0, 1, \ldots, 2^n - 1,
\]

where $\mathcal{N}(0,1/2^{n+2})$ is an independent centered Gaussian sample with variance $1/2^{n+2}$, and $Z_{k/2^n}^{(n+1)} := Z_{k/2^n}^{(n)}$, $k = 0, 1, \ldots, 2^n$.

In the sequel we denote by $(Z_t^{(n)})_{t \in [0,1]}$ the continuous-time random path obtained by linear interpolation of the sequence points in $(Z_{k/2^n}^{(n)})_{k = 0,1,\ldots,2^n}$.

Draw a sample of the first four linear interpolations $(Z_t^{(0)})_{t \in [0,1]}$, $(Z_t^{(1)})_{t \in [0,1]}$, $(Z_t^{(2)})_{t \in [0,1]}$, $(Z_t^{(3)})_{t \in [0,1]}$, and label the values of $Z_{k/2^n}^{(n)}$ on the graphs for $k = 0,1,\ldots,2^n$ and $n = 0,1,2,3$.

e) Using an induction argument, explain why for all $n \geq 0$ the sequence
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\[ Z^{(n)} = (0, Z_{1/2^n}^{(n)}, Z_{2/2^n}^{(n)}, Z_{3/2^n}^{(n)}, Z_{4/2^n}^{(n)}, \ldots, Z_{1}^{(n)}) \]

has same distribution as the sequence

\[ B^{(n)} := (B_0, B_{1/2^n}, B_{2/2^n}, B_{3/2^n}, B_{4/2^n}, \ldots, B_1). \]

**Hint:** Compare the constructions of Questions (c) and (d) and note that under the above linear interpolation, we have

\[ Z_{(2k+1)/2^{n+1}}^{(n)} = \frac{Z_k^{(n)} + Z_{(k+1)/2^n}^{(n)}}{2}, \quad k = 0, 1, \ldots, 2^n - 1. \]

f) Show that for any \( \varepsilon_n > 0 \) we have

\[ P(\|Z^{(n+1)} - Z^{(n)}\|_{\infty} \geq \varepsilon_n) \leq 2^n P(\|Z_{1/2^{n+1}}^{(n+1)} - Z_{1/2^{n+1}}^{(n)}\| \geq \varepsilon_n). \]

**Hint:** Use the inequality

\[ P\left(\bigcup_{k=0}^{2^n-1} A_k\right) \leq \sum_{k=0}^{2^n-1} P(A_k) \]

for a suitable choice of events \((A_k)_{k=0,1,\ldots,2^n-1} .

\]

\[ \text{g) Use the results of Questions (a) and (f) to show that for any } \varepsilon_n > 0 \text{ we have} \]

\[ P(\|Z^{(n+1)} - Z^{(n)}\|_{\infty} \geq \varepsilon_n) \leq \frac{2^{n/2}}{\varepsilon_n \sqrt{2\pi}} \varepsilon^{-2n^2+1} . \]

h) Taking \( \varepsilon_n = 2^{-n/4} \), show that

\[ P\left(\sum_{n \geq 0} \|Z^{(n+1)} - Z^{(n)}\|_{\infty} < \infty\right) = 1. \]

**Hint:** Show first that

\[ \sum_{n \geq 0} P(\|Z^{(n+1)} - Z^{(n)}\|_{\infty} \geq 2^{-n/4}) < \infty, \]

and apply the Borel-Cantelli lemma.

\[ i) \text{ Show that with probability one, the sequence } \{\{Z_t^{(n)}\}_{t \in [0,1]} : n \geq 1\} \text{ converges uniformly on } [0, 1] \text{ to a continuous (random) function } (Z_t)_{t \in [0,1]} . \]

**Hint:** Use the fact that \( C_0([0,1]) \) is a complete space for the \( \| \cdot \|_{\infty} \) norm.

\[ j) \text{ Argue that the limit } (Z_t)_{t \in [0,1]} \text{ is a standard Brownian motion on } [0, 1] \text{ by checking the four relevant properties.} \]
Problem 4.16 Consider \((B_t)_{t \in \mathbb{R}_+}\) a standard Brownian motion, and for any \(n \geq 1\) and \(T > 0\), define the discretized quadratic variation

\[ Q_T^{(n)} := \frac{1}{n} \sum_{k=1}^{n} (B_{kT/n} - B_{(k-1)T/n})^2, \quad n \geq 1. \]

a) Compute \(\mathbb{E} \left[ Q_T^{(n)} \right], n \geq 1.\)

b) Compute \(\text{Var} [Q_T^{(n)}], n \geq 1.\)

c) Show that

\[ \lim_{n \to \infty} Q_T^{(n)} = T, \]

where the limit is taken in \(L^2(\Omega)\), that is, show that

\[ \lim_{n \to \infty} \left\| Q_T^{(n)} - T \right\|_{L^2(\Omega)} = 0, \]

where

\[ \left\| Q_T^{(n)} - T \right\|_{L^2(\Omega)} := \sqrt{\mathbb{E} \left[ (Q_T^{(n)} - T)^2 \right]}, \quad n \geq 1. \]

d) By the result of Question (c), show that the limit

\[ \int_0^T B_t dB_t := \lim_{n \to \infty} \sum_{k=1}^{n} (B_{kT/n} - B_{(k-1)T/n})B_{(k-1)T/n} \]

exists in \(L^2(\Omega)\), and compute it.

*Hint:* Use the identity

\[(x - y)y = \frac{1}{2} (x^2 - y^2 - (x - y)^2), \quad x, y \in \mathbb{R}.\]

e) Consider the modified quadratic variation defined by

\[ \tilde{Q}_T^{(n)} := \sum_{k=1}^{n} (B_{(k-1/2)T/n} - B_{(k-1)T/n})^2, \quad n \geq 1. \]

Compute the limit \(\lim_{n \to \infty} \tilde{Q}_T^{(n)}\) in \(L^2(\Omega)\) by repeating the steps of Questions (a)-(c).

f) By the result of Question (e), show that the limit

\[ \int_0^T B_t \circ dB_t := \lim_{n \to \infty} \sum_{k=1}^{n} (B_{kT/n} - B_{(k-1)T/n})B_{(k-1/2)T/n} \]
exists in $L^2(\Omega)$, and compute it.

**Hint:** Use the identities

$$(x - y)y = \frac{1}{2}(x^2 - y^2 - (x - y)^2),$$

and

$$(x - y)x = \frac{1}{2}(x^2 - y^2 + (x - y)^2), \quad x, y \in \mathbb{R}.$$ 

g) More generally, by repeating the steps of Questions (e) and (f), show that for any $\alpha \in [0, 1]$ the limit

$$\int_0^T B_t \circ d^\alpha B_t := \lim_{n \to \infty} \sum_{k=1}^n (B_{kT/n} - B_{(k-1)T/n})B_{(k-\alpha)T/n}$$

exists in $L^2(\Omega)$, and compute it.

h) Comparison with deterministic calculus. Compute the limit

$$\lim_{n \to \infty} \sum_{k=1}^n (k - \alpha) \frac{T}{n} \left( k \frac{T}{n} - (k-1) \frac{T}{n} \right)$$

for all values of $\alpha$ in $[0, 1]$.

**Exercise 4.17** Let $(B_t)_{t \in \mathbb{R}^+}$ be a standard Brownian motion generating the information flow $(\mathcal{F}_t)_{t \in \mathbb{R}^+}$.

a) Let $0 \leq t \leq T$. What is the probability distribution of $B_T - B_t$?

b) From the answer to Exercise A.4-(b), show that

$$\mathbb{E}[(B_T)^+ | \mathcal{F}_t] = \sqrt{\frac{T-t}{2\pi}} e^{-B_t^2/(2(T-t))} + B_t \Phi \left( \frac{B_t}{\sqrt{T-t}} \right),$$

$0 \leq t \leq T$. **Hint:** Use the time splitting decomposition $B_T = B_T - B_t + B_t$.

c) Let $\sigma > 0$, $\nu \in \mathbb{R}$, and $X_t := \sigma B_t + \nu t, t \in \mathbb{R}^+$. Compute $e^{X_t}$ by applying the Itô formula

$$f(X_t) = f(X_0) + \int_0^t u_s \frac{\partial f}{\partial x}(X_s)dB_s + \int_0^t v_s \frac{\partial f}{\partial x}(X_s)ds + \frac{1}{2} \int_0^t u_s^2 \frac{\partial^2 f}{\partial x^2}(X_s)ds$$

to $f(x) = e^x$, where $X_t$ is written as $X_t = X_0 + \int_0^t u_s dB_s + \int_0^t v_s ds$, $t \in \mathbb{R}^+$.

d) Let $S_t = e^{X_t}, t \in \mathbb{R}^+$, and $r > 0$. For which value of $\nu$ does $(S_t)_{t \in \mathbb{R}^+}$ satisfy the stochastic differential equation
Exercise 4.18  From the answer to Exercise A.4-(b), show that for any \( \beta \in \mathbb{R} \) we have

\[
\mathbb{E}[(\beta - B_T)^+ \mid \mathcal{F}_t] = \sqrt{\frac{T-t}{2\pi}} e^{-\frac{(\beta - B_t)^2}{2(T-t)}} + (\beta - B_t) \Phi\left(\frac{\beta - B_t}{\sqrt{T-t}}\right),
\]

\[0 \leq t \leq T.\]

*Hint:* Use the time splitting decomposition \( B_T = B_T - B_t + B_t.\)