

# Measure theory and stochastic processes

## TA Session Problems No. 6

Agnieszka Borowska

15.10.2014

Note: this is only a draft of the solutions discussed on Wednesday and might contain some typos or more or less imprecise statements. If you find some, please let me know.

### Ex. 4.9 (Shreve)

For a European call expiring at time  $T$  with strike price  $K$ , the Black-Scholes-Merton price at time  $t$ , if the time- $t$  stock price is  $x$ , is

$$c(t, x) = xN(d_+(T-t, x)) - Ke^{-r(T-t)}N(d_-(T-t, x)),$$

where

$$d_+(\tau, x) = \frac{1}{\sigma\sqrt{\tau}} \left[ \log \frac{x}{K} + \left( r + \frac{1}{2}\sigma^2 \right) \tau \right],$$
$$d_-(\tau, x) = d_+(\tau, x) - \sigma\sqrt{\tau},$$

and  $N(y)$  is the cumulative standard normal distribution

$$N(y) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^y e^{-\frac{z^2}{2}} dz = \frac{1}{\sqrt{2\pi}} \int_{-y}^{\infty} e^{-\frac{z^2}{2}} dz.$$

The purpose of this exercise is to show that the function  $c$  satisfies the Black-Scholes-Merton partial differential equation

$$c_t(t, x) + rxc_x(t, x) + \frac{1}{2}\sigma^2x^2c_{xx}(t, x) = rc(t, x), \quad 0 \leq t < T, x > 0, \quad (4.10.3)$$

the terminal condition

$$\lim_{t \uparrow T} c(t, x) = (x - K)^+, \quad x > 0, x \neq K, \quad (4.10.4)$$

and the boundary conditions

$$\lim_{t \downarrow 0} c(t, x) = 0, \lim_{x \rightarrow \infty} \left[ c(t, x) - \left( x - e^{-r(T-t)}K \right) \right] = 0, \quad 0 \leq t < T. \quad (4.10.5)$$

Equation (4.10.4) and the first part of (4.10.5) are usually written more simply but less precisely as

$$c(T, x) = (x - K)^+, \quad x \geq 0$$

and

$$c(t, 0) = 0, \quad 0 \leq t < T.$$

For this exercise, we abbreviate  $c(t, x)$  as simply  $c$  and  $d_{\pm}(T-t, x)$  as simply  $d_{\pm}$ .

(i) Verify first the equation

$$Ke^{-r(T-t)}N'(d_-) = xN'(d_+) \quad (4.10.6)$$

Since  $N$  denotes the standard normal cdf,  $N'$  is a pdf of the standard normal distribution, so we have

$$N'(d_-) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{d_-^2}{2}\right].$$

Next, by definition,  $d_-$  is equal to

$$d_-(\tau, x) = d_+(\tau, x) - \sigma\sqrt{\tau},$$

where

$$d_+(\tau, x) = \frac{1}{\sigma\sqrt{\tau}} \left[ \log \frac{x}{K} + \left(r + \frac{1}{2}\sigma^2\right) \tau \right],$$

with the shorthand notation  $d_{\pm} := d_{\pm}(T-t, x)$ . Hence,

$$\begin{aligned} N'(d_-) &= \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{(d_+ - \sigma\sqrt{T-t})^2}{2}\right] \\ &= \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{d_+^2 - 2d_+\sigma\sqrt{T-t} + \sigma^2(T-t)}{2}\right] \\ &= \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{d_+^2}{2}\right] \exp\left[-\frac{-2d_+\sigma\sqrt{T-t}}{2}\right] \exp\left[-\frac{\sigma^2(T-t)}{2}\right] \\ &= N'(d_+) \exp\left[d_+\sigma\sqrt{T-t}\right] \exp\left[-\frac{\sigma^2(T-t)}{2}\right]. \end{aligned}$$

In the middle term we have

$$\begin{aligned} d_+(T-t, x)\sigma\sqrt{T-t} &= \frac{\sigma\sqrt{T-t}}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left(r + \frac{1}{2}\sigma^2\right) (T-t) \right] \\ &= \log \frac{x}{K} + \left(r + \frac{\sigma^2}{2}\right) (T-t), \end{aligned}$$

so that this term becomes

$$\begin{aligned} \exp\left[d_+\sigma\sqrt{T-t}\right] &= \exp\left[\log \frac{x}{K} + \left(r + \frac{\sigma^2}{2}\right) (T-t)\right] \\ &= \frac{x}{K} \exp\left[\left(r + \frac{\sigma^2}{2}\right) (T-t)\right]. \end{aligned}$$

Finally, we arrive at

$$\begin{aligned} Ke^{-r(T-t)}N'(d_-) &= K \exp[-r(T-t)] N'(d_+) \frac{x}{K} \exp\left[\left(r + \frac{\sigma^2}{2}\right) (T-t)\right] \exp\left[-\frac{\sigma^2(T-t)}{2}\right] \\ &= K \exp[-r(T-t)] \frac{x}{K} \exp\left[\left(r + \frac{\sigma^2}{2}\right) (T-t)\right] \exp\left[-\frac{\sigma^2(T-t)}{2}\right] N'(d_+) \\ &= x \exp\left[-r(T-t) + \left(r + \frac{\sigma^2}{2}\right) (T-t) - \frac{\sigma^2(T-t)}{2}\right] N'(d_+) \\ &= x \exp\left[(T-t) \left(-r + \left(r + \frac{\sigma^2}{2}\right) - \frac{\sigma^2}{2}\right)\right] N'(d_+) \\ &= x \exp[0] N'(d_+) \\ &= xN'(d_+), \end{aligned}$$

which completes the proof

(ii) Show that  $c_x = N(d_+)$ . This is the delta of the option. (Be careful! Remember that  $d_+$  is a function of  $x$ .)

The Black-Scholes-Merton price at time  $t$  is given by

$$c := c(t, x) = xN(d_+(T-t, x)) - Ke^{-r(T-t)}N(d_-(T-t, x)),$$

so

$$c_x = N(d_+(T-t, x)) + x \frac{\partial}{\partial x} \left[ N(d_+(T-t, x)) \right] - xKe^{-r(T-t)} \frac{\partial}{\partial x} \left[ N(d_-(T-t, x)) \right].$$

For the terms  $\frac{\partial}{\partial x} \left[ N(d_{\pm}(T-t, x)) \right]$  we have

$$\begin{aligned} \frac{\partial}{\partial x} \left[ N(d_{\pm}(T-t, x)) \right] &= N'(d_{\pm}(T-t, x)) \frac{\partial}{\partial x} d_{\pm}(T-t, x) \\ &= N'(d_{\pm}(T-t, x)) \frac{\partial}{\partial x} d_+(T-t, x) \\ &= N'(d_{\pm}(T-t, x)) \frac{1}{\sigma\sqrt{T-t}} \frac{1}{x} \frac{K}{x} \\ &= N'(d_{\pm}(T-t, x)) \frac{1}{\sigma\sqrt{T-t}} \frac{1}{x}, \end{aligned}$$

so we can write

$$\begin{aligned} c_x &= N(d_+(T-t, x)) + xN'(d_+(T-t, x)) \frac{1}{\sigma\sqrt{T-t}} \frac{1}{x} - \underbrace{xKe^{-r(T-t)} N'(d_-(T-t, x))}_{(i)} \frac{1}{\sigma\sqrt{T-t}} \frac{1}{x} \\ &= N(d_+(T-t, x)) + xN'(d_+(T-t, x)) \frac{1}{\sigma\sqrt{T-t}} \frac{1}{x} - xN'(d_+(T-t, x)) \frac{1}{\sigma\sqrt{T-t}} \frac{1}{x} \\ &= N(d_+(T-t, x)), \end{aligned}$$

which is the desired result.

(iii) Show that

$$c_t = -rKe^{-r(T-t)}N(d_-) - \frac{\sigma x}{2\sqrt{T-t}}N'(d_+).$$

*This is the theta of the option.*

The Black-Scholes-Merton price at time  $t$  is given by

$$c := c(t, x) = xN(d_+(T-t, x)) - Ke^{-r(T-t)}N(d_-(T-t, x)),$$

so

$$\begin{aligned} c_t &= xN'(d_+(T-t, x)) \frac{\partial}{\partial t} d_+(T-t, x) \\ &\quad - rKe^{-r(T-t)}N(d_-(T-t, x)) - Ke^{-r(T-t)}N'(d_-(T-t, x)) \frac{\partial}{\partial t} d_-(T-t, x). \end{aligned}$$

For the term  $\frac{\partial}{\partial t} d_-(T-t, x)$  we have

$$\frac{\partial}{\partial t} d_-(T-t, x) = \frac{\partial}{\partial t} d_+(T-t, x) + \frac{\sigma}{2\sqrt{T-t}},$$

so we can write

$$\begin{aligned} c_t &= xN'(d_+(T-t, x)) \frac{\partial}{\partial t} d_+(T-t, x) \\ &\quad - rKe^{-r(T-t)}N(d_-(T-t, x)) - \underbrace{Ke^{-r(T-t)}N'(d_-(T-t, x))}_{(i)} \frac{\partial}{\partial t} d_-(T-t, x) \\ &= xN'(d_+(T-t, x)) \frac{\partial}{\partial t} d_+(T-t, x) \\ &\quad - rKe^{-r(T-t)}N(d_-(T-t, x)) - xN'(d_+) \left[ \frac{\partial}{\partial t} d_+(T-t, x) + \frac{\sigma}{2\sqrt{T-t}} \right] \\ &= -rKe^{-r(T-t)}N(d_-(T-t, x)) - xN'(d_+) \frac{\sigma}{2\sqrt{T-t}}, \end{aligned}$$

which is the required formula.

(iv) Use the formulas above to show that  $c$  satisfies (4.10.3).

We had that

$$c_x = N(d_+(T-t, x)),$$

so

$$c_{xx} = N'(d_+(T-t, x)) \frac{\partial}{\partial x} d_+(T-t, x).$$

Plugging of all the above results in (4.10.3) gives

$$\begin{aligned} c_t + rxc_x + \frac{1}{2}\sigma^2 x^2 c_{xx} &= -rKe^{-r(T-t)} N(d_-(T-t, x)) - \underline{xN'(d_+(T-t, x)) \frac{\sigma}{2\sqrt{T-t}}} + rxN(d_+(T-t, x)) \\ &\quad + \underline{\frac{1}{2}\sigma^2 x^2 N'(d_+(T-t, x)) \frac{\partial}{\partial x} d_+(T-t, x)}. \end{aligned}$$

Now consider the underlined terms. We have

$$\begin{aligned} -xN'(d_+) \frac{\sigma}{2\sqrt{T-t}} + \frac{1}{2}\sigma^2 x^2 N'(d_+) \frac{\partial}{\partial x} d_+ &= \frac{\sigma}{2} x N'(d_+) \left( \sigma x \frac{\partial d_+}{\partial x} - \frac{1}{\sqrt{T-t}} \right) \\ &= \frac{\sigma}{2} x N'(d_+) \left( \sigma x \frac{1}{\sigma\sqrt{T-t}x} - \frac{1}{\sqrt{T-t}} \right) \\ &= 0. \end{aligned}$$

Therefore,

$$\begin{aligned} c_t + rxc_x + \frac{1}{2}\sigma^2 x^2 c_{xx} &= rxN(d_+(T-t, x)) - rKe^{-r(T-t)} N(d_-(T-t, x)) \\ &= r \left[ xN(d_+(T-t, x)) - Ke^{-r(T-t)} N(d_-(T-t, x)) \right] \\ &= rc(t, x), \end{aligned}$$

which completes the proof.

(v) Show that for  $x > K$ ,  $\lim_{t \uparrow T} d_{\pm} = \infty$ , but for  $0 < x < K$ ,  $\lim_{t \uparrow T} d_{\pm} = -\infty$ . Use these equalities to derive the terminal condition (4.10.4).

We need to arrive at

$$\lim_{t \uparrow T} c(t, x) = (x - K)^+, \quad x > 0, x \neq K.$$

Recall,

$$\begin{aligned} d_+(T-t, x) &= \frac{1}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left( r + \frac{1}{2}\sigma^2 \right) (T-t) \right], \\ d_-(T-t, x) &= d_+(T-t, x) - \sigma\sqrt{T-t} \\ &= \frac{1}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left( r - \frac{1}{2}\sigma^2 \right) (T-t) \right], \\ d_{\pm}(T-t, x) &= \frac{1}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left( r \pm \frac{1}{2}\sigma^2 \right) (T-t) \right]. \end{aligned}$$

Notice that if  $x > K$ , then  $\frac{x}{K} > 1$ , so  $\log \frac{x}{K} > 0$  and  $d_+ > 0$ ; if  $x < K$ , then  $\log \frac{x}{K} < 0$ . When  $t \uparrow T$  then  $\sqrt{T-t} \downarrow 0$ , so we have

$$\begin{aligned} \lim_{t \uparrow T} d_{\pm}(T-t, x) &= \lim_{t \uparrow T} \frac{1}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left( r \pm \frac{1}{2}\sigma^2 \right) (T-t) \right] \\ &= \lim_{t \uparrow T} \frac{1}{\sigma\sqrt{T-t}} \log \frac{x}{K} + \lim_{t \uparrow T} \frac{1}{\sigma\sqrt{T-t}} \left( r \pm \frac{1}{2}\sigma^2 \right) (T-t) \\ &= \lim_{t \uparrow T} \frac{1}{\sigma\sqrt{T-t}} \log \frac{x}{K} + \underbrace{\lim_{t \uparrow T} \frac{\sqrt{T-t}}{\sigma} \left( r \pm \frac{1}{2}\sigma^2 \right)}_{=0} \\ &= \begin{cases} \infty, & \text{if } x > K, \\ -\infty, & \text{if } x < K. \end{cases} \end{aligned}$$

Next,

$$\lim_{t \uparrow T} N(d_{\pm}(T-t, x)) = \begin{cases} 1, & \text{if } x > K, \\ 0, & \text{if } x < K. \end{cases}$$

Finally,

$$\begin{aligned} \lim_{t \uparrow T} c(t, x) &= \lim_{t \uparrow T} \left( xN(d_+(T-t, x)) - Ke^{-r(T-t)}N(d_-(T-t, x)) \right) \\ &= \begin{cases} x \cdot 1 - Ke^{-r(T-T^-)} \cdot 1, & \text{if } x > K, \\ x \cdot 0 - Ke^{-r(T-T^-)} \cdot 0, & \text{if } x < K, \end{cases} \\ &= \begin{cases} x - K, & \text{if } x > K, \\ 0, & \text{if } x < K, \end{cases} \\ &= (x - K)^+, \end{aligned}$$

which establishes the terminal condition (4.10.4).

(vi) Show that for  $0 \leq t < T$ ,  $\lim_{x \downarrow 0} d_{\pm} = -\infty$ . Use this fact to verify the first part of boundary condition (4.10.5) as  $x \downarrow 0$ .

Let  $0 \leq t < T$ . When  $x \downarrow 0$  then  $\log \frac{x}{K} \rightarrow -\infty$  and

$$\begin{aligned} \lim_{x \downarrow 0} d_{\pm}(T-t, x) &= \lim_{x \downarrow 0} \frac{1}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left( r \pm \frac{1}{2}\sigma^2 \right) (T-t) \right] \\ &= -\infty, \end{aligned}$$

so that

$$\lim_{x \downarrow 0} N(d_{\pm}(T-t, x)) = 0.$$

Thus,

$$\begin{aligned} \lim_{x \downarrow 0} c(t, x) &= \lim_{x \downarrow 0} \left( xN(d_+(T-t, x)) - Ke^{-r(T-t)}N(d_-(T-t, x)) \right) \\ &= 0, \end{aligned}$$

establishing the first part of the boundary condition (4.10.5).

(vii) Show that for  $0 \leq t < T$ ,  $\lim_{x \rightarrow \infty} d_{\pm} = \infty$ . Use this fact to verify the second part of boundary condition (4.10.5) as  $x \rightarrow \infty$ . In this verification, you will need to show that

$$\lim_{x \rightarrow \infty} \frac{N(d_+) - 1}{x^{-1}} = 0.$$

This is an indeterminate form  $\frac{0}{0}$ , and L'Hôpital's rule implies that this limit is

$$\lim_{x \rightarrow \infty} \frac{\frac{d}{dx} [N(d_+) - 1]}{\frac{d}{dx} x^{-1}}.$$

Work out this expression and use the fact that

$$x = K \exp \left\{ \sigma\sqrt{T-t}d_+ - (T-t) \left( r + \frac{1}{2}\sigma^2 \right) \right\}$$

to write this expression solely in terms of  $d_+$  (i.e., without the appearance of any  $x$  except the  $x$  in the argument of  $d_+(T-t, x)$ ). Then argue that the limit is zero as  $d_+ \rightarrow \infty$ .

Let  $0 \leq t < T$ . We need to show that

$$\lim_{x \rightarrow \infty} \left[ c(t, x) - \left( x - e^{-r(T-t)}K \right) \right] = 0.$$

When  $x \rightarrow \infty$  then  $\log \frac{x}{K} \rightarrow \infty$  and

$$\begin{aligned} \lim_{x \rightarrow \infty} d_{\pm}(T-t, x) &= \lim_{x \rightarrow \infty} \frac{1}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left( r \pm \frac{1}{2}\sigma^2 \right) (T-t) \right] \\ &= \infty, \end{aligned}$$

so that

$$\lim_{x \rightarrow \infty} N(d_{\pm}(T-t, x)) = 1.$$

Next,

$$\begin{aligned} \lim_{x \rightarrow \infty} \left[ c(t, x) - \left( x - e^{-r(T-t)} K \right) \right] &= \lim_{x \rightarrow \infty} \left[ xN(d_+(T-t, x)) - Ke^{-r(T-t)}N(d_-(T-t, x)) - \left( x - e^{-r(T-t)} K \right) \right] \\ &= \lim_{x \rightarrow \infty} [xN(d_+(T-t, x)) - x] \\ &= \lim_{x \rightarrow \infty} x[N(d_+(T-t, x)) - 1] \\ &= \lim_{x \rightarrow \infty} \frac{N(d_+(T-t, x)) - 1}{x^{-1}}. \end{aligned} \tag{1}$$

If the above limit exists, it is equal to

$$\begin{aligned} \lim_{x \rightarrow \infty} \frac{N(d_+(T-t, x)) - 1}{x^{-1}} &= \lim_{x \rightarrow \infty} \frac{\frac{d}{dx} [N(d_+(T-t, x)) - 1]}{-x^{-2}} \\ &= \lim_{x \rightarrow \infty} \frac{N'(d_+(T-t, x)) \frac{\partial}{\partial x} d_+(T-t, x)}{-x^{-2}} \\ &= \lim_{x \rightarrow \infty} \frac{N'(d_+(T-t, x)) \frac{1}{x\sigma\sqrt{T-t}}}{-x^{-2}} \\ &= \lim_{x \rightarrow \infty} -\frac{N'(d_+(T-t, x)) \frac{1}{\sigma\sqrt{T-t}}}{x^{-1}} \\ &= -\frac{1}{\sigma\sqrt{T-t}} \lim_{x \rightarrow \infty} xN'(d_+(T-t, x)) \\ &= -\frac{1}{\sigma\sqrt{T-t}} \lim_{x \rightarrow \infty} x \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{d_+^2(T-t, x)}{2} \right\} \\ &= -\frac{1}{\sigma\sqrt{2\pi(T-t)}} \lim_{x \rightarrow \infty} x \exp \left[ -\frac{d_+^2(T-t, x)}{2} \right] \\ &\stackrel{(*)}{=} -\frac{1}{\sigma\sqrt{2\pi(T-t)}} \lim_{d_+ \rightarrow \infty} K \exp \left[ \sigma\sqrt{T-t}d_+ - \left( r + \frac{1}{2}\sigma^2 \right) (T-t) \right] \exp \left[ -\frac{d_+^2}{2} \right] \\ &= -\frac{K}{\sigma\sqrt{2\pi(T-t)}} \exp \left[ -\left( r + \frac{1}{2}\sigma^2 \right) (T-t) \right] \lim_{d_+ \rightarrow \infty} \exp \left[ \sigma\sqrt{T-t}d_+ - \frac{d_+^2}{2} \right] \\ &= 0, \end{aligned}$$

where in (\*) we used the hint and expressed  $x$  using the formula for  $d_+$  as follows

$$\begin{aligned} d_+ &= \frac{1}{\sigma\sqrt{T-t}} \left[ \log \frac{x}{K} + \left( r + \frac{1}{2}\sigma^2 \right) (T-t) \right], \\ x &= K \exp \left[ \sigma\sqrt{T-t}d_+ - \left( r + \frac{1}{2}\sigma^2 \right) (T-t) \right] \end{aligned}$$

as well as took the limit w.r.t.  $d_+$ , since when  $x \rightarrow \infty$  also  $d_+ \rightarrow \infty$ . So the limit in (1) exists and is equal to 0, which finally establishes the second boundary condition in (4.10.5).

## Ex. 4.14 (Shreve)

In the derivation of the Itô-Doebelin formula, Theorem 4.4.1, we considered only the case of the function  $f(x) = \frac{1}{2}x^2$ , for which  $f''(x) = 1$ . This made it easy to determine the limit of the last term,

$$\frac{1}{2} \sum_{j=0}^{n-1} f''(W(t_j)) [W(t_{j+1}) - W(t_j)]^2,$$

appearing in (4.4.5). Indeed,

$$\begin{aligned} \lim_{\|\Pi \rightarrow 0\|} \sum_{j=0}^{n-1} f''(W(t_j)) [W(t_{j+1}) - W(t_j)]^2 &= \lim_{\|\Pi \rightarrow 0\|} \sum_{j=0}^{n-1} [W(t_{j+1}) - W(t_j)]^2 \\ &= [W, W](T) = T \\ &= \int_0^T f''(W(t)) dt. \end{aligned}$$

If we had been working with an arbitrary function  $f(x)$ , we could not replace  $f''(W(t_i))$  by 1 in the argument above. It is tempting in this case to just argue that  $[W(t_{j+1}) - W(t_j)]^2$  is approximately equal to  $t_{j+1} - t_j$ , so that

$$\sum_{j=0}^{n-1} f''(W(t_j)) [W(t_{j+1}) - W(t_j)]^2$$

is approximately equal to

$$\sum_{j=0}^{n-1} f''(W(t_j))(t_{j+1} - t_j)$$

and this has limit  $\int_0^T f''(W(t)) dt$  as  $\|\Pi\| \rightarrow 0$ . However, as discussed in Remark 3.4.4, it does not make sense to say that  $[W(t_{j+1}) - W(t_j)]^2$  is approximately equal to  $t_{j+1} - t_j$ . In this exercise, we develop a correct explanation for the equation

$$\lim_{\|\Pi \rightarrow 0\|} \sum_{j=0}^{n-1} f''(W(t_j)) [W(t_{j+1}) - W(t_j)]^2 = \int_0^T f''(W(t)) dt. \quad (4.10.22)$$

Define

$$Z_j = f''(W(t_j)) \left[ (W(t_{j+1}) - W(t_j))^2 - (t_{j+1} - t_j) \right]$$

so that

$$\sum_{j=0}^{n-1} f''(W(t_j)) [W(t_{j+1}) - W(t_j)]^2 = \sum_{j=0}^{n-1} Z_j + \sum_{j=0}^{n-1} f''(W(t_j))(t_{j+1} - t_j)^2. \quad (4.10.23)$$

For completeness, recall the mentioned remark.

**Rem. 3.4.4.** In the proof above, we derived the equations (3.4.6) and (3.4.7):

$$\mathbb{E} \left[ (W(t_{j+1}) - W(t_j))^2 \right] = t_{j+1} - t_j$$

and

$$\text{Var} \left[ (W(t_{j+1}) - W(t_j))^2 \right] = 2(t_{j+1} - t_j)^2.$$

It is tempting to argue that when  $t_{j+1} - t_j$  is small,  $(t_{j+1} - t_j)^2$  is very small, and therefore  $(W(t_{j+1}) - W(t_j))^2$ , although random, is with high probability near its mean  $t_{j+1} - t_j$ . We could therefore claim that

$$(W(t_{j+1}) - W(t_j))^2 \approx t_{j+1} - t_j \quad (3.4.8)$$

This approximation is trivially true because, when  $t_{j+1} - t_j$  is small, both sides are near zero. It would also be true if we squared the right-hand side, multiplied the right-hand side by 2, or made any of several other

significant changes to the right-hand side. In other words, (3.4.8) really has no content. A better way to try to capture what we think is going on is to write

$$(W(t_{j+1}) - W(t_j))^2 \approx t_{j+1} - t_j \quad (3.4.9)$$

instead of (3.4.8). However,

$$\frac{(W(t_{j+1}) - W(t_j))^2}{t_{j+1} - t_j}$$

is in fact not near 1, regardless of how small we make  $t_{j+1} - t_j$ . It is the square of the standard normal random variable

$$Y_{j+1} = \frac{W(t_{j+1}) - W(t_j)}{\sqrt{t_{j+1} - t_j}}$$

and its distribution is the same, no matter how small we make  $t_{j+1} - t_j$ .

(...)

We write informally

$$dW(t)dW(t) = dt \quad (3.4.10)$$

but this should not be interpreted to mean either (3.4.8) or (3.4.9).

(...)

we conclude that

Brownian motion accumulates quadratic variation at rate one per unit time.

(i) Show that  $Z_j$  is  $\mathcal{F}(t_{j+1})$ -measurable and

$$\mathbb{E}[Z_j | \mathcal{F}(t_j)] = 0, \quad \mathbb{E}[Z_j^2 | \mathcal{F}(t_j)] = 2[f''(W(t_j))]^2 (t_{j+1} - t_j)^2.$$

First, notice that  $Z_j \in \mathcal{F}(t_{j+1})$  and that the Brownian motion increment  $W(t_{j+1}) - W(t_j) \perp \mathcal{F}(t_j)$ , with the variance  $t_{j+1} - t_j$ . Then, we have

$$\begin{aligned} \mathbb{E}[Z_j | \mathcal{F}(t_j)] &= f''(W(t_j)) \mathbb{E} \left[ (W(t_{j+1}) - W(t_j))^2 - (t_{j+1} - t_j) \middle| \mathcal{F}(t_j) \right] \\ &= f''(W(t_j)) [(t_{j+1} - t_j) - (t_{j+1} - t_j)] \\ &= 0. \end{aligned}$$

Next, recall that for  $X \sim N(0, s)$  we have  $\mathbb{E}X^4 = 3\mathbb{E}[X^2]^2 = 3s^2$ . Then,

$$\begin{aligned} \text{Var}[Z_j | \mathcal{F}(t_j)] &= [f''(W(t_j))]^2 \mathbb{E} \left[ \left[ (W(t_{j+1}) - W(t_j))^2 - (t_{j+1} - t_j) \right]^2 \middle| \mathcal{F}(t_j) \right] \\ &= [f''(W(t_j))]^2 \mathbb{E} \left[ (W(t_{j+1}) - W(t_j))^4 - 2(W(t_{j+1}) - W(t_j))^2 (t_{j+1} - t_j) + (t_{j+1} - t_j)^2 \middle| \mathcal{F}(t_j) \right] \\ &\stackrel{\text{lin.}}{=} [f''(W(t_j))]^2 \left[ \mathbb{E} \left[ (W(t_{j+1}) - W(t_j))^4 \middle| \mathcal{F}(t_j) \right] - 2\mathbb{E} \left[ (W(t_{j+1}) - W(t_j))^2 (t_{j+1} - t_j) \middle| \mathcal{F}(t_j) \right] \right. \\ &\quad \left. + \mathbb{E} \left[ (t_{j+1} - t_j)^2 \middle| \mathcal{F}(t_j) \right] \right] \\ &= [f''(W(t_j))]^2 [3(t_{j+1} - t_j)^2 - 2(t_{j+1} - t_j)^2 + (t_{j+1} - t_j)^2] \\ &= 2[f''(W(t_j))]^2 (t_{j+1} - t_j)^2, \end{aligned}$$

which completes the proof.

It remains to show that

$$\lim_{\|\Pi \rightarrow 0\|} \sum_{j=0}^{n-1} Z_j = 0 \quad (4.10.24)$$

This will cause us to obtain (4.10.22) when we take the limit in (4.10.23). Prove (4.10.24) in the following steps.



(iii) Show that  $\mathbb{E} \sum_{j=0}^{n-1} Z_j = 0$ .

Using iterated conditioning and linearity of conditional expectation we can write

$$\begin{aligned} \mathbb{E} \sum_{j=0}^{n-1} Z_j &= \mathbb{E} \left[ \sum_{j=0}^{n-1} \mathbb{E} [Z_j | \mathcal{F}(t_j)] \right] \\ &\stackrel{(i)}{=} \mathbb{E} \left[ \sum_{j=0}^{n-1} 0 \right] \\ &= 0, \end{aligned}$$

which is the required result.

(iv) Under the assumption that  $\mathbb{E} \int_0^T [f''(W(t))]^2 dt$  is finite, show that

$$\lim_{\|\Pi\| \rightarrow 0} \text{Var} \left[ \sum_{j=0}^{n-1} Z_j \right] = 0.$$

(Warning: The random variables  $Z_1, Z_2, \dots, Z_{n-1}$  are not independent.)

$$\begin{aligned} \text{Var} \left[ \sum_{j=0}^{n-1} Z_j \right] &= \mathbb{E} \left[ \left( \sum_{j=0}^{n-1} Z_j \right)^2 \right] \\ &= \mathbb{E} \left[ \sum_{j=0}^{n-1} Z_j^2 + 2 \sum_{0 \leq i < j \leq n} Z_i Z_j \right] \\ &\stackrel{\text{lin. ic}}{=} \sum_{j=0}^{n-1} \mathbb{E} [\mathbb{E} [Z_j^2 | \mathcal{F}(t_j)]] + 2 \sum_{0 \leq i < j \leq n} \mathbb{E} [Z_i \mathbb{E} [Z_j^2 | \mathcal{F}(t_j)]] \\ &= \sum_{j=0}^{n-1} \mathbb{E} [2 [f''(W(t_j))]^2 (t_{j+1} - t_j)^2] \\ &= 2 \sum_{j=0}^{n-1} (t_{j+1} - t_j)^2 \mathbb{E} [f''(W(t_j))]^2 \\ &\leq 2 \underbrace{\max_{0 \leq j \leq n-1} |t_{j+1} - t_j|}_{\rightarrow 0} \underbrace{\sum_{j=0}^{n-1} \mathbb{E} [f''(W(t_j))]^2}_{(**)} (t_{j+1} - t_j) \\ &\rightarrow 0, \end{aligned}$$

where in (\*\*) we use the assumption that  $\mathbb{E} \int_0^T [f''(W(t))]^2 dt < \infty$  as then

$$\begin{aligned} \lim_{\|\Pi\| \rightarrow 0} \sum_{j=0}^{n-1} \mathbb{E} [f''(W(t_j))]^2 (t_{j+1} - t_j) &= \lim_{\|\Pi\| \rightarrow 0} \mathbb{E} \left[ \sum_{j=0}^{n-1} [f''(W(t_j))]^2 (t_{j+1} - t_j) \right] \\ &= \mathbb{E} \int_0^T [f''(W(t))]^2 dt \\ &< \infty. \end{aligned}$$

This completes the proof.

From (iii), we conclude that  $\sum_{j=0}^{n-1} Z_j = 0$  converges to its mean, which by (ii) is zero. This establishes (4.10.24).