1. (i)
$$\mathbf{E}(S_{n+m}|S_n) = \mathbf{E}(S_n + X_{n+1} + \dots + X_{n+m}|S_n) \stackrel{\text{CE1}}{=} \mathbf{E}(S_n|S_n) + \mathbf{E}(X_{n+1} + \dots + X_{n+m}|S_n) \stackrel{\text{CE2,CE3}}{=} S_n + \mathbf{E}(X_{n+1} + \dots + X_{n+m}) = S_n + m\mu.$$
(ii) Using CE2 and the hint, $S_n = \mathbf{E}(X_1 + \dots + X_n + \dots + X_n + \dots) = S_n + m\mu.$

$$E(X_{n+1} + \cdots + X_{n+m} | S_n) = S_n + \mathbf{E}(X_{n+1} + \cdots + X_{n+m}) = S_n + \mathbf{E}(X_n + 1 + \cdots + X_n + 1) = S_n + m\mu.$$
(ii) Using CE2 and the hint, $S_n = \mathbf{E}(X_1 + \cdots + X_n | S_n) = \sum_{k \le n} \mathbf{E}(X_k | S_n) = \sum_{k \le n} \mathbf{E}(X$

$$\begin{array}{l}
\text{nE}(X_1|S_n). \text{ Hence } \mathbf{E}(X_1|S_n) = S_n/n. \\
\text{(iii) } \mathbf{E}(S_{n+m}^2|S_n) = \mathbf{E}((S_n + X_{n+1} + \dots + X_{n+m})^2|S_n) = \mathbf{E}(S_n^2|S_n) + 2\mathbf{E}(S_n(X_{n+1} + \dots + X_{n+m})|S_n) + \mathbf{E}((X_{n+1} + \dots + X_{n+m})^2|S_n) = S_n^2 + 2S_n\mathbf{E}(X_{n+1} + \dots + X_{n+m}) + \mathbf{E}(X_{n+1} + \dots + X_{n+m})^2 = S_n^2 + 2S_nm\mu + m\sigma^2 + m^2\mu^2 = (S_n + m\mu)^2 + m\sigma^2.
\end{array}$$

(iv) $\mathbf{E}(S_m | S_n) = \sum_{k \le m} \mathbf{E}(X_k | S_n) = \frac{m}{n} S_n$ from (ii).

2. (i)
$$\mathbf{E}(N_{t+s}|\mathcal{F}_t) = \mathbf{E}(N_t + N_{t+s} - N_s|\mathcal{F}_t) \stackrel{\text{CE1}}{=} \mathbf{E}(N_t|\mathcal{F}_t) + \mathbf{E}(N_{t+s} - N_s|\mathcal{F}_t) \stackrel{\text{CE2,CE3}}{=} N_t + \mathbf{E}(N_{t+s} - N_s) = N_t + \lambda s.$$

- (ii) $\mathbf{E}(N_{t+s}^2|\mathcal{F}_t) = (N_t + \lambda s)^2 + \lambda s$ (the argument is basically the same as in solution to part (iii) in the previous problem, just recall that $\mathbf{E} N_s = \text{Var}(N_s) =$
- (iii) $\mathbf{E}(N_s | \mathcal{F}_t) = N_s$, $\mathbf{E}(N_s^2 | \mathcal{F}_t) = N_s^2$ by CE2, as N_s (and hence N_s^2 as well) is \mathcal{F}_t -measurable.
- (iv) We know that $\mathbf{E}(N_s|N_t) =: \eta(N_s)$ is a function of N_t , with $\eta(n) =$ $\mathbf{E}(N_s|N_t=n)$. From Example 2.5 we know that $(N_s|N_t=n)\sim B_{n,s/t}$ (see also the proof of Theorem 5.2). Hence $\eta(n) = sn/t$, and so $\mathbf{E}(N_s|N_t) = \frac{s}{t}N_t$. Similarly, one can find that $\mathbf{E}(N_s^2|N_t) = \frac{s(t-s)}{t^2} N_t + \frac{s^2}{t^2} N_t^2$.
- **3.** (i) $\{\tau \leq t\} = \Omega$ if $m \leq t$ and $= \emptyset$ if m > t. In either case, the set is an element of \mathcal{F}_t . This is an ST.
- (ii) $\{\tau_1 \wedge \tau_2 \leq t\} = \{\tau_1 \leq t\} \cup \{\tau_2 \leq t\} \in \mathcal{F}_t$ as each of the events in the union belongs to \mathcal{F}_t . Likewise, $\{\tau_1 \vee \tau_2 \leq t\} = \{\tau_1 \leq t\} \cap \{\tau_2 \leq t\} \in \mathcal{F}_t$. This is an ST.
- (iii) $\{\tau > t\} = \bigcap_{k=0}^t \{X_{k+1}/X_k \le 1\}$, where the last event in the intersection does not need to belong to \mathcal{F}_t (as X_{t+1} is, generally speaking, not \mathcal{F}_t -measurable). So $\{\tau \leq t\} = \{\tau > t\}^c$ does not need to belong to \mathcal{F}_t as well, and hence τ may not be an ST.
- (iv) $\{\tau > t\} = \bigcap_{j=0}^{t} \{\sum_{k=0}^{t} X_k \le X_t^2\} \in \mathcal{F}_t$ as each of the events in the intersection $\in \mathcal{F}_t$. So $\{\tau \le t\} = \{\tau > t\}^c \in \mathcal{F}_t$ as well. This is an ST.

 (v) $\{\tau = t\} = \{X_t > 10\} \cap \left[\bigcap_{k=t+1}^{10} \{X_k \le 10\}\right]$. Here, generally speaking,
- $[\cdots] \not\in \mathcal{F}_t$, so τ does not need to be an ST.
- 4. That $\{X_t\}$ is adapted follows from the definition of CE. Integrability is obvious from CE4. The latter also implies the MG property, as for $0 \le s < t$, one has $\mathbf{E}(X_t|\mathcal{F}_s) = \mathbf{E}(\mathbf{E}(Y|\mathcal{F}_t)|\mathcal{F}_s) = \mathbf{E}(Y|\mathcal{F}_s) = X_s$.
- **5.** As X_{t_1}, X_{t_2} are \mathcal{F}_{t_3} -measurable, $\mathbf{E}(X_{t_2} X_{t_1})(X_{t_4} X_{t_3})$ $\mathbf{E}((\cdot \cdot \cdot) | \mathcal{F}_{t_3}) = \mathbf{E}[(X_{t_2} - X_{t_1})\mathbf{E}(X_{t_4} - X_{t_3} | \mathcal{F}_{t_3})] = 0 \text{ since } \mathbf{E}(X_{t_4} - X_{t_3} | \mathcal{F}_{t_3}) =$ $\mathbf{E}(X_{t_4}|\mathcal{F}_{t_3}) - X_{t_3} = 0$, $\{X_t\}_{t\geq 0}$ being an MG. Square integrability is needed to ensure that the expectation of the product exists (by Cauchy-Bunyakovskii's inequality).
- **6.** The SP is clearly adapted. Integrability: $\mathbf{E}|X_n| = \mathbf{E}|S_n^2 n\sigma^2| \leq \mathbf{E}S_n^2 + n\sigma^2$ $n\sigma^2 = \operatorname{Var}(S_n) + (\mathbf{E} S_n)^2 + n\sigma^2 = 2n\overline{\sigma}^2 < \infty.$
- (i) $\mathbf{E}(X_{n+1}|\mathcal{F}_n) = \mathbf{E}((S_n + Y_{n+1})^2 (n+1)\sigma^2|\mathcal{F}_n) = \mathbf{E}(S_n^2 + 2S_nY_{n+1} + Y_{n+1}^2|\mathcal{F}_n) (n+1)\sigma^2, \text{ where } \mathbf{E}(S_n^2|\mathcal{F}_n) = S_n^2, \mathbf{E}(S_nY_{n+1}|\mathcal{F}_n) = S_n\mathbf{E}(Y_{n+1}|\mathcal{F}_n) = S_n\mathbf{E}(Y_{n+1}|\mathcal{F}_n) = S_n\mathbf{E}(Y_{n+1}|\mathcal{F}_n) = \mathbf{E}(S_n^2|\mathcal{F}_n) = \mathbf{E}(S_n^$ $S_n^2 - n\sigma^2 = X_n$, that's an MG!
- (ii) As all $X_k = S_k^2 k\sigma^2$, k = 1, ..., n, are functions of $Y_1, ..., Y_n$, one has $\mathcal{F}'_n \subset \mathcal{F}_n$. Hence, using CE4, $\mathbf{E}(X_n|\mathcal{F}'_n) = \mathbf{E}[\mathbf{E}(X_n|\mathcal{F}_n)|\mathcal{F}'_n] = \mathbf{E}(X_n|\mathcal{F}'_n) =$
- 7. DIY. This is no different from the proof of Theorem 11.6 (use the fact the this is a process with independent increments and, for part (iii), the explicit form
- 8. (i) We know from Example 11.2 that $\{S_n\}$ is an MG. By Theorem 11.2, $0 = \mathbf{E} S_0 = \mathbf{E} S_{\tau} = a \mathbf{P} (S_{\tau} = a) + b \mathbf{P} (S_{\tau} = b) = (a - b) \mathbf{P} (S_{\tau} = a) + b$, so that $\mathbf{P}(S_{\tau} = a) = \frac{b}{b-a}, \, \mathbf{P}(S_{\tau} = b) = \frac{-a}{b-a}.$

(ii) By Theorem 11.2 applied to the MG $X_n := S_n^2 - n\sigma^2 \equiv S_n^2 - n$, and the (11) by one has $0 = \mathbf{E} X_0 = \mathbf{E} X_\tau = \mathbf{E} (S_\tau^2 - \tau) = \frac{a^2b}{b-a} + \frac{b^2(-a)}{b-a} - \mathbf{E} \tau = \frac{a^2b}{b-a}$. Therefore, $\mathbf{E} \tau = -ab$. Therefore, $\mathbf{E} \tau = -ab$.

9. (i) The SP $\{Z_n\}$ is clearly adapted to F. Integrability follows from the 9. (1) $|Z_n| \leq \max_{j \leq n} |X_j - X_{j-1}| \sum_{k \leq n} |Y_k| \leq \sum_{k \leq n} C_n$. The MG property:

bound $|E_n| = \mathbb{E}(Z_{n+1} - Z_n | \mathcal{F}_n) = \mathbb{E}(Y_{n+1}(X_{n+1} - X_n) | \mathcal{F}_n) = Y_{n+1}\mathbb{E}(X_{n+1} - X_n) | \mathcal{F}_n$ is an MG. $\chi_n | \mathcal{F}_n \rangle = 0$ as $\{X_n\}$ is an MG. (ii) $Y_1 = 1$, and for n > 1, one has $Y_n = 2Y_{n-1}$ if $X_{n-1} - X_{n-2} = -1$ (loss) and $Y_n = 1$ if $X_{n-1} - X_{n-2} = 1$ (win).

(iii) The RVs $\xi_n := X_n - X_{n-1}$ are i.i.d., $\mathbf{P}(\xi_1 = \pm 1) = \frac{1}{2}$. Hence one has $p(\tau = n) = \mathbf{P}(\xi_1 = \xi_2 = \dots = \xi_{n-1} = -1, \xi_n = 1) = 2^{-n}, n = 1, 2, \dots$ (the P(1) in the expectation, either compute $\sum_{n=1}^{\infty} n2^{-n}$ or, geometry, first compute the GF $g_{\tau}(z) = z/(2-z)$ of τ (it's just the sum of a geometric series) and then take $\mathbf{E}\tau = \gamma_{\tau}'(1) = 2$. The statement of Theorem 11.2 does not hold as $0 = Z_0$, but as your fortune at the time of your first win is

always $Z_{\tau} = 1$ (verify that!), one has $\mathbf{E} Z_{\tau} = 1$. (iv) $\mathbf{E}(Z_n; \tau > n) = \mathbf{E}(Z_n; \xi_1 = \xi_2 = \dots = \xi_n = -1) = -\sum_{j=1}^{n-1} 2^j \times 2^{-n} =$ $-\frac{2^{n}-1}{2-1}2^{-n} = 2^{-n} - 1 \nrightarrow 0$ as $n \to \infty$. Condition (11.11) is not satisfied. 10. (i) As no filtration is specified, we consider the natural one. Integra-

bility follows from boundedness $(0 < X_n \le 2^{2n})$. Setting $Y_n := S_n - S_{n-1}$, $n \ge 1$, we have $\mathbf{E}(X_{n+1}|\mathcal{F}_n) = \mathbf{E}(2^{-S_n - Y_{n+1}}|\mathcal{F}_n) = 2^{-S_n}\mathbf{E}(2^{-Y_{n+1}}|\mathcal{F}_n) = 2^{-S_n}\mathbf{E}(2^{-Y_{n+1}}|\mathcal{F}_n) = 2^{-S_n}\mathbf{E}(2^{-Y_{n+1}}|\mathcal{F}_n)$ $X_n \to X_n = X_n \text{ since } \mathbf{E} \, 2^{-Y_{n+1}} = 2^{-1} \times \frac{6}{7} + 2^2 \times \frac{1}{7} = 1.$

(ii) Note that $\{X_n \leq 0.1\} = \{S_n \geq \log_2 10\} = \{S_n \geq 4\}$ (as S_n is integervalued). Hence $\tau = \min\{n \geq 0 : S_n \geq 4\} = \min\{n \geq 0 : S_n = 4\}$ as the RW $\{S_n\}$ is skip-free, and so $\mathbf{P}(S_{\tau}=4)=1$ (the RW $\{S_n\}$ crosses any positive level

w.p. 1 as it has positive trend: $\mathbf{E}Y_1 = 1 \times \frac{6}{7} - 2 \times \frac{1}{7} = \frac{4}{7}$.) By Theorem 11.2, $0 = \mathbf{E} Z_0 = \mathbf{E} Z_{\tau} = \mathbf{E} (S_{\tau} - \frac{4}{7}\tau) = 4 - \frac{4}{7}\mathbf{E} \tau$. Hence $\mathbf{E} \tau = 7$. 11. (i) Use the natural filtration. Integrability is obvious from boundedness.

Set $Y_n := S_n - S_{n-1}$, $n \ge 1$. We have $\mathbf{E}(X_{n+1} | \mathcal{F}_n) = \mathbf{E}((q/p)^{S_n + Y_{n+1}} | \mathcal{F}_n) = \mathbf{E}((q/p)^{S_n + Y_{n+1}} | \mathcal{F}_n)$ $(q/p)^{S_n} \mathbf{E} ((q/p)^{Y_{n+1}} | \mathcal{F}_n) = X_n \mathbf{E} (q/p)^{Y_{n+1}} = X_n ((q/p)^1 p + (q/p)^{-1} q) = X_n.$ (ii) Clearly, either $S_{\tau} = a$ or $S_{\tau} = b$. Set r := q/p. By Theorem 11.2,

 $1 = \mathbf{E} X_0 = \mathbf{E} X_{\tau} = r^a \mathbf{P} (S_{\tau} = a) + r^b \mathbf{P} (S_{\tau} = b) = (r^a - r^b) \mathbf{P} (S_{\tau} = a) + r^b, \text{ so}$ that $\mathbf{P}(S_{\tau} = a) = 1 - \mathbf{P}(S_{\tau} = b) = (r^b - 1)/(r^b - r^a)$.

Apply Theorem 11.2 to $\{Z_n\}$: $0 = \mathbf{E}Z_0 = \mathbf{E}Z_\tau = \mathbf{E}(S_\tau - (p-q)\tau) = \mathbf{E}Z_0$ $\mathbf{E}S_{\tau} - (2p-1)\mathbf{E}\tau = a\mathbf{P}(S_{\tau} = a) + b(1 - \mathbf{P}(S_{\tau} = a)) - (2p-1)\mathbf{E}\tau$. Hence $\mathbf{E}_{\tau} = (b(1-r^a) + a(r^b-1))/[(2p-1)(r^b-r^a)].$

12. Suppose $\omega \in \Omega$ is such that $\{U_1(\omega), U_2(\omega), \ldots\}$ is not everywhere dense in [0,1]. That means that there exist points $t_1 < t_2$ in [0,1] s.t. $U_j(\omega) \notin (t_1, t_2)$, j = 1, 2j=1,2,... Hence, for the EDFs F_n^* corresponding to the samples consisting of the first of the first n RVs U_j , one has $F_n^*(t_1) = F_n^*(t_2)$, n = 1, 2, ... But that clearly contradict (2.27) contradicts (2.87) as the limiting DF is F(t) = t, $t \in [0,1]$. Therefore the set of such wsuch ω 's must have zero probability.

13. The RW X is normal as a linear transformation of a Gaussian vector,

One just one just needs to compute its mean and variance. Clearly, $\mathbf{E}(2W_{t_1}-W_{t_2})=$

 $2\mathbf{E} W_{t_1} - \mathbf{E} W_{t_2} = 0, \text{ Var } (X) = \mathbf{E} X^2 = \mathbf{E} (2W_{t_1} - W_{t_2})^2 = 4\mathbf{E} W_{t_1}^2 - 4\mathbf{E} W_{t_1} W_{t_2} + \mathbf{E} W_{t_2}^2 = 4t_1 - 4(t_1 \wedge t_2) + t_2 = t_2. \text{ So } 2W_{t_1} - W_{t_2} \sim N(0, t_2).$

Alternatively, one may wish to use independence of the increments of the BM: $X = 2W_{t_1} - W_{t_2} = W_{t_1} - (W_{t_2} - W_{t_1})$, the summands on the right-hand side being independent with distributions $N(0, t_2)$ and $N(0, t_2 - t_1)$, resp. Hence the same answer as above.

- 14. As in Problem 13, X will be normal with zero mean. One can compute Var(X) from the covariance function of the BM (cf. solution to Problem 13; DIY!) or using independence of increments and the following alternative representation for the RV: $X = 2W_2 + (W_3 W_2) + 2(W_4 W_3) \sim N(0, 13)$.
- 15. In the notation of (2.33), we have $X = (W_{t_1} W_{t_0}, \dots, W_{t_n} W_{t_{n-1}}),$ $Y = (W_{t_1}, \dots, W_{t_n}),$ and g(x) = xA, where

$$A = \begin{pmatrix} 1 & 1 & 1 & \cdots & 1 \\ 0 & 1 & 1 & \cdots & 1 \\ 0 & 0 & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}.$$

Hence g^{-1} is also a linear transform, $|J(g^{-1}(y))| = |\det A^{-1}| = |\det A|^{-1} = 1$, and so

$$f_{\mathbf{Y}}(\mathbf{y}) = f_{\mathbf{X}}(\mathbf{g}^{-1}(\mathbf{y})) = \prod_{j=1}^{n} f_{W_{t_j} - W_{t_{j-1}}}(x_j - x_{j-1}),$$

which is clearly the same as $f_{t_1,\ldots,t_k}(x_1,\ldots,x_n)$ (see (11.22)).

16. Cf. solution to the previous problem. The transformation matrix is

$$A = \begin{pmatrix} \sqrt{t_1 - t_0} & \sqrt{t_1 - t_0} & \sqrt{t_1 - t_0} & \cdots & \sqrt{t_1 - t_0} \\ 0 & \sqrt{t_2 - t_1} & \sqrt{t_2 - t_1} & \cdots & \sqrt{t_2 - t_1} \\ 0 & 0 & \sqrt{t_3 - t_2} & \cdots & \sqrt{t_3 - t_2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & \cdots & \sqrt{t_n - t_{n-1}} \end{pmatrix}.$$

For the arithmetic BM, multiply the matrix by σ (and don't forget that there can be a non-zero drift!).

- 17. (i) Observing that $2W_3 \sim N(0,12)$ and $(W_5|2W_3 = x) \sim N(x/2,2)$ by independent increments, by the formula (2.80) for conditional densities, $f_{(2W_3,W_5)}(x,y) = f_{W_5|2W_3}(y|x)f_{2W_3}(x) = \frac{1}{\sqrt{2\pi\cdot2}}e^{-(y-x/2)^2/4}\frac{1}{\sqrt{2\pi\cdot12}}e^{-x^2/24} = \frac{1}{4\pi\sqrt{6}}\exp\{-\frac{y^2}{4} + \frac{xy}{4} \frac{5x^2}{48}\}.$
- (ii) Arguing as in (i), compute $f_{(W_2,2W_3)}(x,y) = \frac{1}{4\pi\sqrt{2}} \exp\{-\frac{y^2}{8} + \frac{xy}{2} \frac{3x^2}{4}\}$. Next note that, due to independent increments, $(W_5|(W_2,2W_3)) = (x,y) \stackrel{d}{=} (W_5|2W_3 = y) \sim N(y/2,2)$, as in (i). Now use $f_{(W_2,2W_3,W_5)}(x,y,z) = f_{W_5|(W_2,2W_3)}(z|(x,y))f_{(W_2,2W_3)}(x,y) = \frac{1}{\sqrt{2\pi\cdot2}}e^{-(z-y/2)^2/4}f_{(W_2,2W_3)}(x,y) =$

- $\sup_{\frac{1}{85\sqrt{2\pi}}} \exp\left\{-\frac{3x^2}{4} + \frac{xy}{2} \frac{3y^2}{16} + \frac{yz}{4} \frac{z^2}{4}\right\}.$
- 18. Clearly, $\mathbf{E}\widetilde{W}_t = 0$. For 0 < s < t, one has $\mathbf{E}\widetilde{W}_s\widetilde{W}_t = st\mathbf{E}W_{1/s}W_{1/t} = s$ since $\frac{1}{s}\wedge\frac{1}{t} = \frac{1}{t}$. Since $\{\widetilde{W}_t\}$ is a Gaussian process (indeed, \widetilde{W}_{t_1} , \widetilde{W}_{t_n}) = $(t_1W_{1/t_1}, \dots, t_nW_{1/t_n})$ is just a linear transform of the Gaussian process. (indeed, $(W_{t_1}, \ldots, W_{1/t_n})$, and so is Gaussian itself), Theorem 11.4 yields the desired assertion.
- 19. Using the MG $\{Y_t := W_t^2 t\}_{t \ge 0} : 0 = \mathbf{E} Y_0 = \mathbf{E} Y_\tau = \mathbf{E} (W_\tau^2 \tau) = (1 b)\mathbf{E} \tau$. Hence $\mathbf{E} \tau = \frac{a}{2}$ $\mathbf{E}(a+b\tau-\tau)=a-(1-b)\mathbf{E}\tau$. Hence $\mathbf{E}\tau=\frac{a}{1-b}$.
- 20. (i) Using the first MG: $0 = \mathbf{E} W_0 = \mathbf{E} W_\tau = \mathbf{E} (2\tau 4) = 2\mathbf{E} \tau 4$. so that $\mathbf{E} \tau = 2$.
- hat $\mathbf{E}^{\tau} = \mathbf{E}^{\tau}$.

 (ii) Using the second MG $\{Y_t := W_t^2 t\}_{t \ge 0} : 0 = \mathbf{E} Y_0 = \mathbf{E} Y_\tau = \mathbf{E} (W_\tau^2 \tau) = \mathbf{E}^{\tau} = \mathbf{E$ (11) USING (12) $= \mathbf{E} Y_0 = \mathbf{$
- $\operatorname{E} e^{-s\tau} = e^{4u}$ for $s := u^2/2 - 2u$. Solving for u: $u = 2 \pm \sqrt{2(s+2)}$; choosing "-" (why?), we obtain $l_{\tau}(s) = \exp\{8 - 4\sqrt{2(s+2)}\}$.
- (iv) By Theorem 11.2, $0 = \mathbf{E} W_0 = \mathbf{E} W_\tau$, $0 = \mathbf{E} Y_0 = \mathbf{E} Y_\tau = \mathbf{E} W_\tau^2 \mathbf{E} \tau$, so that $\mathbf{E} W_{\tau} = 0$, $\mathbf{E} W_{\tau}^{2} = \mathbf{E} \tau = 2$.
- **21.** (i) Clearly, $\mathbf{P}(W_{\tau} = a) = 1 \mathbf{P}(W_{\tau} = b)$, and, by Theorem 11.2 for the MG $\{W_t\}$, one has $0 = \mathbf{E} W_0 = \mathbf{E} W_\tau = a \mathbf{P} (W_\tau = a) + b \mathbf{P} (W_\tau = b) = b \mathbf{E} W_\tau = a \mathbf{P} (W_\tau = a) + b \mathbf{P} (W_\tau = b) = b \mathbf{P} (W_\tau = b)$ $(a-b)\mathbf{P}(W_{\tau}=a)+b$, so that $\mathbf{P}(W_{\tau}=a)=\frac{b}{b-a}$.
 - (ii) $\mathbf{E} \tau = -ab$ (see (12.31)).
- (iii) Using the third MG and Theorem 11.2, for any $u \in \mathbb{R}$, one has 1 = $\mathbf{E} Z_0 = \mathbf{E} Z_{\tau} = \mathbf{E} e^{uW_{\tau} - u^2 \tau/2} = \mathbf{E} \mathbf{E} \left(e^{uW_{\tau} - u^2 \tau/2} \middle| \tau \right) = \mathbf{E} \left(e^{-u^2 \tau/2} \mathbf{E} \left(e^{uW_{\tau}} \middle| \tau \right) \right).$ By symmetry, $W_{\tau} = \pm a$ independently of τ , with equal probabilities, so we obtain $1 = \frac{1}{2}(e^{au} + e^{-au})\mathbf{E} e^{-u^2\tau/2}$. Therefore $l_{\tau}(s) = \mathbf{E} e^{-s\tau} = 1/\cosh(\sqrt{2sa}), s \ge 0$.
- (iv) By the chain rule, $l_{\tau}(s)' = \frac{\sinh(\sqrt{2s}a)}{\cosh^2(\sqrt{2s}a)} \frac{a}{\sqrt{2s}} \to a^2$ as $s \to 0$, which is the same answer as in (ii) in the case a = -b.
 - (v) DIY. Just keep differentiating.
- 22. One can assume w.l.o.g. that the simple processes have a common time partition $0 = t_0 < t_1 < \dots < t_n = T$: $f_t = X_k$ and $g_t = Y_k$ for $t \in [t_{k-1}, t_k)$, for some $\mathcal{F}_{t_{k-1}}$ -measurable RVs X_k and Y_k , $k=1,2,\ldots,n$. Then

$$\mathbf{E} I_{t}(f)I_{t}(g) = \mathbf{E} \sum_{k=1}^{n} X_{k}(W_{t_{k}} - W_{t_{k-1}}) \sum_{j=1}^{n} Y_{j}(W_{t_{j}} - W_{t_{j-1}})$$

$$= \sum_{k=1}^{n} \mathbf{E} \left(X_{k} Y_{k}(W_{t_{k}} - W_{t_{k-1}})^{2} \right) + \sum_{j \neq k} \mathbf{E} X_{k} Y_{j}(W_{t_{k}} - W_{t_{k-1}})(W_{t_{j}} - W_{t_{j-1}}),$$

$$= \sum_{k=1}^{n} \mathbf{E} \left(X_{k} Y_{k}(W_{t_{k}} - W_{t_{k-1}})^{2} \right) + \sum_{j \neq k} \mathbf{E} X_{k} Y_{j}(W_{t_{k}} - W_{t_{k-1}})(W_{t_{j}} - W_{t_{j-1}}),$$

$$= :B_{jk}$$

$$= :B_{jk}$$

where, by CE4, $A_k = \mathbf{E} \mathbf{E} \left(X_k Y_k (W_{t_k} - W_{t_{k-1}})^2 \middle| \mathcal{F}_{t_{k-1}} \right) = \mathbf{E} \left(X_k Y_k \mathbf{E} \left((W_{t_k} - W_{t_{k-1}})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left(X_k Y_k \mathbf{E} \left((W_{t_k} - W_{t_{k-1}})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left(X_k Y_k \mathbf{E} \left((W_{t_k} - W_{t_{k-1}})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left(X_k Y_j (W_{t_j} - Y_k) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right) = \mathbf{E} \left((X_k Y_j (W_{t_j} - W_{t_k})^2 \middle| \mathcal{F}_{t_{k-1}} \right) \right)$ $j < k, B_{jk} = \mathbf{E} \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}})^2 = (t_k - t_{k-1})^2 \mathbf{E} \mathbf{E} \left(X_k Y_j (W_{t_j} - W_{t_{k-1}}) \right) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_{k-1}}) (W_{t_j} - W_{t_{j-1}}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_k}) (W_{t_k} - W_{t_k}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_k}) (W_{t_k} - W_{t_k}) (W_{t_k} - W_{t_k}) \right) = \mathbf{E} \left(X_k Y_j (W_{t_k} - W_{t_k}) (W_{t_k} -$

 $W_{t_{j-1}}$) $\mathbf{E}(W_{t_k} - W_{t_{k-1}} | \mathcal{F}_{t_{k-1}})$) = 0 as the last CE is zero. Thus, $\mathbf{E}I_t(f)I_t(g) = \sum_{k=1}^n (t_k - t_{k-1})\mathbf{E}X_kY_k = \int_0^t \mathbf{E}f_sg_s\,ds$.

The identity is actually an immediate consequence of Itô's isometry (Theorem 11.7(iii)) and the following simple general fact: suppose $L: H_1 \to H_2$ is a linear mapping of one inner product space H_1 into another (H_2) such that, for any $u \in H_1$ one has ||Lu|| = ||u||. Then the inner products are also preserved: for any $u, v \in H_1$, one has (Lu, Lv) = (u, v). To verify that, just compare the first expression with the last one in the following chain of equalities: $||u||^2 + ||v||^2 + 2(u, v) = ||u + v||^2 = ||L(u + v)||^2 = ||Lu||^2 + ||Lv||^2 + 2(Lu, Lv) = ||u||^2 + ||v||^2 + 2(Lu, Lv)$.

- **23.** One has $Y_t = f(X_t)$ with $f(x) = e^x$ (so that f'(x) = f''(x) = f(x)) and $dX_t = g_t dW_t \frac{1}{2}g_t^2 dt$. By Itô's formula, $dY_t = f'(X_t)dX_t + \frac{1}{2}f''(X_t)(dX_t)^2 = f(X_t)(g_t dW_t \frac{1}{2}g_t^2 dt) + \frac{1}{2}f(X_t)g_t^2 dt = f(X_t)g_t dW_t$, showing that $\{Y_t\}$ is an MG (Remark 11.3).
- **24.** Here $X_t = f(W_t)$ with $f(x) = \cos x$, $f'(x) = -\sin x$, $f''(x) = -\cos x$, and so Itô's formula yields $dX_t = -\sin(W_t)dW_t \frac{1}{2}\cos(W_t)dt$.
- **25.** (i) For $f(x) = e^{-2x}$ one has f'(x) = -2f(x), f''(x) = 4f(x), so by Itô's formula $df(X_t) = -2f(X_t)(dt + dW_t) + \frac{1}{2}4f(X_t)(dt + dW_t)^2 = -2f(X_t)dt 2f(X_t)dW_t + 2f(X_t)dt = -2f(X_t)dW_t$.
 - (ii) It is an MG indeed, using Remark 11.3.
- **26.** (i) Clearly, $c = S_0 = 5$ and $S_t = f(t, W_t)$ with $f(t, x) = 5e^{at+bx}$, so that $\partial_t f = af$, $\partial_x f = bf$, $\partial_{xx} f = b^2 f$. So, by Itô's formula, $dS_t = af(t, W_t)dt + \partial_x f(t, W_t)dW_t + \frac{1}{2}b^2 f(t, W_t)(dW_t)^2 = (a + \frac{b^2}{2})S_t dt + bS_t dW_t$. Comparing that with the assumed SDE, we obtain that $a + \frac{b^2}{2} = 0.2$, b = 1. So yes, the suspected form of S_t is correct, with a = -0.3, b = 1, c = 5.
- (ii) Either you apply Itô's formula to the verified representation $X_t := 1/S_t = (5e^{-0.3t+W_t})^{-1} = 0.5e^{0.3t-W_t}$, or you apply it directly to $f(S_t) = 1/S_t$ using the assumed SDE. Using the latter approach, one has $f'(x) = -x^{-2}$, $f''(x) = 2x^{-3}$, so that $df(S_t) = -S_t^{-2}(0.2S_t dt + S_t dW_t) + \frac{1}{2} 2S_t^{-3} (dS_t)^2 = -0.2S_t^{-1} dt S_t^{-1} dW_t + S_t^{-3} S_t^2 dt = 0.8X_t dt X_t dW_t$, QED.
- **27.** (i) Here $f(x) = \sqrt{x}$, $f'(x) = \frac{1}{2} x^{-1/2}$, $f''(x) = -\frac{1}{4} x^{-3/2}$, x > 0. So, by Itô's formula, $dZ_t = \frac{1}{2} V_t^{-1/2} ((1 V_t) dt + 2\sqrt{V_t} dW_t) + \frac{1}{2} (-\frac{1}{4} V_t^{-3/2}) (2\sqrt{V_t})^2 dt = -\frac{1}{2} V^{1/2}(t) dt + dW_t = -\frac{1}{2} Z dt + dW_t$, which is a special case of (11.46) (with $\alpha = \sigma = 1$). Clearly, $Z_0 = \sqrt{V_0} = 1$.
- (ii) Use the product rule of Itô's calculus (Theorem 11.10) with $X_t = e^{-t/2}$, $Y_t = 1 + \int_0^t e^{s/2} dW_s$. As one the factors is smooth $(dX_t = -\frac{1}{2} e^{-t/2} dt = -\frac{1}{2} X_t dt)$, by Remark 11.2 this will be just the usual product rule: $dZ_t = dX_t \cdot Y_t + X_t \cdot dY_t = -\frac{1}{2} X_t Y_t dt + X_t e^{-t/2} dW_t = -\frac{1}{2} Z_t dt + dW_t$. Obviously, $Z_0 = e^0 \left(1 + \int_0^0 \right) = 1$.