

① (a) See Lecture 2 and Lecture 4

(b) Note that for every n , we have

$$\begin{aligned} P(X_n > n) &= \int_n^\infty (a-1)x^{-a} I_{(1,\infty)}(x) dx \\ &= (a-1) \int_n^\infty x^{-a} dx = (a-1) \frac{x^{1-a}}{1-a} \Big|_n^\infty \\ &= n^{1-a} \end{aligned}$$

For $a \leq 2$, we have

$$\sum_{n=1}^{\infty} P(X_n > n) = \sum_{n=1}^{\infty} n^{1-a} = \infty,$$

so $X_n > n$ happens infinitely often with probability 1 by the second Borel-Cantelli lemma.

For $a > 2$,

$$\sum_{n=1}^{\infty} P(X_n > n) = \sum_{n=1}^{\infty} n^{1-a} < \infty,$$

so $X_n > n$ only happens finitely often with probability 1 by the first Borel-Cantelli lemma.

② Suppose X is integrable. Then X_n is also integrable, since

$$E(|X_n|) = E(\min(X, n)) \leq E(X) < \infty$$

For every $\varepsilon > 0$, there exists K such that

$$E(|X|; |X| > K) = E(X; X > K) < \varepsilon$$

For this K , we also have

$$E(|X_n|; |X_n| > K) \leq E(X; X > K) < \varepsilon$$

since $|X_n| = X_n \leq X$
thus $|X_n| > K$ implies $X > K$

showing uniform integrability.

Conversely, assume that the family $\{X_n; n \geq 0\}$ is uniformly integrable. There exists $K > 0$ such that

$$E(|X_n|; |X_n| > K) < \varepsilon \quad \text{for all } n$$

$$\Rightarrow E(\min(X, n); \min(X, n) > k) < 1 \quad \text{for all } n$$

Note that $\min(X, n) \cdot \mathbb{I}_{\{\min(X, n) > k\}}$ is monotone in n ; as $n \rightarrow \infty$, we have $\min(X, n) \rightarrow X$. Thus by monotone convergence,

$$E(\min(X, n); \min(X, n) > k) = E(\min(X, n) \cdot \mathbb{I}_{\{\min(X, n) > k\}}) \\ \xrightarrow{n \rightarrow \infty} E(X \mathbb{I}_{\{X > k\}}) = E(X; X > k)$$

It follows that

$$E(|X|) = E(X) = E(X; X \leq k) + E(X; X > k) \\ \leq k + 1 < \infty,$$

so X is integrable.

③ See Lecture 5

$$\begin{aligned} \text{④ (a) We have } E(\Theta^{X_n} | \mathcal{F}_{n-1}) &= E(\Theta^{X_{n-1} + Y_n} | \mathcal{F}_{n-1}) \\ &= \Theta^{X_{n-1}} E(\Theta^{Y_n}) \\ &= \Theta^{X_{n-1}} \left(\frac{1}{2} \Theta + \frac{1}{4} + \frac{1}{4} \Theta^{-1} \right) \end{aligned}$$

For Θ^{X_n} to be a martingale, we need

$$\frac{1}{2} \Theta + \frac{1}{4} + \frac{1}{4} \Theta^{-1} = 1 \Leftrightarrow \Theta^2 - \frac{3}{2} \Theta + \frac{1}{2} = 0 \\ \Leftrightarrow \Theta = 1 \text{ or } \Theta = \frac{1}{2}$$

So $(\frac{1}{2})^{X_n} = 2^{-X_n}$ is a martingale.

$$\begin{aligned} \text{(b) Since } E(X_n | \mathcal{F}_{n-1}) &= E(X_{n-1} + Y_n | \mathcal{F}_{n-1}) \\ &= X_{n-1} + E(Y_n) \\ &= X_{n-1} + \left(\frac{1}{2} \cdot 1 + \frac{1}{4} \cdot 0 + \frac{1}{4} \cdot (-1) \right) \\ &= X_{n-1} + \frac{1}{4} \end{aligned}$$

Taking $f(n) = \frac{n}{4}$, we obtain

$$E\left(X_n - \frac{n}{4} \mid \mathcal{F}_{n-1}\right) = X_{n-1} + \frac{1}{4} - \frac{n}{4} = X_{n-1} - \frac{(n-1)}{4}$$

showing that $X_n - \frac{n}{4}$ is a martingale.

(c) Consider the stopping time $\tau = \inf \{n: X_n = a \text{ or } X_n = -b\}$.

By the optional stopping theorem, we have

$$E(2^{-X_\tau}) = E(2^{-X_0}) = 1$$

On the other hand, $X_T \in \{a, -b\}$ by definition.

$$\Rightarrow E(2^{X_T}) = 2^{-a} P(X_T = a) + 2^b P(X_T = -b)$$

$P(X_T = a)$ is exactly the probability to reach a before $-b$.

We obtain

$$2^{-a} P(X_T = a) + 2^b (1 - P(X_T = a)) = 1$$

$$\Rightarrow P(X_T = a) = \frac{2^b - 1}{2^b - 2^{-a}}.$$

⑤ (a) True: If both $E(X_n | \mathcal{F}_{n-1}) \geq X_{n-1}$ (submartingale) and $E(X_n | \mathcal{F}_{n-1}) \leq X_{n-1}$ (supermartingale) then $E(X_n | \mathcal{F}_{n-1}) = X_{n-1}$, so X_n is a martingale.

(b) False: Consider for example the martingale given by $X_0 = 1$ and

$$X_n = \begin{cases} 2X_{n-1} & \text{with probability } \frac{1}{2} \\ 0 & \text{with probability } \frac{1}{2} \end{cases}$$

Now $T = \inf \{n : X_n = 0\}$ satisfies $P(T < \infty) = 1$, but $E(X_T) = 0 \neq 1 = E(X_0)$

(c) False: Consider for example the martingale given by $X_0 = 1$ and

$$X_n = \begin{cases} 2X_{n-1} & \text{with probability } \frac{1}{3} \\ \frac{1}{2}X_{n-1} & \text{with probability } \frac{2}{3} \end{cases}$$

We can write $X_n = X_{n-1} Y_n$, where

$$Y_n = \begin{cases} 2 & \text{with probability } \frac{1}{3} \\ \frac{1}{2} & \text{with probability } \frac{2}{3} \end{cases}$$

Note that

$$\ln X_n = \ln Y_1 + \ln Y_2 + \dots + \ln Y_n$$

$$\text{and } E(\ln Y_n) = \frac{1}{3} \cdot \ln 2 + \frac{2}{3} \cdot \ln \frac{1}{2} = -\frac{1}{3} \ln 2 < 0$$

By the strong law of large numbers,
 $\frac{\ln X_n}{n} \rightarrow -\frac{1}{3} \ln 2$ almost surely

Thus also

$$\lim_{n \rightarrow \infty} \ln X_n = -\infty$$

almost surely

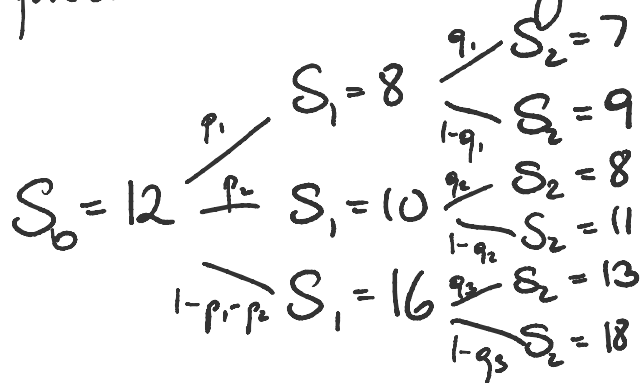
$$\lim_{n \rightarrow \infty} X_n = 0$$

even though clearly $X_n > 0$ for all n .

⑥ See Lecture 14

⑦ (a) See Lecture 15

(b) The probabilities in the diagram



should be such that $\bar{S}_t = S_t$ becomes a martingale.
 We need

$$\begin{aligned} 12 &= 8p_1 + 10p_2 + 16(1-p_1-p_2) \Leftrightarrow 8p_1 + 6p_2 = 4 \\ &\Leftrightarrow 4p_1 + 3p_2 = 2 \\ &\Leftrightarrow p_2 = \frac{1}{3}(2-4p_1) \end{aligned}$$

It follows that $1-p_1-p_2 = \frac{1}{3} + \frac{p_1}{3}$; p_1 can be arbitrary in the interval $(0, \frac{1}{2})$.

Moreover,

$$\begin{aligned} 8 &= 7q_1 + 9(1-q_1) & 10 &= 8q_2 + 11(1-q_2) & 16 &= 13q_3 + 18(1-q_3) \\ \Leftrightarrow q_1 &= \frac{1}{2} & \Leftrightarrow q_2 &= \frac{1}{3} & \Leftrightarrow q_3 &= \frac{2}{5} \end{aligned}$$

There exists an equivalent martingale measure, but it is not unique. Thus the model is viable, but not complete.

⑧ See Lectures 15 and 16