

- [10 pts] 1. Suppose $X : (\Omega, \mathcal{H}) \rightarrow (E, \mathcal{E})$ is a random variable taking values in the measurable space (E, \mathcal{E}) . Show that $V \in \sigma X$ iff there exists some measurable function $f : (E, \mathcal{E}) \rightarrow (\mathbb{R}, \mathcal{B}_{\mathbb{R}})$ such that $V = f \circ X$.

Solution: If $V = f \circ X$ then $V \in \sigma X$.

σX is generated by the p -system $\mathcal{P} = \{X^{-1}(B) : B \subseteq \mathbb{R} \text{ Borel}\}$. Let $H = X^{-1}(B)$ then $\mathbf{1}_H = \mathbf{1}_{X^{-1}(B)} = \mathbf{1}_B \circ X$.

That is, if $\mathcal{C} = \{V \in \sigma X : V = f \circ X \text{ for some measurable } f : E \rightarrow \mathbb{R}\}$ then $\mathbf{1}_H \in \mathcal{C}$. If V and W are in \mathcal{C} then there exist measurable f and g such that $V = f \circ X$ and $W = g \circ X$. Thus $cV + W = cf \circ X + g \circ X = (cf + g) \circ X \in \mathcal{C}$.

Finally, suppose $V_n \nearrow V$ for $V_n \in \mathcal{C}$. Then there exist measurable functions f_n so that $V_n = f_n \circ X$. We may assume that f_n is identically 0 on the complement of $X(\Omega)$ by multiplying by the appropriate indicator function if necessary. Define f on the image of X by

$$f(x) = \lim f_n(x) \quad x = X(\omega)$$

If we take f to be identically 0 on the complement of $X(\Omega)$ then $f_n \nearrow f$ and hence f is measurable. It follows that $V = f \circ X$ and thus \mathcal{C} is a monotone class. Since \mathcal{C} contains \mathcal{P} it contains all measurable functions in σX .

- [10 pts] 2. Suppose X_n are real-valued random variables with mean 0 and set $S_n = X_1 + \cdots + X_n$. Show that for every $a > 0$,

$$\mathbb{P}\{\max_{k \leq n} |S_k| > a\} \leq \frac{E[S_n^2]}{a^2}.$$

Solution: This is simply Kolmogorov's inequality. Define the random variable $N(\omega) = \inf\{k : |S_k(\omega)| > a\}$. Note that $\mathbf{1}_{N=k}$ can be given in terms of the random variables X_1, \dots, X_k and hence $U := \mathbf{1}_{N=k} S_k$ depends only on the variables X_1, \dots, X_k and is independent of $V := S_n - S_k$. Since $E[V] = 0$, we have

$$0 = E[V]E[U] = E[VU] = E[S_k(S_n - S_k)\mathbf{1}_{N=k}]$$

Also, $S_n^2 = [S_k + (S_n - S_k)]^2 \geq S_k^2 + 2(S_n - S_k)S_k$ and on the event $\{N = k\}$, $S_k^2 > a^2$. Thus,

$$E[S_n^2 \mathbf{1}_{N=k}] \geq a^2 E[\mathbf{1}_{N=k}] + 2E[S_k(S_n - S_k)\mathbf{1}_{N=k}] = a^2 \mathbb{P}\{N = k\},$$

and

$$a^2 \mathbb{P}\{N \leq n\} \leq \sum_{k=1}^n E[S_n^2 \mathbf{1}_{N=k}] = E[S_n^2 \mathbf{1}_{N \leq n}] \leq E[S_n^2] = \text{Var}(S_n).$$

This completes the proof since $\{N \leq n\} = \{\max_{k \leq n} |S_k| > a\}$.

- [10 pts] 3. Suppose (μ_n) is a tight sequence of probability measures on \mathbb{R} . Show that every subsequence of (μ_n) has a further subsequence that is weakly convergent. If you use Helly's theorem, give the precise statement, though you need not prove it.

Solution: Let (c_n) be the corresponding sequence of distribution functions of (μ_n) . By Helly's Theorem there is a subsequence $(c_{n'})$ and a distribution function c so that $c_{n'}$ converges to c at every point of continuity of c . Without tightness there is no guarantee that c is a distribution function in the sense of probability. That is, it remains to show

$$\lim_{x \rightarrow -\infty} c(x) = 0 \quad \text{and} \quad \lim_{x \rightarrow \infty} c(x) = 1$$

By tightness, there exists a closed interval $[a, b]$ such that $\mu_n[a, b] > 1 - \epsilon$ for all n . Thus, $\mu_n(-\infty, a) < \epsilon$ and $\mu_n(-\infty, b] > 1 - \epsilon$. This implies that $c(a) < \epsilon$ and $c(b) > 1 - \epsilon$. Since ϵ was arbitrary this shows that c is a distribution function in the sense of probability. If μ is the corresponding probability measure on \mathbb{R} then $\mu_{n'}$ converges weakly to μ .

4. Given probability space $(\Omega, \mathcal{H}, \mathbb{P})$, and sub-sigma algebra $\mathcal{F} \subset \mathcal{H}$.

- [3 pts] (a) What does it mean for $\mathbb{P}_{\mathcal{F}}$ to have a regular version? Be precise and define all relevant terms.

Solution: $Q(\omega, B)$ is a regular version for $\mathbb{P}_{\mathcal{F}}$ if Q is a probability kernel from (Ω, \mathcal{H}) into (Ω, \mathcal{F}) so that

$$E_{\mathcal{F}}[\mathbf{1}_H](\omega) = Q(\omega, H).$$

- [7 pts] (b) Suppose $\mathbb{P}_{\mathcal{F}}$ has a regular version Q and X is a real-valued random variable in L^1 . Show that a version of $E_{\mathcal{F}}[X]$ is given by

$$\omega \mapsto \int_{\Omega} X(\omega') Q_{\omega}(d\omega')$$

Solution: Note that by definition,

$$E_{\mathcal{F}}[\mathbf{1}_H](\omega) = Q(\omega, H) = \int_{\Omega} \mathbf{1}_H(\omega') Q_{\omega}(d\omega')$$

Monotone class, or definition of conditional expectation with monotone convergence does the rest.

5. Let $0 < T_1 < T_2 < \dots$ be a sequence of random times and define the process $N = (N_t)$ by

$$N_t = \sum_{n=1}^{\infty} 1_{[0, t]} \circ T_n$$

Let \mathcal{F} be the filtration generated by N .

- [3 pts] (a) Show that T_k is a stopping time of \mathcal{F} .

Solution: $\{T_k \leq t\} = \{N_t \geq k\} \in \mathcal{F}_t$

- [7 pts] (b) Suppose $T_k = t_1 + \dots + t_k$ for some independency of positive random variables $\{t_j\}$. Suppose $E[t_j] = 1/j^2$. Suppose $\text{Var}(t_j) = \frac{1}{j^6}$ and show that with probability 1 there is a random time T such that T is almost surely finite, and $N_T = +\infty$ almost surely.

Solution: Note that if $t_k < 2/k^2$ for all but finitely many then $T = \sum t_k$ is finite, and $N_T = \infty$. Thus it suffices to show that $t_k \geq 2/k^2$ only finitely often almost surely. By Chebyshev's inequality, for $\sigma_k^2 = \text{Var}(t_k) = 1/k^6$

$$\mathbb{P}\{|t_k - 1/k^2| \geq c\sigma_k\} \leq \frac{1}{c^2}$$

With $c = k$ this becomes

$$\mathbb{P}\{|t_k - 1/k^2| \geq \frac{1}{k^2}\} \leq \frac{1}{k^2}.$$

Moreover,

$$\mathbb{P}\{t_k \geq 2/k^2\} \leq \mathbb{P}\{|t_k - 1/k^2| \geq \frac{1}{k^2}\} \leq \frac{1}{k^2}.$$

Borel-Cantelli then implies that $\{t_k \geq 2/k^2\}$ happens only finitely often almost surely, and we're done.

- [10 pts] 6. Let $\mathbb{T} = \mathbb{N}$ and suppose F is a bounded predictable process with respect to filtration \mathcal{F} . Show that if M is a martingale with respect to \mathcal{F} then so too is $X = \int F dM$.

Solution: By definition,

$$X_n = M_0 F_0 + (M_1 - M_0) F_1 + \dots + (M_n - M_{n-1}) F_n.$$

To show that X_n is integrable, there exists $b > 0$ so that $|F_m| < b$ for all m . Hence

$$\begin{aligned} E[|X_n|] &\leq E[|M_0 F_0|] + E[|M_1 - M_0| |F_1|] + \dots + E[|M_n - M_{n-1}| |F_n|] \\ &\leq b(E[|M_0|] + E[|M_1 - M_0|] + \dots + E[|M_n - M_{n-1}|]) \\ &\leq 2b(E[|M_0|] + E[|M_1|] + \dots + E[|M_n|]) < \infty \end{aligned}$$

since each of the M_m are integrable.

Adaptability is obvious, since M_0, \dots, M_n and F_0, \dots, F_n are in \mathcal{F}_n .

Finally,

$$E_n[X_{n+1} - X_n] = E_n[F_{n+1}(M_{n+1} - M_n)] = F_{n+1}E_n[M_{n+1} - M_n] = 0.$$

[10 pts] 7. Let X be a martingale and ζ a stopping time. Show that $\widehat{X} = (X_{t \wedge \zeta})$ is a martingale.

Solution: If ζ is bounded, and $S \leq \zeta$, then $E_S[X_\zeta] = X_S$. In particular, $X_{t \wedge \zeta} = E_{t \wedge \zeta}[X_\zeta]$ and for $s < t$, $E_s[X_{t \wedge \zeta}] = E_s[E_{t \wedge \zeta}[X_\zeta]] = E_{s \wedge \zeta}[X_\zeta] = X_{s \wedge \zeta}$. Hence, in this situation, \widehat{X} is a martingale. (Something about integrability)

For the general case, we will show that \widehat{X} is a Doob martingale on $[0, b]$ for all b . Let T be a stopping time bounded by b . Then, $T \wedge \zeta$ is bounded by b , and $E[X_{T \wedge \zeta}] = E[X_0]$. Since $X_{T \wedge \zeta} = \widehat{X}_T$ and $X_0 = \widehat{X}_0$, we have $E[\widehat{X}_T] = E[\widehat{X}_0]$ for all stopping times T bounded by b . It follows that \widehat{X} is a Doob martingale on $[0, b]$ for all b , and hence is a martingale.

8. Let $W = (W_t)$ be a standard Wiener process.

[5 pts] (a) Show that $W^2 - t$ is a martingale.

Solution: Since $E[W_t^2] = t$ we see that $W_t^2 - t$ is integrable. For the martingale condition, let $s < t$ and note

$$W_t^2 = (W_s + W_t - W_s)^2 = W_s^2 + 2W_s(W_t - W_s) + (W_t - W_s)^2$$

Thus,

$$E_s[W_t^2] = W_s^2 + 2W_s E_s[W_t - W_s] + E_s[(W_t - W_s)^2].$$

Since $W_t - W_s$ is independent of \mathcal{F}_s , we see $E_s[W_t - W_s] = E[W_t - W_s] = E[W_{t-s}] = 0$ and $E_s[(W_t - W_s)^2] = E[(W_{t-s})^2] = t - s$. Thus,

$$E_s[W_t^2] = W_s^2 + t - s$$

as desired.

[5 pts] (b) Let $T_a = \inf\{t > 0 : |W_t| \geq a\}$. Compute $E[T_a]$.

Solution: Assuming we can use the stopping time theorem, then

$$0 = E[W_0^2] = E[W_{T_a}^2 - T_a] = a^2 - E[T_a]$$

and hence $E[T_a] = a^2$. The student should make some effort to justify why the stopping time theorem is applicable.