mas550 homework

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Problem (1.1.2)**.**

Let $A = \Pi_{i=1}^{d}(a_i, b_i]$*. Then*

$$A = \left(\Pi_{i=1}^{d}[a_i - 1, b_i]\right) \cap \left(\Pi_{I=1}^{d}(a_i, b_i + 1)\right)$$

which is intersection of open set and closed set. So, $A \in \mathcal{R}^d$ *therefore* $\sigma(S_d) \subset \mathcal{R}^d$*.*

On the other hand, let $B = \Pi_{i=1}^{d}(a_i, b_i)$ *where* $-\infty < a_i < b_i < \infty$*. We can choose sequences* $\{a_{i,j}\}_{j=1}^{\infty}$ *and* $\{b_{i,j}\}_{j=1}^{\infty}$ *for each* $1 \leq i \leq d$ *such that* $a_{i,j} \downarrow a_i$ *and* $b_{i,j} \uparrow b_i$*. Then* $B_n = \Pi_{i=1}^{d}(a_{i,n}, b_{i,n}] \uparrow B$*. So* B *is a countable union of open rectangles, hence* $B \in \sigma(S_d)$*. Since such* B *forms basis of topology on* $\mathbb{R}^d$*, we can conclude that* $\mathcal{R}^d \subset \sigma(S_d)$*.*

Problem (1.2.3)**.**

Let F *be a distribution function. It is nonnegative, nondecreasing. So* $\lim_{y \downarrow x} F(y)$ *and* $\lim_{y \uparrow x} F(y)$ *always exist. Let* x *be a point where* F *is discontinuous. Since* F *is discontinuous at* x*, we can assume without loss of generality* $\lim_{y \downarrow x} F(y) > F(x)$*. Choose a rational number* $q_x \in (F(x), \lim_{y \downarrow x} F(y))$*. Then function* $x \mapsto q_x$ *is injective since* F *is nondecreasing. So there is injection from set of discontinuities to rational numbers. Now we can conclude that set of discontinuities is at most countable.*

Problem (1.3.4)**.**

(a) Let $f : \mathbb{R}^d \to \mathbb{R}$ *be a continuous function. Consider* $\mathcal{B} = \left\{U \subset \mathbb{R} : f^{-1}(U) \in \mathcal{R}^d\right\}$*. It is well known that* $\mathcal{B}$ *is a* σ*-field. By continuity of* f*,* $\mathcal{B}$ *contains every open set of* $\mathbb{R}$*, hence* $\mathcal{R} \subset \mathcal{B}$*. Therefore* f *is a measurable function.*

(b) Let $\mathcal{F}$ *be a* σ*-field that makes all the continuous functions measurable. Let* $\pi_i : \mathbb{R}^d \to \mathbb{R}$ *be the projection on* i*-th factor, which is continuous. Then* $\cap_{i=1}^{d} \pi_i^{-1}((a_i, b_i)) = \Pi_{i=1}^{d}(a_i, b_i) \in \mathcal{F}$*. Since* $\mathcal{F}$ *contains every open rectangles in* $\mathbb{R}^d$*, we can conclude that* $\mathcal{R}^d \subset \mathcal{F}$*. This means* $\mathcal{R}^d$ *is the smallest such* σ*-field. The fact that* $\mathcal{R}^d$ *makes all the continuous functions measurable is written in (a).*

Problem (1.3.1)**.**

Since $\sigma(X)$ *is the smallest* σ*-field which makes* X *measurable, it sufficient to show that* X *is measurable with respect to* $\sigma\left(X^{-1}(\mathcal{A})\right)$.

Let $X : \Omega \to S$. *It is clear that* $\{X \in A\} \in \sigma\left(X^{-1}(\mathcal{A})\right)$ *for all* $A \in \mathcal{A}$. *But by theorem 1.3.1, since* $\mathcal{A}$ *generates* $\mathcal{S}$, X *is measurable with respect to* $\sigma\left(X^{-1}(\mathcal{A})\right)$.

Therefore we can conlude that $\sigma\left(X^{-1}(\mathcal{A})\right) \subset \sigma(X)$, *and reverse inclusion is canonical since* $X^{-1}(\mathcal{A}) \subset \sigma(X)$.

Problem (1.4.1)**.**

Let $E_n = \left\{x : f(x) > \frac{1}{n}\right\}$. *Then* $\int f d\mu \geq \int_{E_n} f d\mu \geq \int_{E_n} \frac{1}{n} d\mu = \frac{1}{n}\mu(E_n)$. *Therefore* $\mu(E_n) = 0$ *for every positive integer* n. *So,* $\mu(\{f > 0\}) = \sum_{n=1}^{\infty} \mu(E_n) = 0$. *This says* $f = 0$ *a.e.*

Problem (1.4.2)**.** *Since* $E_{n+1,2m} \cup E_{n+1,2m+1} = E_{n,m}$ *and* $\frac{2m+1}{2^{n+1}} \geq \frac{m}{2^n}$, *we can easily see that* $\sum_{m\geq 1} \frac{m}{2^n}\mu(E_{n,m})$ *is monotonically increasing as* n *grows.*

For every positive integer M, $\sum_{m=1}^{M} \frac{m}{2^n}\mu(E_{n,m}) \leq \int f d\mu$. *So* $\sum_{m\geq 1} \frac{m}{2^n}\mu(E_{n,m}) \leq \int f d\mu$.

Let $s_n = \sum_{m=1}^{n2^n} \frac{m}{2^n} 1_{E_{n,m}}$. *Then* $\int s_n d\mu \leq \sum_{m\geq 1} \frac{m}{2^n}\mu(E_{n,m}) \leq \int f d\mu$. *But* $s_n \uparrow f$ *monotonically. By monotone convergence theorem,* $\lim_{n\to\infty} \int s_n d\mu = \int f d\mu$. *Hence by sandwich lemma, the desired result follows.*

Problem (1.5.1).

First, we will show that $|g| \leq \|g\|_\infty$ *a.e.*

It is true because

$$\begin{aligned}\mu\left(|g| > \|g\|_\infty\right) &= \mu\left(\bigcup_{n=1}^{\infty}\left\{|g| \geq \|g\|_\infty + \frac{1}{n}\right\}\right)\\ &\leq \sum_{n=1}^{\infty}\mu\left(\left\{|g| > \|g\|_\infty + \frac{1}{n}\right\}\right)\\ &= 0\end{aligned}$$

by definition of $\|g\|_\infty$.

Hence $|g| \leq \|g\|_\infty$ *a.e.*

Then, $\int |fg| d\mu \leq \|g\|_\infty \int |f| d\mu = \|g\|_\infty \|f\|_1$.

Problem (1.5.3).

(a) *Since* $p > 1$, $x \mapsto |x|^p$ *is convex function.* $|f+g|^p \leq 2^{p-1}(|f|^p + |g|^p)$ *follows from convexity of* $|x|^p$.

$\int |f+g|^p d\mu \leq \int 2^p |f|^p d\mu + \int 2^p |g|^p d\mu$. *Therefore finiteness of* $\|f\|_p$ *and* $\|g\|_p$ *leads* $\|f+g\|_p < \infty$.

Now, consider $\int |f+g|^p d\mu = \int |f+g||f+g|^{p-1} d\mu \leq \int |f||f+g|^{p-1} d\mu + \int |g||f+g|^{p-1} d\mu$. *Let* q *be Holder conjugate of* p. *Then by applying Holder inequality, we get* $\|f+g\|_p^p \leq \|f+g\|_p^{p/q}(\|f\|_p + \|g\|_p)$. *Simple calculating leads Minkowski's inequality.*

(b) *First consider* $p = 1$. *By using triangle inequaltiy, the result follows directly. Next consider* $p = \infty$. $|f+g| \leq |f| + |g| \leq \|f\|_\infty + \|g\|_\infty$ *a.e. Therefore* $\|f+g\|_\infty \leq \|f\|)\infty + \|g\|_\infty$.

Problem (1.6.8).

First assume $g = 1_A$. *Then* $\int g d\mu = \mu(A) = \int_A f(x) dx = \int 1_A f dm$ *where* m *is Lebesgue measure.*

Next, assume $g = \sum_i a_i 1_{A_i}$, *simple function. Then* $\int g d\mu = \sum_i a_i \mu(A_i) = \sum_i a_i \int 1_{A_i} f dm$.

Next, assume g *is nonnegative measurable. Let* $\{s_n\}_{n=1}^\infty$ *be increasing sequence of simple function converges to g pointwisely. Then* $\int g d\mu = \lim_{n\to\infty} \int s_n d\mu =$

$\lim_{n\to\infty}\int s_n f dm$. *But* $s_n f \uparrow gf$ *since* f *is nonnegative. By monotone convergence theorem, we can get* $\int g d\mu = \int gf dm$.

Last, assume g *is integrable function. We can decompose* g *by* $g = g^+ - g^-$. *Applying 3rd step for* g^+, g^- *each, we can get* $\int g d\mu = \int g^+ f dm - \int g^- f dm = \int gf dm$ *since* f *is nonnegative.*

Problem (1.6.13)**.**

Since $X_n \uparrow X$, $X_n^+ \uparrow X^+$ *and* $X_n^- \downarrow X^-$. *And note that* $X_n^- \leq X_1^-$ *which is integrable. Apply monotone convergence theorem to* X_n^+ *and apply dominated convergence theorem to* X_n^- *to get* $\lim EX_n = \lim EX_n^+ - \lim EX_n^- = EX^+ - EX^- = EX$.

Problem (1.7.1)**.**

We need to show that $\int_{X\times Y} |f| d(\mu_1 \times \mu_2) < \infty$*.*

Since $|f|^{\pm}$ *is nonnegative, by Fubini's theorem,* $\int_X \int_Y |f|^{\pm} \mu_2(dy)\mu_1(dx) < \infty$*. Then, their sum is also finite, and the sum is* $\int_{X\times Y} |f| d(\mu_1 \times \mu_2)$ *by Fubini's theorem. This leads the conclusion of the exercise.*

Corollary is immediate if we take $\mu_1 = c$ *and* $\mu_2 = \mu$*.*

Problem (1.7.3)**.**

1.

$$\begin{aligned}\int_{(a,b]} \{F(y) - F(a)\}\, dG(y) &= \int_{(a,b]} \int_{(a,y]} 1\mu(dx)\nu(dy) \\ &= \int_{a<x\le y\le b} 1 d(\mu\times\nu) \\ &= \mu\times\nu(1 < X \le Y \le b)\end{aligned}$$

by Fubini's theorem on nonnegative function 1*.*

2.

$$\begin{aligned}\int_{(a,b]} F(y)dG(y) &= \int_{(a,b]} \int_{-\infty}^{y} 1\mu(dx)\nu(dy) \\ &= \int_{(-\infty,a]} \int_{(a,b]} 1\nu(dy)\mu(dx) + \int_{(a,b]} \int_{[x,b]} \nu(dy)\mu(dx) \\ &= F(a)\{G(b) - G(a)\} + G(b)\{F(b) - F(a)\} \\ &- \int_{(a,b]} G(x)\mu(dx) + \int_{(a,b]} G(x) - G(x^-)\mu(dx)\end{aligned}$$

We can get similar result for $\int_{(a,b]} G(y)dF(y)$*. By simple calculation, we get the conclusion of (2).*

3. *If* $F = G$ *continuous, Then* $\mu(\{x\}) = \nu(\{x\}) = F(x) - F(x^-) = G(x) - G(x^-) = 0)$*. Therefore, by using (2), we can get the conclusion.*

Problem (2.1.3)**.**

1. *If* $h(\alpha) = 0$ *for some* $\alpha > 0$*, by mean value theorem,* $h'(\beta) = 0$ *for some* $\beta \in (0, \alpha)$*. It contradicts to* $h'(x) > 0$ *for positive* x*. Therefore* $h > 0$ *for positive* x*.*

$x = y$ iff $\rho(x,y) = 0$ iff $h(\rho(x,y)) = 0$. And $h(\rho(x,y)) = h(\rho(y,x))$ since $\rho(x,y) = \rho(y,x)$.

Now consider $x \geq y > 0$ and $\frac{h(x+y)-h(x)}{y} = h'(x+\theta)$ and $\frac{h(y)}{y} = h'(y-\delta)$. Since h' is decreasing, $h(x+y) - h(x) \leq h(y)$. Using this, we can prove triangle inequality of $h \circ \rho$.

2. *$h(x) = 1 - \frac{1}{1+x}$ so $h'(x) = \frac{1}{(1+x)^2}$ and $h''(x) = \frac{-2}{(1+x)^3}$. Given h satisfies all of (1).*

Problem (2.1.9)**.**

Let $\mathcal{A}_1 = \{\{1,2\},\{1,3\}\}, \mathcal{A}_2 = \{\{1,4\}\}$. For $A_1 \in \mathcal{A}_1$ and $A_2 \in \mathcal{A}_2$, $P(A_1 \cap A_2) = P(A_1)P(A_2) = 1/4$. But, $\sigma(\mathcal{A}_1) = 2^\Omega$ and $\sigma(\mathcal{A}_2) = \{\Omega, \{1,4\}, \{2,3\}, \emptyset\}$. They are not independent by considering $A_1 = \{2,3,4\}$ and $A_2 = \{2,3\}$.

Problem (2.2.3)**.**

(a) *$f(U_i)$'s are iid because* $P\left(\bigcap_i (f \circ U_i) \in B_i\right) = P\left(\bigcap_i \left\{U_i \in f^{-1}(B_i)\right\}\right) = \Pi_i P\left(U_i \in f^{-1}(B_i)\right) = \Pi_i P\left(f(U_i) \in B_i\right)$. *Also, for borel set* B, $P\left(f(U_i) \in B\right) = P\left(U_i \in f^{-1}(B_i)\right)$ *are all same for* i.

$Ef(U_i) = \int_0^1 f(x)dx$, $E|f(U_i)| = \int_0^1 |f(x)|dx < \infty$.

Now, by WLLN, $\frac{\sum f(U_i)}{n}$ *converges to* $\int_0^1 f(x)dx$ *in probability.*

(b) $P\left(|I_n - I| > a/n^{0.5}\right) \le \frac{n}{a^2} E|I_n - I|^2 = \frac{n}{a^2} Var(I_n) = Var(\sum f(U_i))/na^2 = Var(f(U_i))/a^2 = \left[\int_0^1 f(x)^2 dx - \left(\int_0^1 f(x)dx\right)^2\right]/a^2$.

Problem (2.2.5)**.**

Note that $P(X_i \le a) = 0$ *for all* $a < e$.

$xP(X_i > x) = \frac{e}{\log x} \to 0$ *as* $x \to \infty$.

$E|X_i| = EX_i = \int_e^\infty P(X_i > x)dx = \int_e^\infty \frac{e}{x \log x} dx = \infty$ *since* $X_i \ge 0$ *almost surely.*

But $\mu_n = \int_{|X_i| \le n} X_i dP \uparrow EX_i = \infty$ *by monotone convergence theorem.*

Now, theorem 2.2.12 says $\frac{s_n}{n} - \mu_n$ *converges to* 0 *in probability.*

Problem (2.3.5)**.**

(a) *Let* $F_N = \{Y \le N\}$ *and* $Y_n = Y 1_{F_n}$*. Then* $EY_n \uparrow EY$ *by MCT. So choose* N *so that* $EY - EY_N < \varepsilon$*. Now consider* $|EX_n - EX| \le E|X_n - X| \le \int_{|X_n - X| > \varepsilon} 2Y dP + \int_{|X_n - X| \le \varepsilon} |X_n - X| dP \le \varepsilon + \int_{|X_n - X| > \varepsilon} 2Y dP$*.*

Let $E_n = \{|X_n - X| > \varepsilon\}$*. Then* $\int_{E_n} 2Y dP = \int_{E_n} 2Y - 2Y_N + 2Y_N dP \le E(2Y - 2Y_N) + 2NP(E_n)$*, where the last term goes to* 0 *as* $n \to \infty$*.*

(b) *Let* h, g *be continuous functions,* $h(0) = 0$*,* $g > 0$ *for large* x*,* $|h|/g \to 0$ *as* $|x| \to \infty$*, and* $Eg(X_n) \le C < \infty$*.*

Choose M *so large that* $g > 0$ *on* $|x| > M$*.* $\varepsilon_M = \sup_{|x| \ge M} |h|/g$ *and* $\bar{Y} = Y 1_{|Y| \le M}$*.*

Then $|Eh(X_n) - Eh(X)| \le E|h(X_n) - Eh(\bar{X}_n)| + E|h(\bar{X}_n - h(\bar{X})| + E|h(\bar{X}) - h(X)|$*. First term and third term are bounded by* $\varepsilon_M C$ *which goes to* 0 *as* $M \to \infty$*. And the second term goes to* 0 *as* $n \to \infty$ *by bounded convergence thm.*

Therefore the conclusions hold.

Problem (2.3.6.)**.**

(a) *We already show that* $\rho(x, y) = \frac{|x-y|}{1+|x-y|}$ *is a metric in problem 2.1.3.*

First consider $d(X, Y) = 0$ *iff* $E\frac{|X-Y|}{1+|X-Y|} = 0$ *iff* $\frac{|X-Y|}{1+|X-Y|} = 0$ *a.s. iff* $X = Y$ *a.s.*

Next, it is trivial to check $d(X, Y) = d(Y, X)$*.*

Lastly, $d(X, Z) = E\rho(X, Z) \le E\left(\rho(X, Y) + \rho(Y, Z)\right) = E\rho(X, Y) + E\rho(Y, Z) = d(X, Y) + d(Y, Z)$*.*

Therefore given function is a metric of class of random variables.

(b) *First assume* $X_n \to X$ *in probability. Then* $\frac{|X_n - X|}{1+|X_n - X|} \le 1$ *and it goes to* 0 *in probability. So bounded convergence thm implies* $d(X_n, X) \to 0$*.*

Next assume $d(X_n, X) \to 0$ *as* $n \to 0$*.*

$$\begin{aligned} P(|X_n - X| > \varepsilon) &= P\left(\frac{|X_n - X|}{1 + |X_n - X|} > \frac{\varepsilon}{1+\varepsilon}\right) \\ &\le E\frac{|X_n - X|}{1 + |X_n - X|}\frac{1+\varepsilon}{\varepsilon} \\ &= d(X_n, X)\frac{1+\varepsilon}{\varepsilon} \to 0 \end{aligned}$$

by Markov's inequality.

Problem (2.3.8)**.**

Independence of A_n implies independence of A_n^c. Let $B_n = \cap_{k=1}^n A_k^c$. Then $0 = P\left(\bigcap_{n=1}^\infty A_n^c\right) = \lim_{n\to\infty} P(B_n)$.

So, for arbitrary $\varepsilon > 0$, there is a positive integer N_ε such that $n \ge N_\varepsilon$ implies $P(B_n) = P\left(\cap_{k=1}^n A_k^c\right) = \Pi_{k=1}^n \left(1 - P(A_k)\right) = e^{\sum_{k=1}^n \log(1-P(A_k))} < \varepsilon$. But as $n \to \infty$

$$\lim_{n\to\infty} e^{\sum_{k=1}^n \log(1-P(A_k))} = 0$$

This means that $\sum_{k=1}^\infty \log\left(1 - P(A_k)\right) = -\infty$, therefore $\log\left(1 - P(A_k)\right)$ does not converge to 0, which is equivalent to that $P(A_k)$ does not converge to 0. Therefore $\sum_{n=1}^\infty P(A_n) = \infty$.

Problem (2.3.12)**.**

Let $\Omega = \{\omega_i : i \in \mathbb{N}\}$. Without loss of generality, we can assume $P(\{\omega_i\}) > 0$ for all $i \in \mathbb{N}$.

If there is ω_i such that $X_n(\omega_i)$ does not converge to $X(\omega_i)$, then for some $\varepsilon > 0$, and for all $N \in \mathbb{N}$, there is $n_N \ge N$ but $|X_{n_N}(\omega_i) - X(\omega_i)| > \varepsilon$.

This means $\{|X_{n_N} - X| > \varepsilon\}$ contains ω_i for all N. So $0 < P(\{\omega_i\}) \le P\left(|X_{n_N} - X| > \varepsilon\right)$.

But $X_n \to X$ in probability implies $X_{n_N} \to X$ in probability. This contradicts to above. Therefore there is no such w_i hence X_n converges to X almost surely.