

Probability Theory

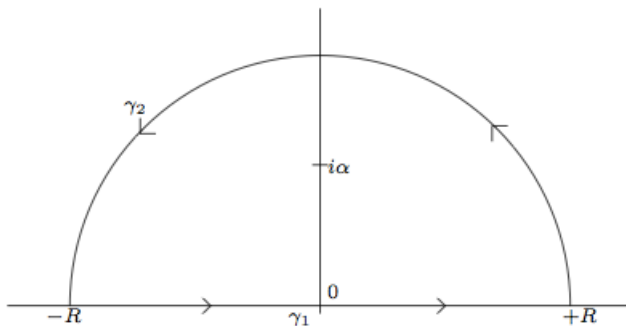
Solution sheet 5

Solution 5.1

(a) We calculate

$$\begin{aligned}
 E[e^{itX}] &= \int_{\mathbb{R}} e^{itx} (1 - |x|) 1_{[-1,1]}(x) dx = \int_{-1}^1 (1 - |x|) e^{itx} dx \\
 &= \int_{-1}^1 e^{itx} dx + \int_{-1}^0 x e^{itx} dx - \int_0^1 x e^{itx} dx \\
 &= \frac{1}{it} (e^{it} - e^{-it}) + \left(\frac{e^{-it}}{it} + \frac{1}{t^2} - \frac{e^{-it}}{t^2} \right) - \left(\frac{e^{it}}{it} + \frac{e^{it}}{t^2} - \frac{1}{t^2} \right) \\
 &= \frac{2}{t} \sin(t) - \frac{2}{t} \sin(t) - \frac{2}{t^2} \cos(t) + \frac{2}{t^2} = \frac{2}{t^2} (1 - \cos(t)).
 \end{aligned}$$

(b) We use the Residue Theorem (for more details on Residue theorem and contour integrals we refer you to the book “Real and complex analysis” by Rudin) for $f(x) = \frac{e^{itx}}{x^2 + \alpha^2}$ to calculate $E[e^{itX}] = \frac{\alpha}{\pi} \int_{-\infty}^{+\infty} \frac{e^{itx}}{x^2 + \alpha^2} dx$. Extend f to \mathbb{C} by $f(z) = \frac{e^{itz}}{z^2 + \alpha^2}$. Let us consider the curve $\gamma = \gamma_1 \cup \gamma_2$ as follows:



Thus, we calculate for all $R > \alpha$,

$$\oint_{\gamma} f(z) dz = 2\pi i \cdot \underbrace{n(\gamma, i\alpha)}_{=1} \cdot \text{Res}_{i\alpha}(f) = 2\pi i \cdot \lim_{z \rightarrow i\alpha} (z - i\alpha) f(z) = 2\pi i \cdot \lim_{z \rightarrow i\alpha} \frac{e^{itz}}{z + i\alpha} = \frac{\pi}{\alpha} e^{-\alpha t}.$$

Since we have, for $t \geq 0$,

$$\begin{aligned} \left| \int_{\gamma_2} f(z) dz \right| &= \left| \int_0^\pi f(Re^{i\theta}) iRe^{i\theta} d\theta \right| = \left| \int_0^\pi \frac{e^{itRe^{i\theta}} iRe^{i\theta}}{R^2 e^{2i\theta} + \alpha^2} d\theta \right| \\ &\leq \int_0^\pi \left| \frac{e^{itRe^{i\theta}} iRe^{i\theta}}{R^2 e^{2i\theta} + \alpha^2} \right| d\theta = \int_0^\pi \frac{Re^{-Rt \sin(\theta)}}{|R^2 e^{2i\theta} + \alpha^2|} d\theta \\ &\leq \int_0^\pi \frac{R}{|R^2 e^{2i\theta} + \alpha^2|} d\theta \leq \int_0^\pi \frac{R}{R^2 - \alpha^2} d\theta = \frac{\pi R}{R^2 - \alpha^2} \xrightarrow{R \rightarrow \infty} 0, \end{aligned}$$

we obtain that

$$E[e^{itX}] = \lim_{R \rightarrow \infty} \frac{\alpha}{\pi} \int_{\gamma_1} f(z) dz = \lim_{R \rightarrow \infty} \frac{\alpha}{\pi} \int_\gamma f(z) dz = e^{-\alpha t}.$$

For $t < 0$, one can use a similar argument to show $E[e^{itX}] = e^{\alpha t}$. Thus, we get, for $t \in \mathbb{R}$,

$$E[e^{itX}] = e^{-\alpha|t|}.$$

Solution 5.2

- (a) Take $y \in \mathbb{R}$. For $y < 0$, because the exponential distribution is concentrated on $[0, \infty)$, we have that

$$P[nY_n \leq y] = 0 = P[Z \leq y] \text{ for all } n \in \mathbb{N}.$$

Hence without loss of generality we assume $y \geq 0$. It follows that for all $n \geq y$:

$$\begin{aligned} P[nY_n \leq y] &= P\left[Y_n \leq \frac{y}{n}\right] = P\left[\bigcup_{i=1}^n \left\{X_i \leq \frac{y}{n}\right\}\right] = 1 - P\left[\bigcap_{i=1}^n \left\{X_i > \frac{y}{n}\right\}\right] \\ &= 1 - \prod_{i=1}^n P\left[X_i > \frac{y}{n}\right] = 1 - \left(1 - \frac{y}{n}\right)^n. \end{aligned}$$

Now let $n \rightarrow \infty$, we hence obtain that

$$\lim_{n \rightarrow \infty} P[nY_n \leq y] = 1 - e^{-y} = \int_{-\infty}^y e^{-x} 1_{[0, \infty)}(x) dx.$$

- (b) Take $y \in \mathbb{R}$. Then for all $n \geq e^{-y}$ we have that:

$$\begin{aligned} P[M_n - \log n \leq y] &= P[M_n \leq y + \log n] = P\left[\bigcap_{i=1}^n \{X_i \leq y + \log n\}\right] \\ &= \prod_{i=1}^n \underbrace{P[X_i \leq y + \log n]}_{=1 - e^{-y - \log n} = 1 - \frac{e^{-y}}{n}} = \left(1 - \frac{e^{-y}}{n}\right)^n. \end{aligned}$$

Now let $n \rightarrow \infty$, we hence obtain that

$$\lim_{n \rightarrow \infty} P[M_n - \log n \leq y] = \exp(-e^{-y}) = \int_{-\infty}^y e^{-x} \exp(-e^{-x}) dx.$$

Solution 5.3 We first show that the claim in the hint implies the main claim. (cf. (2.3.25) in lecture notes). We assume that $P_n \xrightarrow{w} P$. Then there exists a point of continuity of $F(\cdot) := P((-\infty, \cdot])$ and a subsequence $n(k)$ with

$$|F_{n(k)}(y) - F(y)| \geq \epsilon \quad \forall k \in \mathbb{N}, \text{ where } F_n(\cdot) := P_n((-\infty, \cdot]).$$

Hence this subsequence has no sub-subsequence converging weakly to P . This contradicts obviously the claim in the hint.

To show the claim in the hint, we need multiple steps. We first show that $(P_n)_{n \in \mathbb{N}}$ is tight. Take $\epsilon > 0$ arbitrary. We obtain that

$$\begin{aligned} P_n([-M, M]^c) &= \int_{-\infty}^{-M} P_n(dx) + \int_M^{\infty} P_n(dx) \leq \int_{-\infty}^{-M} \frac{x^2}{M^2} P_n(dx) + \int_M^{\infty} \frac{x^2}{M^2} P_n(dx) \\ &\leq \frac{1}{M^2} \int_{-\infty}^{\infty} x^2 P_n(dx) \xrightarrow{n \rightarrow \infty} \frac{\alpha_2}{M^2}. \end{aligned}$$

Because $\alpha_2 = \int_{\mathbb{R}} x^2 P(dx) < \infty$, we can choose an $M > 0$ such that $\frac{\alpha_2}{M^2} \leq \frac{\epsilon}{2}$. We can therefore find an $N \in \mathbb{N}$ with $P_n([-M, M]^c) \leq \epsilon \quad \forall n > N$. On the other side it is clear that for each $k \in \{1, \dots, N\}$, an $M_k > 0$ exists with $P_k([-M_k, M_k]^c) \leq \epsilon$. For $M^* := \max\{M, M_1, \dots, M_N\}$ it follows then

$$\sup_{n \in \mathbb{N}} P_n([-M^*, M^*]^c) \leq \epsilon.$$

The tightness implies by (2.2.26) that each subsequence of $(P_n)_{n \in \mathbb{N}}$ has a sub-subsequence $(P_{n_k(l)})_{l \in \mathbb{N}}$ that converges weakly towards a probability measure \tilde{P} .

We now show that $\tilde{P} = P$. By Proposition 2.7 in the lecture notes, there exist random variables $Y_{n_k(l)}$, $l \in \mathbb{N}$ and \tilde{Y} in a probability space (Ω, \mathcal{A}, Q) such that

$$Y_{n_k(l)} \sim P_{n_k(l)}, \quad l \in \mathbb{N}, \quad \tilde{Y} \sim \tilde{P}, \quad \text{and } Y_{n_k(l)} \xrightarrow{l \rightarrow \infty} \tilde{Y} \quad Q\text{-a.s.}$$

We show that the moments of $Y_{n_k(l)}$ for $l \rightarrow \infty$ converge towards those of \tilde{Y} respectively. Let $m \in \mathbb{N}$ and $M > 0$ arbitrary. Hence:

$$\begin{aligned} \left| E^Q [Y_{n_k(l)}^m] - E^Q [\tilde{Y}^m] \right| &\leq E^Q [|Y_{n_k(l)}^m - \tilde{Y}^m|] \\ &\leq E^Q [|Y_{n_k(l)}^m - \tilde{Y}^m| \mathbf{1}_{\{|Y_{n_k(l)}^m| \leq M, |\tilde{Y}^m| \leq M\}}] \\ &\quad + 3E^Q [|Y_{n_k(l)}^m| \mathbf{1}_{\{|Y_{n_k(l)}^m| > M\}}] + 3E^Q [|\tilde{Y}^m| \mathbf{1}_{\{|\tilde{Y}^m| > M\}}]. \end{aligned} \tag{1}$$

The first term converges towards 0 for $l \rightarrow \infty$ thanks to the Lebesgue dominated convergence theorem. For the second term, one has that

$$E^Q [|Y_{n_k(l)}^m| \mathbf{1}_{\{|Y_{n_k(l)}^m| > M\}}] = E^Q \left[\frac{Y_{n_k(l)}^{2m}}{|Y_{n_k(l)}^m|} \mathbf{1}_{\{|Y_{n_k(l)}^m| > M\}} \right] \leq \frac{1}{M} E^Q [Y_{n_k(l)}^{2m}] \xrightarrow{l \rightarrow \infty} \frac{\alpha_{2m}}{M}.$$

Because we can take $M > 0$ arbitrarily big, we obtain that $E^Q [|Y_{n_k(l)}^m| \mathbf{1}_{\{|Y_{n_k(l)}^m| > M\}}] \xrightarrow{l, M \rightarrow \infty} 0$.

We estimate the third term in (1) with the help of Fatou's lemma:

$$E^Q [\tilde{Y}^{2m}] \leq \liminf_{l \rightarrow \infty} E^Q [Y_{n_k(l)}^{2m}] = \alpha_{2m}.$$

Note that each $Y_{n_k(l)}^{2m}$ is non-negative thanks to the even exponent $2m$ so that Fatou's lemma is valid in this case. This implies that $\tilde{Y}^{2m} \in L^1$ and therefore, by Jensen's inequality, $\tilde{Y}^m \in L^1$.

Consequently, $E^Q \left[|\tilde{Y}^m| \mathbf{1}_{\{|\tilde{Y}^m| > M\}} \right] \xrightarrow{M \rightarrow \infty} 0$. By (1) the convergence of the moments follows, i.e. $E^Q [Y_{n_k(l)}^m] \rightarrow E^Q [\tilde{Y}^m]$ as $l \rightarrow \infty$. Since, by assumption, $E^Q [Y_{n_k(l)}^m] \rightarrow \alpha_m$ as $l \rightarrow \infty$, we have that the m th moment of \tilde{P} is α_m for all $m \geq 1$. Since P is the unique measure that satisfies the latter equality for all $m \in \mathbb{N}$, we get $P = \tilde{P}$.

Remark:

Now let us give a more detailed explanation of the remark after Exercise 5.3. For each $a \in [-1, 1]$, we define a measure μ_a on \mathbb{R} via

$$\mu_a(dx) := \frac{1}{\sqrt{2\pi x}} \exp\left(-\frac{(\log x)^2}{2}\right) (1 + a \sin(2\pi \log x)) \mathbf{1}_{(0, \infty)}(x) dx.$$

First let us verify that μ_a actually defines a probability measure for all $a \in [-1, 1]$. Indeed, using the substitution $y = \log(x)$ we have

$$\begin{aligned} \int_{\mathbb{R}} \mu_a(dx) &= \frac{1}{\sqrt{2\pi}} \int_0^\infty \frac{1}{x} \exp\left(-\frac{(\log x)^2}{2}\right) (1 + a \sin(2\pi \log x)) dx \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^\infty \exp\left(-\frac{y^2}{2}\right) (1 + a \sin(2\pi y)) dy \\ &= \underbrace{\frac{1}{\sqrt{2\pi}} \int_{-\infty}^\infty \exp\left(-\frac{y^2}{2}\right) dy}_{=1} + \underbrace{\frac{a}{\sqrt{2\pi}} \int_{-\infty}^\infty \exp\left(-\frac{y^2}{2}\right) \sin(2\pi y) dy}_{=0, \text{ since } \sin \text{ is an odd function}} = 1. \end{aligned}$$

(For $a = 0$, the measure μ_0 is called the distribution of *standard log-normal* random variable, that is, μ_0 is the distribution of random variable $Y = \exp(X)$ with X a standard normal random variable.) We now claim that the k th moment $\int x^k \mu_a(dx)$ does *not* depend on a . Indeed, for any $a \in [-1, 1]$, using the substitution $x = e^{k+u}$ we get:

$$\begin{aligned} \int_{\mathbb{R}} x^k \mu_a(dx) &= \int_0^\infty \frac{x^{k-1}}{\sqrt{2\pi}} \exp\left(-\frac{(\log x)^2}{2}\right) (1 + a \sin(2\pi \log x)) dx \\ &= \int_{-\infty}^\infty \frac{\exp(k(k+u))}{\sqrt{2\pi}} \exp\left(-\frac{(k+u)^2}{2}\right) (1 + a \sin(2\pi(k+u))) du \\ &= \frac{e^{\frac{k^2}{2}}}{\sqrt{2\pi}} \int_{-\infty}^\infty e^{-\frac{u^2}{2}} (1 + a \sin(2\pi(k+u))) du \\ &= \underbrace{\frac{e^{\frac{k^2}{2}}}{\sqrt{2\pi}} \int_{-\infty}^\infty e^{-\frac{u^2}{2}} du}_{=e^{\frac{k^2}{2}}} + \underbrace{\frac{ae^{\frac{k^2}{2}}}{\sqrt{2\pi}} \int_{-\infty}^\infty e^{-\frac{u^2}{2}} \sin(2\pi(k+u)) du}_{=0, \text{ since } \sin \text{ is odd}} = e^{\frac{k^2}{2}}. \end{aligned}$$

Clearly, this counterexample shows that in general a probability measure P can *not* be uniquely determined by its moments. Therefore the hypothesis regarding the uniqueness of P in the statements of Exercise 5.3 can not be removed.