





University of New South Wales

SCHOOL OF MATHEMATICS AND STATISTICS

Assignment 2

Measure Theory

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2.1

Suppose u and ν are σ -finite positive measures on (Ω, \mathcal{F}) . Then suppose that $\mu << \nu$ and $\nu << \mu$. Then for $A \in \mathcal{F}$ we have that $\mu(a) = 0 \Rightarrow \nu(A) = 0$ and $\nu(A) = 0 \Rightarrow \mu(A)$. That is to say that $\nu(A) = 0 \Leftrightarrow \mu(A) = 0$. That is to say that ν and μ have the same null sets. This argument is symmetric so it is clear that the reverse implication also holds.

We now wish to show that there is an \mathcal{F} -measurable function g that satisfies $0 < g(\omega) < +\infty$ at each $\omega \in \Omega$ and is such that $\nu(A) = \int_A g d\mu$ for all $A \in \mathcal{F}$.

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3.1

Firstly note that the definition of the characteristic function is

$$\hat{\mu}_X(u) = \mathbb{E}[\exp(i\langle X, u\rangle)] \tag{1}$$

and so for the random vector cX with $c \in \mathbb{R}$ we have that

$$\hat{\mu}_{cX}(u) = \mathbb{E}[\exp(i\langle cX, u\rangle)] \tag{2}$$

$$= \mathbb{E}[\exp(i\langle X, cu\rangle)] \tag{3}$$

$$=\hat{\mu}_X(cu)\tag{4}$$

3.2

3.3

Let d = 1 and let μ have the Lebesgue density,

$$f(x) = \frac{C}{(1+x^2)\log(e+x^2)}, \quad x \in \mathbb{R}.$$
 (5)

We wish to show that E[X] is not defined but $\hat{\mu}(u)$ is differentiable at 0. Firstly we show that E[X] is not defined.

$$E[X] = \int_{-\infty}^{\infty} \frac{Cx}{(1+x^2)\log(e+x^2)} dx$$
 (6)

$$= \int_{-\infty}^{\infty} \frac{C}{(x^{-1} + x)\log(e + x^2)}$$
 (7)

note that

$$\frac{C}{(x^{-1}+x)\log(e+x^2)} \sim \frac{C}{2x\log(x)} \tag{8}$$

and

$$\int_{a}^{\infty} \frac{C}{2x \log(x)} dx, \text{ and } \int_{-\infty}^{b} \frac{C}{2x \log(x)} dx$$
 (9)

do not converge so $\mathbb{E}[X]$ does not exist.

We now just have to show that $\hat{mu}(u)$ is differentiable at u=0.

$$\hat{\mu}(u) = \int_{-\infty}^{\infty} \frac{e^{iux}C}{(1+x^2)\log(e+x^2)} dx$$
 (10)

and

$$\frac{d}{du}\hat{\mu}(u)\Big|_{u=0} = \int_{-\infty}^{\infty} \frac{ixe^{iux}C}{(1+x^2)\log(e+x^2)} dx \tag{11}$$

4

Let μ be the binomial distribution with n trials and probability of success p, that is $\mu = \text{Bin}(n, p)$, and let ν be the Poisson distribution with mean $\lambda > 0$.

4.1

We wish to verify that $\hat{\mu}(u) = (1 - p + pe^{iu})^n$. Because the binomial distribution is just the convolution of identical independent Bernoulli distributions then we just have to verify that $(1-p+pe^{iu})$ is the characteristic function for Bernoulli(p).

If ν is the Bernoulli measure and X has law ν then

$$\hat{\nu}(u) = \mathbb{E}[\exp(iuX)] \tag{12}$$

$$= \sum_{k \in \{0,1\}} e^{iuk} \nu_X(k) \tag{13}$$

$$= pe^{iu} + (1-p). (14)$$

Then by repeated application of the convolution theorem we get that $\hat{\mu}(u) = (1 - p + pe^{iu})^n$.

4.2

We wish to verify that $\hat{\nu}(u) = \exp(\lambda(e^{iu} - 1))$. The probability mass function of the Poisson distribution is

$$\frac{\lambda^k}{k!}e^{-\lambda} \tag{15}$$

and thus

$$\mathbb{E}[\exp(iuX)] = \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} e^{-\lambda} e^{iuk}$$
(16)

$$=e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} (e^{iu})^k \tag{17}$$

$$=e^{-\lambda} \sum_{k=0}^{\infty} \frac{(\lambda e^{iu})^k}{k!} \tag{18}$$

$$=e^{-\lambda}e^{\lambda e^{iu}}\tag{19}$$

$$=e^{\lambda(e^{iu}-1)}\tag{20}$$

4.3

We wish to show that if p_n is a sequence in [0,1] such that $p_n \downarrow 0$ and $np_n \longrightarrow \lambda$ then $\mu_n \longrightarrow \nu$ in the weak sense where $\mu_n = \text{Bin}(n, p_n)$.

Let $f \in C_b$ then

$$E[f(X_n)] = \sum_{k=0}^{n} f(k)\mu_n(k)$$
(21)

$$= \sum_{k=0}^{n} f(k)\mu_n(k)$$
 (22)

$$= \sum_{k=0}^{n} f(k) \binom{n}{k} p_n^k (1 - p_n)^{n-k}$$
 (23)

then

$$\lim_{n \to \infty} E[f(X_n)] = \lim_{n \to \infty} \sum_{k=0}^n f(k) \binom{n}{k} p_n^k (1 - p_n)^{n-k}$$
(24)

and

$$\mathbb{E}[f(Y)] = f(x)\nu(x) \tag{25}$$

$$=\sum_{k=0}^{\infty}f(k)\frac{\lambda^k}{k!}e^{-\lambda}$$
 (26)

(27)

5

5.1

We wish to show that $\mathbb{P}(B_n) = 1/2$ for every $n \geq 1$. Note that

$$B_n = \bigcup_{k=0}^{2^{n-1}-1} \left[\frac{2k}{2^n}, \frac{2k+1}{2^n} \right)$$
 (28)

and thus

$$\mathbb{P}(B_n) = \mathbb{P}\left(\bigcup_{k=0}^{2^{n-1}-1} \left[\frac{2k}{2^n}, \frac{2k+1}{2^n}\right)\right)$$
 (29)

$$=\sum_{k=0}^{2^{n-1}-1} \mathbb{P}\left(\left[\frac{2k}{2^n}, \frac{2k+1}{2^n}\right)\right)$$
 (30)

$$=\sum_{k=0}^{2^{n-1}-1} \frac{1}{2^n} \tag{31}$$

$$=2^{n-1}\frac{1}{2^n}\tag{32}$$

$$=\frac{1}{2}. (33)$$

5.2

We now wish to show that the sequence of events B_n form an infinite sequence of independent events. Take a finite subset $J \subset \mathbb{N}$ with |J| = m and $\max J = r$ then

$$\mathbb{P}\left(\bigcap_{n\in J} B_n\right) = \mathbb{P}\left(\bigcap_{n\in J} \bigcup_{k=0}^{2^{n-1}-1} \left[\frac{2k}{2^n}, \frac{2k+1}{2^n}\right)\right)$$
(34)

$$= \mathbb{P}\left(\bigcup_{k=0}^{2^{r-m}-1} \left[\frac{2k}{2^r}, \frac{2k+1}{2^r}\right)\right)$$
 (35)

$$= \sum_{k=0}^{2^{r-m}-1} \mathbb{P}\left(\left[\frac{2k}{2^n}, \frac{2k+1}{2^n}\right)\right)$$
 (36)

$$=2^{r-m}\frac{1}{2^r}$$
 (37)

$$=\frac{1}{2^m}\tag{38}$$

$$=\prod_{n\in J}\mathbb{P}\left(B_{n}\right)\tag{39}$$

and so the sequence of events B_n form an infinite sequence of independent events.

5.3