

## Solution to Midterm Exam

1. (a) Clearly,  $\nu(A) \geq 0$  and  $\nu(\emptyset) = 0$ . For any disjoint and countably many sets  $B_1, B_2, \dots$  in  $\mathcal{A}$ ,

$$\begin{aligned} \nu(\cup_{k=1}^{\infty} B_k) &= \sum_{i=1}^n \omega_i \mu(\cup_{k=1}^{\infty} (B_k \cap A_i)) = \sum_{i=1}^n \omega_i \left\{ \sum_{k=1}^{\infty} \mu(B_k \cap A_i) \right\} \\ &= \sum_{k=1}^{\infty} \left\{ \sum_{i=1}^n \omega_i \mu(B_k \cap A_i) \right\} = \sum_{k=1}^{\infty} \nu(B_k). \end{aligned}$$

Thus,  $\nu$  is a measure.

- (b) Clearly, if  $\mu(A) = 0$  then  $\nu(A) = 0$ . Thus,  $\nu \prec\prec \mu$ .

- (c) Note  $\nu(A) = \int_A \{ \sum_{i=1}^n \omega_i I_{A_i}(x) \} d\mu(x)$ . Then

$$\frac{d\nu}{d\mu}(x) = \sum_{i=1}^n \omega_i I_{A_i}(x).$$

2. Since  $|(1 + t/n)^{-n}| \leq (1 + t/2)^{-2}$ , by the dominated convergence theorem,

$$\lim_{n \rightarrow \infty} \int_{t \in [0, \infty)} (1 + t/n)^{-n} d\lambda(t) = \int_{t \in [0, \infty)} \lim_{n \rightarrow \infty} (1 + t/n)^{-n} d\lambda(t) = \int_{t \in [0, \infty)} e^{-t} dt = 1.$$

From the Fubini-Tonelli theorem,

$$\begin{aligned} \int_{(t,x) \in [0, \infty) \times (1,2)} \frac{\exp\{-xt\}}{1+x^2} d(\lambda \times \lambda)(t,x) &= \int_{x \in (1,2)} \int_{t \in [0, \infty)} \frac{\exp\{-xt\}}{1+x^2} d\lambda(t) d\lambda(x) \\ &= \int_1^2 \frac{1}{x(1+x^2)} dx = \int_1^4 \frac{1}{2y(1+y)} dy = \frac{1}{2} \log(8/5). \end{aligned}$$

3. (a) Since  $Cov(X + Y, X - Y) = Cov(X, X) - Cov(Y, Y) = 0$ ,  $X + Y$  and  $X - Y$  are independent. Clearly,  $R^2 = X^2 + Y^2 = [(X + Y)^2 + (X - Y)^2]/2$ .

- (b) Given  $X - Y = 0$ ,  $R^2 = (X + Y)^2/2$ . Moreover, from (a), the conditional distribution of  $R^2$  given  $X - Y = 0$  is the same as the unconditional distribution of  $R^2$ . Since  $(X + Y)/\sqrt{2}$  has a standard normal distribution,  $R^2$  follows a chi-squared distribution with one degree of freedom.

- (c) Using the transformation  $X = R \cos \Theta, Y = R \sin \Theta$ , we obtain the joint density of  $(R, \Theta)$  as

$$r \exp\{-r^2/2\} I(r \geq 0) \times \frac{1}{2\pi} I_{[0, 2\pi)}(\theta).$$

Thus,  $R$  and  $\Theta$  are independent. Moreover,  $R$  has the density function  $r \exp\{-r^2/2\}$   $I(r \geq 0)$  then

$$P(R^2 \leq r) = \exp\{-r/2\}.$$

That is,  $R^2$  has a distribution  $\Gamma(1, 2)$ ; i.e.,  $R^2$  follows a chi-squared distribution with two degrees of freedom.

- (d) This is because the two sub- $\sigma$ -fields are different: one is the  $\sigma$ -field generated by  $\{X - Y = 0\}$ ; the other one is the  $\sigma$ -field generated by  $\{\Theta = \pi/4\}$  or the  $\sigma$ -field generated by  $\{\Theta = 5\pi/4\}$ .

4. “ $\Rightarrow$ ”: If  $X_n \rightarrow_p X$ , then for any small  $\epsilon > 0$ ,

$$P\left(\frac{|X_n - X|}{1 + |X_n - X|} > \epsilon\right) = P(|X_n - X| > \epsilon/(1 - \epsilon)) \rightarrow 0.$$

Thus,

$$\frac{|X_n - X|}{1 + |X_n - X|} \rightarrow_p 0.$$

From the dominated convergence theorem, since  $|X_n - X|/(1 + |X_n - X|) \leq 1$ , we obtain

$$E\left[\frac{|X_n - X|}{1 + |X_n - X|}\right] \rightarrow 0.$$

“ $\Leftarrow$ ”: Since  $g(x) = x/(1 + x)$  is increasing, by the Markov’s inequality,

$$P(|X_n - X| > \epsilon) \leq \frac{E[g(|X_n - X|)]}{g(\epsilon)} \rightarrow 0.$$