

## Math 563 - Homework 7

1. The gamma distribution is a two parameter family of distributions for non-negative random variables. The parameters  $\lambda$  and  $\gamma$  are both positive and the density is

$$f(x) = \frac{\lambda^\gamma}{\Gamma(\gamma)} x^{\gamma-1} e^{-\lambda x}, \quad x \geq 0$$

where  $\Gamma$  is the usual gamma function. ( $\Gamma(z) = \int_0^\infty x^{z-1} e^{-x} dx$ .)

(a) Compute the characteristic function of this distribution.

(b) Show that the gamma distributions are infinitely divisible.

2. Suppose  $X$  is a bounded RV that is infinitely divisible. Show it is a constant. Hint: show its variance is zero.

**Solution:** Let  $M$  be such that  $|X| \leq M$  a.s. Let  $n$  be a positive integer. Infinitely divisible means that there exists i.i.d.  $X_1, X_2, \dots, X_n$  such that  $X_1 + X_2 + \dots + X_n$  is equal in distribution to  $X$ .

If  $X_k > M/n$  for all  $k$ , then  $\sum_{k=1}^n X_k > M$ . So

$$P(X_k > M/n, \forall k) \leq P\left(\sum_{k=1}^n X_k > M\right) = P(X > M) = 0$$

Since they are i.i.d.,  $P(X_k > M/n, \forall k) = P(X_1 > M/n)^n$ .

So  $P(X_1 > M/n) = 0$ . A similar argument shows  $P(X_1 < -M/n) = 0$ . So  $|X_1| \leq M/n$  a.s.

The above bound implies  $\text{var}(X_1) \leq E[X^2] \leq M^2/n^2$ . So

$$\text{var}(X) = \text{var}\left(\sum_{k=1}^n X_k\right) = \sum_{k=1}^n \text{var}(X_k) \leq n \frac{M^2}{n^2} = \frac{M^2}{n}$$

This is true for all  $n$ , so  $\text{var}(X) = 0$ . Hence  $X = E[X]$  a.s.

**Comment:** The conclusion that  $|X_k| \leq M/n$  does not just follow from  $|X| \leq M$ . Consider the following example. Take the probability space to be  $\{1, 2, \dots, n\}$  with the uniform probability measure, i.e., each point has probability  $1/n$ . Define the RV  $X_k$  to be 1 when  $\omega = k$  and 0 when  $\omega \neq k$ . Then  $X_1 + X_2 + \dots + X_n = 1$ . But we do not have  $|X_k| \leq 1/n$ . Note that in this example the  $X_k$  are identically distributed, but not independent.

3. The theorem that we proved in class on Poisson convergence (law of rare events) has the following generalization:

**Theorem** For each  $n$ , let  $\{X_{n,k} : k = 1, 2, \dots, n\}$  be independent random variables whose values are non-negative integers. Let  $p_{n,k} = P(X_{n,k} = 1)$  and  $\epsilon_{n,k} = P(X_{n,k} \geq 2)$ . Suppose that there is a  $\lambda \in (0, \infty)$  such that

- (1)  $\sum_{k=1}^n p_{n,k} \rightarrow \lambda$
- (2)  $\max_{1 \leq k \leq n} p_{n,k} \rightarrow 0$
- (3)  $\sum_{k=1}^n \epsilon_{n,k} \rightarrow 0$

Let  $S_n = \sum_{k=1}^n X_{n,k}$ . Then  $S_n$  converges in distribution to a Poisson distribution with mean  $\lambda$ .

For this problem do one of the following.

(a) Prove the above.

**Solution:** One approach is to adapt the proof of the theorem from class. Here is a shorter, less obvious proof. Define  $X'_{n,k}$  to be 1 when  $X_{n,k}$  is 1, 0 when  $X_{n,k}$  is not 1. Let  $S'_n = \sum_{k=1}^n X'_{n,k}$ . Note that  $P(X'_{n,k} = 1) = p_{n,k}$ . By (1) and (2) and the theorem from class,  $S'_n$  converges to a Poisson RV with parameter  $\lambda$ .

Now

$$P(S'_n \neq S_n) \leq P(\cup_k \{X'_{n,k} \neq X_{n,k}\}) \leq \sum_{k=1}^n P(X'_{n,k} \neq X_{n,k}) = \sum_{k=1}^n \epsilon_{n,k} \rightarrow 0$$

as  $n \rightarrow \infty$ . So  $S'_n - S_n$  converges to 0 in probability. It follows (proved in last homework) that  $S_n + (S'_n - S_n) = S'_n$  converges in distribution to the Poisson distribution.

(b) Use the new theorem to show that if  $N$  is a random variable whose values are non-negative integers and it is infinitely divisible, then it has a Poisson distribution.

**Solution:** This is not true without further conditions. We assume there is a  $\lambda > 0$  such that  $P(N = 0) = e^{-\lambda}$  and  $P(N = 1) = \lambda e^{-\lambda}$ . In particular,  $P(N = 0) > 0$ .

For each  $n$  let  $X_{n,k}$ ,  $k = 1, 2, \dots, n$  be i.i.d. with  $X_{n,1} + \dots + X_{n,n} = N$  in distribution. We first argue that the  $X_{n,k}$  can only take on nonnegative integer values. We have

$$0 = P(N < 0) = P\left(\sum_{k=1}^n X_{n,k} < 0\right) \geq P(X_{n,k} < 0, \forall k) = P(X_{n,1} < 0)^n$$

Hence  $P(X_{n,k} < 0) = 0$ . This implies that  $P(N = 0) = P(X_{n,1} = 0)^n$ . So  $P(X_{n,1} = 0) > 0$ . Now let  $m$  be a positive integer.

Consider  $P(X_{n,k} \in (m-1, m))$ . We have

$$\begin{aligned} P(N \in (m-1, m)) &\geq P(X_{n,1} \in (m-1, m), X_{n,k} = 0, k = 2, 3, \dots) \\ &= P(X_{n,1} \in (m-1, m))P(X_{n,2} = 0)^{n-1} \end{aligned}$$

Since  $P(N \in (m-1, m)) = 0$ , we must have  $P(X_{n,1} \in (m-1, m)) = 0$ . This is true for all  $m$ . So  $X_{n,1}$  only takes non-negative integer values.

Now let  $p_n = P(X_{n,k} = 1)$ ,  $\epsilon_n = P(X_{n,k} \geq 2)$ . So  $P(X_{n,k} = 0) = 1 - p_n - \epsilon_n$ . By our assumptions

$$\begin{aligned} e^{-\lambda} &= P(N = 0) = P(X_{n,k} = 0, k = 1, 2, \dots, n) = (1 - p_n - \epsilon_n)^n \\ \lambda e^{-\lambda} &= P(N = 1) = \sum_{j=1}^n P(X_{n,j} = 1, X_{n,k} = 0, k \neq j) = np_n(1 - p_n - \epsilon_n)^{n-1} \end{aligned}$$

The first equation implies that  $p_n \rightarrow 0$  and  $\epsilon_n \rightarrow 0$ . Dividing the second equation by the first,

$$\lambda = \frac{np_n}{1 - p_n - \epsilon_n}$$

Hence  $np_n \rightarrow \lambda$ . This proves (1) and (2). Now take the ln of first equation:

$$\lambda = -n \ln(1 - p_n - \epsilon_n)$$

For  $x \geq 0$ ,  $-\ln(1 - x) \geq x$ , so

$$\lambda \geq n(p_n + \epsilon_n)$$

Since  $np_n \rightarrow \lambda$ , this implies  $n\epsilon_n \rightarrow 0$  which proves (3).

4. A random variable  $X$  is symmetric if  $\mu_X$  is invariant with respect to the  $x \rightarrow -x$ . Equivalently,  $X$  is symmetric if  $X$  and  $-X$  have the same distribution. Show that if  $X$  is a symmetric random variable with finite variance which is infinitely divisible, then its characteristic function may be written as

$$\exp \left[ 2 \int_{[0, \infty)} \frac{\cos(tx) - 1}{x^2} \mu(dx) \right]$$

where  $\mu$  is a finite measure on  $[0, \infty)$  and  $(\cos(tx) - 1)/x^2$  is understood to be  $-t^2/2$  at  $x = 0$ .

**Solution:** For any random variable,

$$\beta(-t) = E[\exp(-itX)] = \overline{E[\exp(itX)]} = \overline{\beta(t)}$$

If  $X$  is symmetric, then

$$\beta(-t) = E[\exp(-itX)] = E[\exp(itX)] = \beta(t)$$

Hence,  $\beta(t) = \overline{\beta(t)}$ . So  $\beta(t)$  is real.

Since  $X$  is infinitely divisible, by the Levy-Khinchin representation

$$\begin{aligned} \beta(t) &= \exp\left(ibt + \int_{\mathbb{R}} \frac{e^{itx} - 1 - itx}{x^2} \mu(dx)\right) \\ &= \exp\left(\int_{\mathbb{R}} \frac{\cos(itx) - 1}{x^2} \mu(dx)\right) \exp\left(ibt + \int_{\mathbb{R}} \frac{i \sin(tx) - itx}{x^2} \mu(dx)\right) \end{aligned}$$

This is real for all  $t$ , so  $bt + \int_{\mathbb{R}} \frac{\sin(tx) - tx}{x^2} \mu(dx)$  is an integer multiple of  $2\pi$  for all  $t$ . But it is continuous in  $t$  and equals 0 at  $t = 0$ . So this quantity is zero for all  $t$ .

Thus

$$\beta(t) = \exp\left(\int_{\mathbb{R}} \frac{\cos(itx) - 1}{x^2} \mu(dx)\right)$$

Let  $p = \mu(0)$ . Define  $\mu^+$  by  $\mu^+(B) = \mu(B \cap (0, \infty))$ . Define  $\mu^-$  by  $\mu^-(B) = \mu(B \cap (-\infty, 0))$ . Then  $\mu = \mu^+ + \mu^- + p\delta_0$ , where  $\delta_0$  is unit mass at 0. For  $B \subset [0, \infty)$ , define  $\nu(B) = \mu^+(B) + \mu^-(-B) + p\delta_0(B)$ . Then

$$\int_{\mathbb{R}} \frac{\cos(itx) - 1}{x^2} \mu(dx) = \int_{[0, \infty)} \frac{\cos(itx) - 1}{x^2} \nu(dx)$$

**Comment:** If  $\mu(\{0\}) > 0$ , we do not have

$$\int_{\mathbb{R}} f(x)\mu(dx) = \int_0^{\infty} f(x)\mu(dx) + \int_{-\infty}^0 f(x)\mu(dx)$$

In fact,  $\int_0^{\infty} f(x)\mu(dx)$  is ambiguous. It could mean  $\int_{(0, \infty)} f(x)\mu(dx)$  or  $\int_{[0, \infty)} f(x)\mu(dx)$ , and they are not equal.