

# Homework 8

Math 561: Theory of Probability I

Due date: March 23, 2023

Each problem is worth 10 points and only four randomly chosen problems will be graded if there are more than 5 problems. Please indicate whom you worked with, it will not affect your grade in any way.

1. Show that, for  $X_i, i = 1, 2, 3 \dots$  independent (but not identically distributed) random variables with  $\mathbb{E}(X_i) = 0$  and  $\text{Var}(X_i) = 1$  for all  $i$ ,  $n^{-1/2} \sum_{i=1}^n X_i$  need not converge to  $N(0,1)$  in distribution.
2. Lindeberg and Lyapunov impose conditions on moments so that asymptotic normality occurs. However, it is possible to have asymptotic normality even if there are no moments at all. Let  $X_n$  assume the values  $+1$  and  $-1$  with probability  $(1 - 2^{-n})/2$  each and the value  $2^k$  with probability  $2^{-k}$  for  $k > n$ .
  - (a) Show that  $\mathbb{E}(X_n^j) = \infty$  for all positive integers  $j$  and  $n$ .
  - (b) Show that  $n^{-1/2} \sum_{i=1}^n X_i \implies N(0,1)$ .

**Hint:** Use cutoff and characterization of convergence in distribution w.r.t. almost sure convergence.
3. (**Maxima of Gaussian**) Let  $X_1, X_2, \dots$  be i.i.d. standard normal r.v.s with density  $\phi(x) = 1/\sqrt{2\pi}e^{-x^2/2}$  and distribution function  $\Phi(x) = \int_{-\infty}^x \phi(t)dt$ .

(i) Prove Mill's ratio approximation:

$$\frac{1}{x} - \frac{1}{x^3} \leq \frac{1 - \Phi(x)}{\phi(x)} \leq \frac{1}{x}, \quad x > 0,$$

(ii) Prove that for any  $\theta \in \mathbb{R}$ , we have

$$\frac{\mathbb{P}(X_1 > x + \theta/x)}{\mathbb{P}(X_1 > x)} \rightarrow e^{-\theta} \text{ as } x \rightarrow \infty.$$

(iii) Define  $b_n$  such that  $\mathbb{P}(X_1 > b_n) = 1/n$ . Show that for  $M_n = \max_{1 \leq i \leq n} X_i$  we have, for any  $x \in \mathbb{R}$ ,

$$\mathbb{P}(b_n(M_n - b_n) \leq x) \rightarrow \exp(-e^{-x}) \text{ as } n \rightarrow \infty.$$

The distribution with cdf  $e^{-e^{-x}}, x \in \mathbb{R}$  is called the Gumble distribution. This result says that the maxima of  $n$  iid  $N(0,1)$  rvs is concentrated around  $b_n$  with fluctuations of order  $1/b_n$ .

(iv) Using (i), show that  $b_n$  satisfies

$$b_n \left( b_n - \left[ \sqrt{2 \log n} - \frac{\log(4\pi \log n)}{2\sqrt{2 \log n}} \right] \right) \rightarrow 0$$

as  $n \rightarrow \infty$ .

4. (**Total variation distance.**) Given two probability measure  $\mu, \nu$  on  $\mathbb{R}$  we define the *total variation distance* as

$$d_{\text{TV}}(\mu, \nu) = \sup_A |\mu(A) - \nu(A)| \in [0, 1].$$

- (i) Show that this is indeed a distance and strictly stronger than convergence in distribution.
- (ii) If there exists a countable subset  $D$  such that  $\mu(D) = \nu(D) = 1$ , show that

$$d_{\text{TV}}(\mu, \nu) = \frac{1}{2} \sum_{d \in D} |\mu(\{d\}) - \nu(\{d\})|.$$

(iii) If  $X_n$  converges to  $X$  in distribution and  $\mathbb{P}(X_n \in \mathbb{Z}) = 1, n \geq 1$ , then

$$d_{\text{TV}}(\mu_n, \mu) \rightarrow 0 \text{ as } n \rightarrow \infty$$

where  $\mu_n, \mu$  are the distributions of  $X_n, X$ , respectively.

5. **(The Lévy Metric.)** (a) Show that

$$\rho(F, G) = \inf\{\varepsilon : F(x - \varepsilon) - \varepsilon \leq G(x) \leq F(x + \varepsilon) + \varepsilon \text{ for all } x\}$$

defines a metric on the space of distributions and  $\rho(F_n, F) \rightarrow 0$  if and only if  $F_n \xrightarrow{(d)} F$ .

(b) As a corollary prove that, if  $F_n \xrightarrow{(d)} F$  and  $F$  is continuous everywhere, then

$$\sup_x |F_n(x) - F(x)| \rightarrow 0 \text{ as } n \rightarrow \infty.$$

6. **(Converging together lemma.)** (i) If  $X_n \Rightarrow X, Y_n \Rightarrow c$  where  $c > 0$  is a constant and  $X_n, Y_n$  are defined on the same probability space, then  $X_n + Y_n \Rightarrow X + c$  and  $X_n Y_n \Rightarrow cX$ . (We assumed  $c > 0$  only to make the proof simpler.)

(ii) If  $X_1, X_2, \dots$  are i.i.d. with  $\mathbb{E} X_1 = 0, \text{Var}(X_1) < \infty$ , using SLLN, CLT and part (i) prove that

$$\frac{X_1 + X_2 + \dots + X_n}{\sqrt{X_1^2 + X_2^2 + \dots + X_n^2}} \Rightarrow N(0, 1).$$

This is called **Self-normalized Central Limit theorem**.