

## In-Class Problems — Week 15, Mon

**Problem 1.** Prove that the Central Limit Theorem implies the Weak Law of Large Numbers. *Hint:* The only properties of  $N(y)$  needed in the proof are that  $\lim_{y \rightarrow \infty} N(y) = 1$  and  $\lim_{y \rightarrow \infty} N(-y) = 0$ .

**NOTE:** We didn't get to the following problem in class.

**Problem 2.** To clarify the somewhat subtle difference between the Weak and Strong Laws of Large Numbers, we will construct an example of a sequence  $X_1, X_2, \dots$  of mutually independent random variables that satisfies the Weak Law of Large Numbers, but not the Strong Law. The distribution of  $X_i$  will have to depend on  $i$ , because otherwise both laws would be satisfied.<sup>1</sup>

In particular, let  $X_1, X_2, \dots$  be a sequence of mutually independent random variables such that  $X_1 = 0$ , and for each integer  $i > 1$ ,

$$\Pr\{X_i = i\} = \frac{1}{2i \log i}, \quad \Pr\{X_i = -i\} = \frac{1}{2i \log i}, \quad \Pr\{X_i = 0\} = 1 - \frac{1}{i \log i}.$$

Note that  $\mu = E[X_i] = 0$  for all  $i$ .

(a) Show that  $\text{Var}[S_n] = \Theta(n^2 / \log n)$ . *Hint:*  $n / \log n > i / \log i$  for  $2 \leq i \leq n$ .

(b) Show that the sequence  $X_1, X_2, \dots$  satisfies the Weak Law of Large Numbers, *i.e.*, prove that for any  $\epsilon > 0$

$$\lim_{n \rightarrow \infty} \Pr\left\{\left|\frac{S_n}{n}\right| \geq \epsilon\right\} = 0.$$

We now show that the sequence  $X_1, X_2, \dots$  does not satisfy the Strong Law of Large Numbers.

(c) (The first Borel-Cantelli lemma.) Let  $A_1, A_2, \dots$  be any infinite sequence of mutually independent events such that

$$\sum_{i=1}^{\infty} \Pr\{A_i\} = \infty. \tag{1}$$

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<sup>1</sup>This problem is adapted from Grinstead & Snell, *Intro. to Probability*, Ch.8, exercise 16, pp314–315, where is credited to David Maslen.

Prove that

$$\Pr \{ \text{infinitely many } A_i \text{ occur} \} = 1.$$

*Hint:* We know that the probability that no  $A_i$  with  $n \geq i \geq r$  occurs is

$$\leq e^{-E[T_{r,n}]} \quad (2)$$

where  $T_{r,n} ::= \sum_{i=r}^n I_{A_i}$  is the number of events  $A_i$  with  $n \geq i \geq r$  that occur. What happens as  $n \rightarrow \infty$ ?

(d) Show that  $\sum_{i=1}^{\infty} \Pr \{ |X_i| \geq i \}$  diverges. *Hint:*  $\int 1/(x \log x) dx = \log \log x$ .

(e) Conclude that

$$\Pr \left\{ \lim_{n \rightarrow \infty} \frac{S_n}{n} = \mu \right\} = 0. \quad (3)$$

and hence that the Strong Law of Large Numbers *completely* fails for the sequence  $X_1, X_2, \dots$

*Hint:*

$$\frac{X_n}{n} = \frac{S_n}{n} - \frac{n-1}{n} \frac{S_{n-1}}{n-1},$$

so if  $\lim_{n \rightarrow \infty} S_n/n = 0$ , then also  $\lim_{n \rightarrow \infty} X_n/n = 0$ .

## A Appendix

The *probability density function (pdf)* for a random variable,  $R$ , is the function  $f_R : \text{range}(R) \rightarrow [0, 1]$  defined by:

$$f_R(x) ::= \Pr \{ R = x \}.$$

Random variables  $R_1, R_2, \dots$  are *mutually independent* iff

$$\Pr \left\{ \bigcap_i [R_i = x_i] \right\} = \prod_i \Pr \{ R_i = x_i \},$$

for all  $x_1, x_2, \dots \in \mathbb{R}$ . They are *k-wise independent* iff  $\{R_i \mid i \in J\}$  are mutually independent for all subsets  $J \subset \mathbb{N}$  with  $|J| = k$ .

**Theorem (Weak Law of Large Numbers).** Let  $S_n ::= \sum_{i=1}^n X_i$ , where  $X_1, \dots, X_n, \dots$  are pairwise independent variables with the same expectation,  $\mu$ , and standard deviation,  $\sigma$ . For any  $\epsilon > 0$ ,

$$\lim_{n \rightarrow \infty} \Pr \left\{ \left| \frac{S_n}{n} - \mu \right| \geq \epsilon \right\} = 0.$$

**Theorem (The Strong Law of Large Numbers).** Let  $S_n ::= \sum_{i=1}^n X_i$  where  $X_1, \dots, X_i, \dots$  are mutually independent, identically distributed random variables with finite expectation,  $\mu$ . Then

$$\Pr \left\{ \lim_{n \rightarrow \infty} \frac{S_n}{n} = \mu \right\} = 1.$$

**Definition.** For any random variable,  $R$ , with finite mean,  $\mu_R$ , and deviation,  $\sigma_R$ , let  $R^*$  be the random variable

$$R^* ::= \frac{R - \mu_R}{\sigma_R}.$$

$R^*$  is called the “normalized” version of  $R$ .

**Definition.** The *normal density function* is the function

$$\eta(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2},$$

and the *normal distribution function* is its integral

$$N(y) = \int_{-\infty}^y \eta(x) dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^y e^{-x^2/2} dx.$$

The function  $\eta(x)$  defines the standard *Bell curve*, centered about the origin with height  $1/\sqrt{2\pi}$  and about two-thirds of its area within unit distance of the origin. The normal distribution function  $N(y)$  approaches 0 as  $y \rightarrow -\infty$ . As  $y$  approaches zero from below,  $N(y)$  grows rapidly towards  $1/2$ . Then as  $y$  continues to increase beyond zero,  $N(y)$  rapidly approaches 1.

**Theorem (Central Limit Theorem).** Let  $S_n = \sum_{i=1}^n X_i$  where  $X_1, \dots, X_i, \dots$  are mutually independent variables with the same mean,  $\mu$ , and deviation,  $\sigma$ , and let  $S_n^*$  be the normalized version of  $S_n$ . Then

$$\lim_{n \rightarrow \infty} \Pr \{S_n^* \leq \beta\} = N(\beta) \tag{4}$$

for any real number  $\beta$ .