

## MATH 170B LECTURE NOTE 5: LIMIT THEOREMS

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### 5. WHAT CAN WE SAY FROM OBSERVING REPEATED EXPERIMENTS?

**5.1. Overview of limit theorems.** The primary subject in this section is the sequence of i.i.d. RVs and their partial sums. Namely, let  $X_1, X_2, \dots$  be an (infinite) sequence of i.i.d. RVs, and define their  $n$ th partial sum  $S_n = X_1 + X_2 + \dots + X_n$  for all  $n \geq 1$ . If we call  $X_i$  the  $i$ th step size or *increment*, then the sequence of RVs  $(S_n)_{n \geq 1}$  is called a *random walk*, where we usually set  $S_0 = 0$ . Think of  $X_i$  as the gain or loss after betting once in a casino. Then  $S_n$  is the net gain of fortune after betting  $n$  times. Of course there are ups and downs in the short term, but what we want to analyze using probability theory is the long-term behavior of the random walk  $(S_n)_{n \geq 1}$ . Results of this type is called limit theorems.



FIGURE 1. Simulation of simple random walks

Suppose each increment  $X_k$  has a finite mean  $\mu$ . Then by linearity of expectation and independence of the increments, we have

$$\mathbb{E}\left(\frac{S_n}{n}\right) = \frac{\mathbb{E}[S_n]}{n} = \mu, \quad (1)$$

$$\text{Var}\left(\frac{S_n}{n}\right) = \frac{\text{Var}(S_n)}{n^2} = \frac{n\text{Var}(X_1)}{n^2} = \frac{\text{Var}(X_1)}{n}. \quad (2)$$

So the sample mean  $S_n/n$  has constant expectation and shrinking variance. Hence it makes sense to guess that it should behave as the constant  $\mu$ , without taking the expectation. That is,

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

But this expression is shaky, since the left hand side is a limit of RVs while the right hand side is a constant. In what sense the random sample means converge to  $\mu$ ? This is the content of the *law of large numbers*, for which we will prove a weak and a strong versions.

The first limit theorem we will encounter is called the Weak Law of Large Numbers (WLLN), which is stated below:

**Theorem 5.1** (WLLN). *Let  $(X_k)_{k \geq 1}$  be i.i.d. RVs with mean  $\mu < \infty$  and let  $S_n = \sum_{k=1}^n X_i$ ,  $n \geq 1$  be a random walk. Then for any positive constant  $\varepsilon > 0$ ,*

$$\lim_{n \rightarrow \infty} \mathbb{P} \left( \left| \frac{S_n}{n} - \mu \right| > \varepsilon \right) = 0. \quad (4)$$

In words, the probability that the sample mean  $S_n/n$  is *not* within  $\varepsilon$  distance from its expectation  $\mu$  decays to zero as  $n$  tends to infinity. In this case, we say the sequence of RVs  $(S_n/n)_{n \geq 1}$  converges to  $\mu$  *in probability*.

The second version of law of large numbers is call the *strong law of large numbers* (SLLN), which is available if the increments have finite variance.

**Theorem 5.2** (SLLN). *Let  $(X_k)_{k \geq 1}$  be i.i.d. RVs and let  $S_n = \sum_{k=1}^n X_i$ ,  $n \geq 1$  be a random walk. Suppose  $\mathbb{E}[X_1] = \mu < \infty$  and  $\mathbb{E}[X_1^2] < \infty$ . Then*

$$\mathbb{P} \left( \lim_{n \rightarrow \infty} \frac{S_n}{n} = \mu \right) = 1. \quad (5)$$

To make sense out of this, notice that the limit of sample mean  $\lim_{n \rightarrow \infty} S_n/n$  is itself a RV. Then SLLN says that this RV is well defined and its value is  $\mu$  with probability 1. In this case, we say the sequence of RVs  $(S_n/n)_{n \geq 1}$  converges to  $\mu$  *with probability 1* or *almost surely*.

Perhaps one of the most celebrated theorems in probability theory is the *central limit theorem* (CLT), which tells about how the sample mean  $S_n/n$  “fluctuates” around its mean  $\mu$ . From 2, if we denote  $\sigma^2 = \text{Var}(X_1) < \infty$ , we know that  $\text{Var}(S_n/n) = \sigma^2/n \rightarrow 0$  as  $n \rightarrow \infty$ . So the fluctuation decays as we add up more increments. To see the effect of fluctuation, we first center the sample mean by subtracting its expectation and “zoom in” by dividing by the standard deviation  $\sigma/\sqrt{n}$ . This is where the name ‘central limit’ comes from: it describes the limit of centered random walks.

**Theorem 5.3** (CLT). *Let  $(X_k)_{k \geq 1}$  be i.i.d. RVs and let  $S_n = \sum_{k=1}^n X_i$ ,  $n \geq 1$  be a random walk. Suppose  $\mathbb{E}[X_1] = \mu < \infty$  and  $\mathbb{E}[X_1^2] = \sigma^2 < \infty$ . Let  $Z \sim N(0, 1)$  be a standard normal RV and define*

$$Z_n = \frac{S_n - \mu n}{\sigma \sqrt{n}} = \frac{S_n/n - \mu}{\sigma/\sqrt{n}}. \quad (6)$$

*Then for all  $z \in \mathbb{R}$ ,*

$$\lim_{n \rightarrow \infty} \mathbb{P}(Z_n \leq z) = \mathbb{P}(Z \leq z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-\frac{x^2}{2}} dx. \quad (7)$$

In words, the centered and rescaled RV  $Z_n$  is asymptotically distributed as a standard normal RV  $Z \sim N(0, 1)$ . In this case, we say  $Z_n$  converges to  $Z$  as  $n \rightarrow \infty$  *in distribution*. This is a remarkable result since as long as the increments  $X_k$  have finite mean and variance, it does not matter which distribution that they follow: the ‘central limit’ always looks like a standard normal distribution. Later in this section, we will prove this result by using the MGF of  $S_n$  and Taylor-expanding it up to the second order term.

**5.2. Bounding tail probabilities.** In this subsection, we introduce two general inequalities called the Markov’s and Chebyshev’s inequalities. They are useful in bounding tail probabilities of the form  $\mathbb{P}(X \geq x)$  using the expectation  $\mathbb{E}[X]$  and variance  $\text{Var}(X)$ , respectively. Their proofs are quite simple but they have lots of nice applications and implications.

**Proposition 5.4** (Markov’s inequality). *Let  $X \geq 0$  be a nonnegative RV with finite expectation. Then for any  $a > 0$ , we have*

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}[X]}{a}. \quad (8)$$

*Proof.* Consider an auxiliary RV  $Y$  define as follows:

$$Y = \begin{cases} a & \text{if } X \geq a \\ 0 & \text{if } X < a. \end{cases} \quad (9)$$

Note that we always have  $Y \leq X$ . Hence we should have  $\mathbb{E}[Y] \leq \mathbb{E}[X]$ . But since  $\mathbb{E}[Y] = a\mathbb{P}(X \geq a)$ , we have

$$a\mathbb{P}(X \geq a) \leq \mathbb{E}[X]. \quad (10)$$

Dividing both sides by  $a > 0$  gives the assertion.  $\square$

**Example 5.5.** In Exercise 2.11 (ii), we have shown that  $\mathbb{E}[Z^2 = 0]$  implies  $\mathbb{P}(Z = 0) = 1$ . Markov's inequality gives a simple proof of this fact. Indeed, for any  $a > 0$ ,

$$\mathbb{P}(Z^2 \geq a) \leq \frac{\mathbb{E}[Z^2]}{a} = 0. \quad (11)$$

This means that  $\mathbb{P}(Z^2 = 0) = 1$ , so  $\mathbb{P}(Z = 0) = 1$ .

**Proposition 5.6** (Chebyshev's inequality). *Let  $X$  be any RV with  $\mathbb{E}[X] = \mu < \infty$  and  $\text{Var}(X) < \infty$ . Then for any  $a > 0$ , we have*

$$\mathbb{P}(|X - \mu| \geq a) \leq \frac{\text{Var}(X)}{a^2}. \quad (12)$$

*Proof.* Applying Markov's inequality for the nonnegative RV  $(X - \mu)^2$ , we get

$$\mathbb{P}(|X - \mu| \geq a) = \mathbb{P}((X - \mu)^2 \geq a^2) \leq \frac{\mathbb{E}[(X - \mu)^2]}{a^2} = \frac{\text{Var}(X)}{a^2}. \quad (13)$$

$\square$

**Example 5.7.** Let  $X \sim \text{Exp}(\lambda)$ . Since  $\mathbb{E}[X] = 1/\lambda$ , for any  $a > 0$ , the Markov's inequality gives

$$\mathbb{P}(X \geq a) \leq \frac{1}{a\lambda}, \quad (14)$$

while the true probability is

$$\mathbb{P}(X \geq a) = e^{-\lambda a}. \quad (15)$$

On the other hand,  $\text{Var}(X) = 1/\lambda^2$  so Chebyshev's inequality gives

$$\mathbb{P}(|X - 1/\lambda| \geq a) = \frac{1}{a^2\lambda^2}. \quad (16)$$

If  $1/\lambda \leq a$ , the true probability is

$$\mathbb{P}(|X - 1/\lambda| \geq a) = \mathbb{P}(X \geq a + 1/\lambda) + \mathbb{P}(X \leq -a + 1/\lambda) \quad (17)$$

$$= \mathbb{P}(X \geq a - 1/\lambda) = e^{-\lambda(a - 1/\lambda)} = e^{1 - \lambda a}. \quad (18)$$

As we can see, both Markov's and Chebyshev's inequalities give loose estimates, but the latter gives a slightly stronger bound.

**Example 5.8** (Chebyshev's inequality for bounded RVs). Let  $X$  be a RV taking values from the interval  $[a, b]$ . Suppose we don't know anything else about  $X$ . Can we say anything useful about tail probability  $\mathbb{P}(X \geq \lambda)$ ? If we were to use Markov's inequality, then certainly  $a \leq \mathbb{E}[X] \leq b$  and in the worst case  $\mathbb{E}[X] = b$ . Hence we can at least conclude

$$\mathbb{P}(X \geq \lambda) \leq \frac{b}{\lambda}. \quad (19)$$

On the other hand, let's get a bound on  $\text{Var}(X)$  and use Chebyshev's inequality instead. We claim that

$$\text{Var}(X) \leq \frac{(b-a)^4}{4}, \quad (20)$$

which would yield by Chebyshev's inequality that

$$\mathbb{P}(|X - \mathbb{E}[X]| \leq \lambda) \leq \frac{(b-a)^2}{4\lambda^2}. \quad (21)$$

Intuitively speaking,  $\text{Var}(X)$  is the largest when the value of  $X$  is as much spread out as possible at the two extreme values,  $a$  and  $b$ . Hence the largest variance will be achieved when  $X$  takes  $a$  and  $b$  with equal probabilities. In this case,  $\mathbb{E}[X] = (a+b)/2$  so

$$\text{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \frac{a^2 + b^2}{2} - \frac{(a+b)^2}{4} = \frac{(b-a)^2}{4}. \quad (22)$$

**Exercise 5.9.** Let  $X$  be a RV taking values from the interval  $[a, b]$ .

(i) Use the usual 'completing squares' trick for a second moment to show that

$$0 \leq \mathbb{E}[(X-t)^2] = (t - \mathbb{E}[X])^2 + \text{Var}(X) \quad \forall t \in \mathbb{R}. \quad (23)$$

(ii) Conclude that  $\mathbb{E}[(X-t)^2]$  is minimized when  $t = \mathbb{E}[X]$  and the minimum is  $\text{Var}(X)$ .

(iii) By plugging in  $t = (a+b)/2$  in (23), show that

$$\text{Var}(X) = \mathbb{E}[(X-a)(X-b)] + \frac{(b-a)^2}{4} - \left( \mathbb{E}[X] - \frac{a+b}{2} \right)^2. \quad (24)$$

(iv) Show that  $\mathbb{E}[(X-a)(X-b)] \leq 0$ .

(v) Conclude that  $\text{Var}(X) \leq (b-a)^2/4$ , where the equality holds if and only if  $X$  takes the extreme values  $a$  and  $b$  with equal probabilities.

**5.3. The WLLN and convergence in probability.** In this subsection, we prove the weak law of large numbers (Theorem 5.1) and study the notion of convergence in probability. Assuming finite variance for each increment, the weak law is an easy consequence of Chebyshev's inequality.

**Theorem 5.10** (WLLN with second moment). *Let  $(X_k)_{k \geq 1}$  be i.i.d. RVs with finite mean  $\mu < \infty$  and finite variance. Let  $S_n = \sum_{k=1}^n X_k$ ,  $n \geq 1$ . Then for any positive constant  $\varepsilon > 0$ ,*

$$\lim_{n \rightarrow \infty} \mathbb{P} \left( \left| \frac{S_n}{n} - \mu \right| > \varepsilon \right) = 0. \quad (25)$$

*Proof.* By Chebyshev's inequality, for any  $\varepsilon > 0$  we have

$$\mathbb{P} \left( \left| \frac{S_n}{n} - \mu \right| > \varepsilon \right) \leq \frac{\text{Var}(S_n/n)}{\varepsilon^2} = \frac{\text{Var}(X_1)}{n\varepsilon^2}, \quad (26)$$

where the last expression converges to 0 as  $n \rightarrow \infty$ .  $\square$

The proof of the full WLLN without the finite second moment assumption needs another technique called 'truncation'. We won't cover this technicality in this course and take Theorem 5.1 for granted.

The weak law of large numbers is the first time that we encounter the notion of 'convergence in probability'. We say a sequence of RVs converge to a constant in probability if the probability of staying away from that constant goes to zero:

**Definition 5.11.** *Let  $(X_n)_{n \geq 1}$  be a sequence of RVs and let  $\mu \in \mathbb{R}$  be a constant. We say  $X_n$  converges to  $\mu$  in probability if for each  $\varepsilon > 0$ ,*

$$\lim_{n \rightarrow \infty} \mathbb{P} \left( |X_n - \mu| > \varepsilon \right) = 0. \quad (27)$$

Before we proceed further, let us take a moment and think about the definition of convergence in probability. Recall that a sequence of real numbers  $(x_n)_{n \geq 0}$  converges to  $x$  if for each ‘error level’  $\varepsilon > 0$ , there exists a large integer  $N(\varepsilon) > 0$  such that

$$|x_n - x| < \varepsilon \quad \forall n \geq N(\varepsilon). \quad (28)$$

If we would like to say that a sequence of RVs  $(X_n)_{\geq 0}$  ‘converges’ to some real number  $x$ , how should we formulate this? Since  $X_n$  is an RV,  $\{|X_n - x| < \varepsilon\}$  is an event. On the other hand, we can also view each  $x_n$  as an RV, even though it is a real number. Then we can rewrite (30) as

$$\mathbb{P}(|X_n - x| < \varepsilon) = 1 \quad \forall n \geq N(\varepsilon). \quad (29)$$

For general RVs, requiring  $\mathbb{P}(|X_n - x| < \varepsilon) = 1$  for any large  $n$  might not be possible. But we can fix any desired level of ‘confidence’,  $\delta > 0$ , and require

$$\mathbb{P}(|X_n - x| < \varepsilon) \geq 1 - \delta \quad (30)$$

for sufficiently large  $n$ . This is precisely (27).

**Example 5.12** (Empirical frequency). Let  $A$  be an event of interest. We would like to estimate the unknown probability  $p = \mathbb{P}(A)$  by observing a sequence of independent experiments, namely, let  $(X_k)_{k \geq 0}$  be a sequence of i.i.d. RVs where  $X_k = \mathbf{1}(A)$  is the indicator variable of the event  $A$  for each  $k \geq 1$ . Let  $\hat{p}_n := (X_1 + \dots + X_n)/n$ . Since  $\mathbb{E}[X_1] = \mathbb{P}(A) = p$ , by WLLN we conclude that

$$\hat{p}_n \rightarrow p \quad \text{in probability as } n \rightarrow \infty. \quad (31)$$

**Example 5.13** (Polling). Let  $E_A$  be the event that a randomly selected voter supports candidate  $A$ . Using a poll, we would like to estimate  $p = \mathbb{P}(E_A)$ , which can be understood as the proportion of supporters of candidate  $A$ . As before, we observe a sequence of i.i.d. indicator variables  $X_k = \mathbf{1}(E_A)$ . Let  $\hat{p}_n := S_n/n$  be the empirical proportion of supporters of  $A$  out of  $n$  samples. We know by WLLN that  $\hat{p}_n$  converges to  $p$  in probability. But if we want to guarantee a certain confidence level  $\alpha$  for an error bound  $\varepsilon$ , how many samples should be taken?

By Chebyshev’s inequality, we get the following estimate:

$$\mathbb{P}(|\hat{p}_n - p| > \varepsilon) \leq \frac{\text{Var}(\hat{p}_n)}{\varepsilon^2} = \frac{\text{Var}[X_1]}{n\varepsilon^2} \leq \frac{1}{4n\varepsilon^2}. \quad (32)$$

Note that for the last inequality, we noticed that  $X_1 \in [0, 1]$  and used Exercise 5.9 (or you can use that for  $Y \sim \text{Bernoulli}(p)$ ,  $\text{Var}(Y) = p(1 - p) \leq 1/4$ ). Hence, for instance, if  $\varepsilon = 0.01$  and  $\alpha = 0.95$ , then we would need to set  $n$  large enough so that

$$\mathbb{P}(|\hat{p}_n - p| > 0.01) \leq \frac{10000}{4n} \leq 0.05. \quad (33)$$

This yields  $n \geq 50,000$ . In other words, if we survey at least  $n = 50,000$  independent voters, then the empirical frequency  $\hat{p}_n$  is between  $p - 0.01$  and  $p + 0.01$  with probability at least 0.95. Still in other words, the true frequency  $p$  is between  $\hat{p}_n - 0.01$  and  $\hat{p}_n + 0.01$  with probability at least 0.95 if  $n \geq 50,000$ . We don’t actually need this many samples. We will improve this result later using central limit theorem.

**Exercise 5.14** (Monte Carlo integration). Let  $(X_k)_{k \geq 1}$  be i.i.d.  $\text{Uniform}([0, 1])$  RVs and let  $f : [0, 1] \rightarrow \mathbb{R}$  be a continuous function. For each  $n \geq 1$ , let

$$I_n = \frac{1}{n} (f(X_1) + f(X_2) + \dots + f(X_n)). \quad (34)$$

- (i) Suppose  $\int_0^1 |f(x)| dx < \infty$ . Show that  $I_n \rightarrow I := \int_0^1 f(x) dx$  in probability.
- (ii) Further assume that  $\int_0^1 |f(x)|^2 dx < \infty$ . Use Chebyshev’s inequality to show that

$$\mathbb{P}(|I_n - I| \geq a/\sqrt{n}) \leq \frac{\text{Var}(f(X_1))}{a^2} = \frac{1}{a^2} \left( \int_0^1 f(x)^2 dx - I^2 \right). \quad (35)$$

**Exercise 5.15.** Let  $(X_n)_{n \geq 0}$  be a sequence of i.i.d.  $\text{Exp}(\lambda)$  RVs. Define  $Y_n = \min(X_1, X_2, \dots, X_n)$ .

- (i) For each  $\varepsilon > 0$ , show that  $\mathbb{P}(|Y_n - 0| > \varepsilon) = e^{-\lambda \varepsilon n}$ .
- (ii) Conclude that  $Y_n \rightarrow 0$  in probability as  $n \rightarrow \infty$ .

**Example 5.16.** For each integer  $n \geq 1$ , define a RV  $X_n$  by

$$X_n = \begin{cases} n & \text{with prob. } 1/n \\ 1/n & \text{with prob. } 1 - 1/n. \end{cases} \quad (36)$$

Then  $X_n \rightarrow 0$  in probability as  $n \rightarrow \infty$ . Indeed, for each  $\varepsilon > 0$ ,

$$\mathbb{P}(|X_n - 0| > \varepsilon) = \mathbb{P}(X_n > \varepsilon) = 1/n \quad (37)$$

for all  $n > 1/\varepsilon$ . Hence  $\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - 0| > \varepsilon) = 0$ . However, note that

$$\mathbb{E}[X_n] = 1 + n^{-1} - n^{-2} \rightarrow 1 \quad \text{as } n \rightarrow \infty. \quad (38)$$

This example indicates that convergence in probability only cares about probability of the event  $\mathbb{P}(|X_n - \mathbb{E}[X_n]| > \varepsilon)$  but not the actual value of  $X_n$  when that ‘bad’ event occurs.

**Example 5.17** (Coupon collector’s problem). Let  $(X_t)_{t \geq 0}$  be a sequence of i.i.d.  $\text{Uniform}(\{1, 2, \dots, n\})$  variables. Think of the value of  $X_t$  as the label of the coupon you collect at  $t$ th trial. We are interested in how many times we need to reveal a new random coupon to collect a full set of  $n$  distinct coupons. That is, let

$$\tau^n = \min\{r \geq 1 \mid \#\{X_1, X_2, \dots, X_r\} = n\}. \quad (39)$$

Because of the possible overlap, we expect  $n$  reveals should not get us the full set of  $n$  coupons. Indeed,

$$\mathbb{P}(\tau^n = n) = \frac{n-1}{n} \cdot \frac{n-2}{n} \cdots \frac{1}{n} = \frac{n!}{n^n}. \quad (40)$$

Certainly this probability rapidly goes to zero as  $n \rightarrow \infty$ . So we need to reveal more than  $n$  coupons. But how many? The answer turns out to be  $\tau^n \approx n \log n$ . More precisely,

$$\frac{\tau^n}{n \log n} \rightarrow 1 \quad \text{as } n \rightarrow \infty \text{ in probability.} \quad (41)$$

A change of perspective might help us. Instead of waiting to collect all  $n$  coupons, let’s progressively collect  $k$  distinct coupons for  $k = 1$  to  $n$ . Namely, for each  $1 \leq k \leq n$ , define

$$\tau^k = \min\{r \geq 1 \mid \#\{X_1, X_2, \dots, X_r\} = k\}. \quad (42)$$

So  $\tau^k$  is the first time that we collect  $k$  distinct coupons.

Now consider what has to happen to collect  $k+1$  distinct coupons from  $k$  distinct coupons? Here is an example. Say at time  $\tau^2$  we have coupons  $\{1, 3\}$ .  $\tau^3$  is the first time that we pick up a new coupon from  $\{1, 3\}$  except 1 and 3. This happens with probability  $(n-2)/n$  and since each draw is i.i.d.,

$$\tau^3 - \tau^2 \sim \text{Geom}\left(\frac{n-2}{n}\right). \quad (43)$$

A similar reasoning shows

$$\tau^{k+1} - \tau^k \sim \text{Geom}\left(\frac{n-k}{n}\right). \quad (44)$$

So starting from the first coupon, we wait a  $\text{Geom}(1/n)$  time to get a new coupon, and wait a  $\text{Geom}(2/n)$  time to get another new coupon, and so on. Note that these geometric waiting times are all independent. So we can decompose  $\tau^n$  into a sum of independent geometric RVs:

$$\tau^n = \sum_{k=1}^{n-1} (\tau^{k+1} - \tau^k). \quad (45)$$

Then using the estimates in Exercise 5.18, it is straightforward to show that

$$\mathbb{E}[\tau^n] \approx n \log n, \quad \text{Var}(\tau^n) \leq n^2. \quad (46)$$

In Exercise 5.19, we will show (41) using Chebyshev's inequality.

**Exercise 5.18.** In this exercise, we estimate some partial sums using integral comparison.

(i) For any integer  $d \geq 1$ , show that

$$\sum_{k=2}^n \frac{1}{k^d} \leq \int_1^n \frac{1}{x^d} dx \leq \sum_{k=1}^{n-1} \frac{1}{k^d} \quad (47)$$

by considering the upper and lower sum for the Riemann integral  $\int_1^n x^{-d} dx$ .

(ii) Show that

$$\log n \leq \sum_{k=1}^{n-1} \frac{1}{k} \leq 1 + \log(n-1). \quad (48)$$

(iii) Show that for all  $d \geq 2$ ,

$$\sum_{k=1}^{n-1} \frac{1}{k^d} \leq \sum_{k=1}^{\infty} \frac{1}{k^d} \leq 1 + \int_1^{\infty} \frac{1}{x^d} dx \leq 2. \quad (49)$$

**Exercise 5.19.** For each  $n \geq 1$ , let  $X_{1,n}, X_{2,n}, \dots, X_{n,n}$  be a sequence of independent geometric RVs where  $X_{k,n} \sim \text{Geom}((n-k)/n)$ . Define  $\tau^n = X_{1,n} + X_{2,n} + \dots + X_{n,n}$ .

(i) Show that  $\mathbb{E}[\tau^n] = n \sum_{k=1}^{n-1} k^{-1}$ . Using Exercise 5.18 (ii), deduce that

$$n \log n \leq \mathbb{E}[\tau^n] \leq n \log(n-1) + n. \quad (50)$$

(ii) Using  $\text{Var}(\text{Geom}(p)) = (1-p)/p^2 \leq p^{-2}$  and Exercise 5.18 (iii), show that

$$\text{Var}(\tau^n) \leq n^2 \sum_{k=1}^{n-1} k^{-2} \leq 2n^2. \quad (51)$$

(iii) By Chebyshev's inequality, show that for each  $\varepsilon > 0$ ,

$$\mathbb{P}(|\tau^n - \mathbb{E}[\tau^n]| > \varepsilon n \log n) \leq \frac{\text{Var}(\tau^n)}{\varepsilon^2 n^2 \log^2 n} \leq \frac{2}{\varepsilon^2 \log^2 n}. \quad (52)$$

Conclude that

$$\frac{\tau^n - \mathbb{E}[\tau^n]}{n \log n} \rightarrow 0 \quad \text{as } n \rightarrow \infty \text{ in probability.} \quad (53)$$

(iv) By using part (i), conclude that

$$\frac{\tau^n}{n \log n} \rightarrow 1 \quad \text{as } n \rightarrow \infty \text{ in probability.} \quad (54)$$

**5.4. Central limit theorem.** Let  $(X_t)_{t \geq 0}$  be a sequence of i.i.d. RVs with finite mean  $\mu$  and variance  $\sigma^2$ . Let  $S_n = X_1 + \dots + X_n$  for  $n \geq 1$ . We have calculated the mean and variance of the sample mean  $S_n/n$ :

$$\mathbb{E}[S_n/n] = \mu, \quad \text{Var}(S_n/n) = \sigma^2/n. \quad (55)$$

Since  $\text{Var}(S_n/n) \rightarrow 0$  as  $n \rightarrow \infty$ , we expect the sequence of RVs  $S_n/n$  to converge its mean  $\mu$  in probability.

Central limit theorem is a limit theorem for the sample mean with different regime, namely, it describes the 'fluctuation' of the sample mean around its expectation, as  $n \rightarrow \infty$ . For this purpose, we need to standardize the sample mean so that the mean is zero and variance is unit. Namely, let

$$Z_n = \frac{S_n/n - \mu}{\sigma/\sqrt{n}} = \frac{S_n - n\mu}{\sigma\sqrt{n}}, \quad (56)$$

so that

$$\mathbb{E}[Z_n] = 0, \quad \text{Var}(Z_n) = 1. \quad (57)$$

Since the variance is kept at 1, we should not expect the sequence of RVs  $(Z_n)_{n \geq 0}$  converge to some constant in probability, as in the law of large number situation. Instead,  $Z_n$  should converge to some other RV, if it ever converges in some sense. Central limit theorem states that  $Z_n$  converges to the standard normal RV  $Z \sim N(0, 1)$  ‘in distribution’.

**Definition 5.20.** Let  $(X_n)_{n \geq 1}$  be a sequence of RVs. We say  $X_n$  converges to a RV  $X$  in distribution, in which case we denote  $X_n \Rightarrow X$  as  $n \rightarrow \infty$ , when the CDF of  $X_n$  converges to that of  $X$ , that is,

$$\lim_{n \rightarrow \infty} \mathbb{P}(X_n \leq x) = \mathbb{P}(X \leq x) \quad (58)$$

for all  $x \in \mathbb{R}$  at which  $\mathbb{P}(X \leq t)$  is continuous at  $t = x$ .

Let us state the central limit theorem (Theorem 5.3) here with the above notion of convergence in distribution.

**Theorem 5.21 (CLT).** Let  $(X_k)_{k \geq 1}$  be i.i.d. RVs and let  $S_n = \sum_{k=1}^n X_i$ ,  $n \geq 1$ . Suppose  $\mathbb{E}[X_1] < \infty$  and  $\mathbb{E}[X_1^2] = \sigma^2 < \infty$ . Let  $Z \sim N(0, 1)$  be a standard normal RV and define

$$Z_n = \frac{S_n - \mu n}{\sigma \sqrt{n}} = \frac{S_n/n - \mu}{\sigma / \sqrt{n}}. \quad (59)$$

Then  $Z_n$  converges to  $Z$  as  $n \rightarrow \infty$  in distribution.

*Proof.* First notice that we can assume  $\mathbb{E}[X_1] = 0$  without loss of generality (why?). Then  $\sigma^2 = \text{Var}(X_1) = \mathbb{E}[X_1^2] - \mathbb{E}[X_1]^2 = \mathbb{E}[X_1^2]$ . Our proof is based on computing moment generating function of  $Z_n$ , and we will show that this converges to the MGF of the standard normal. (This is why we learned moment generating function.)

Since the increments  $X_i$ ’s are i.i.d., we have

$$\mathbb{E}[e^{tS_n}] = \mathbb{E}[e^{tX_1}] \mathbb{E}[e^{tX_2}] \cdots \mathbb{E}[e^{tX_n}] = \mathbb{E}[e^{tX_1}]^n. \quad (60)$$

Since we are assuming  $\mathbb{E}[X_1] = 0$  and  $\mathbb{E}[X_1^2] < \infty$ , we have

$$\mathbb{E}[e^{tX_1}] = 1 + \frac{\sigma^2}{2} t^2 + O(t^3), \quad (61)$$

where  $O(t^3)$  contains the rest of terms of order  $t \geq 3$ . Hence

$$\mathbb{E}[e^{tS_n}] = \left( 1 + \frac{\sigma^2}{2} t^2 + O(t^3) \right)^n. \quad (62)$$

This yields

$$\mathbb{E}[e^{tZ_n}] = \mathbb{E}[e^{tS_n / (\sigma \sqrt{n})}] = \mathbb{E}[e^{(t/\sigma \sqrt{n})S_n}] \quad (63)$$

$$= \left( 1 + \frac{t^2}{2n} + O(n^{-3/2}) \right)^n. \quad (64)$$

Recall that

$$\lim_{n \rightarrow \infty} \left( 1 + \frac{t^2}{2n} \right)^n = e^{t^2/2} = \mathbb{E}[e^{tZ}]. \quad (65)$$

Since the  $O(n^{-3/2})$  term vanishes as  $n \rightarrow \infty$ , this shows that  $\mathbb{E}[e^{tZ_n}] \rightarrow \mathbb{E}[e^{tZ}]$  as  $n \rightarrow \infty$ . Since MGFs determine distribution of RVs (see Theorem 4.14 (ii) in Note 4), it follows that the CDF of  $Z_n$  converges to that of  $Z$ .  $\square$

As a typical application of CLT, we can approximate Poisson( $n\lambda$ ) and Binomial( $n, p$ ) variables by normal RVs.

**Exercise 5.22.** Let  $(X_n)_{n \geq 1}$  be a sequence of i.i.d.  $\text{Poisson}(\lambda)$  RVs. Let  $S_n = X_1 + \dots + X_n$ .

(i) Let  $Z_n = (S_n - n\lambda)/\sqrt{n\lambda}$ . Show that as  $n \rightarrow \infty$ ,  $Z_n$  converges to the standard normal RV  $Z \sim N(0, 1)$  in distribution.

(ii) Conclude that if  $Y_n \sim \text{Poisson}(n\lambda)$ , then

$$\frac{Y_n - n\lambda}{\sqrt{n\lambda}} \Rightarrow Z \sim N(0, 1). \quad (66)$$

(iii) From (ii) deduce that we have the following approximation

$$\mathbb{P}(Y_n \leq x) \approx \mathbb{P}\left(Z \leq \frac{x - n\lambda}{\sqrt{n\lambda}}\right), \quad (67)$$

which becomes more accurate as  $n \rightarrow \infty$ .

**Exercise 5.23.** Let  $(X_n)_{n \geq 1}$  be a sequence of i.i.d.  $\text{Bernoulli}(p)$  RVs. Let  $S_n = X_1 + \dots + X_n$ .

(i) Let  $Z_n = (S_n - np)/\sqrt{np(1-p)}$ . Show that as  $n \rightarrow \infty$ ,  $Z_n$  converges to the standard normal RV  $Z \sim N(0, 1)$  in distribution.

(ii) Conclude that if  $Y_n \sim \text{Binomial}(n, p)$ , then

$$\frac{Y_n - np}{\sqrt{np(1-p)}} \Rightarrow Z \sim N(0, 1). \quad (68)$$

(iii) From (ii), deduce that have the following approximation

$$\mathbb{P}(Y_n \leq x) \approx \mathbb{P}\left(Z \leq \frac{x - np}{\sqrt{np(1-p)}}\right), \quad (69)$$

which becomes more accurate as  $n \rightarrow \infty$ .

**Example 5.24** (Polling revisited). Let  $(X_n)_{n \geq 1}$  be a sequence of i.i.d.  $\text{Bernoulli}(p)$  RVs. Denote  $\hat{p}_n = n^{-1}(X_1 + \dots + X_n)$ . In Exercise 5.13, we used Chebyshev's inequality to deduce that

$$\mathbb{P}(|\hat{p}_n - p| \leq 0.01) \geq 0.95 \quad (70)$$

whenever  $n \geq 50,000$ . In this example, we will use CLT to improve this lower bound on  $n$ .

First, from Exercise 5.23, it is immediate to deduce the following convergence in distribution

$$\frac{\hat{p}_n - p}{\sqrt{p(1-p)/n}} \Rightarrow Z \sim N(0, 1). \quad (71)$$

Hence for any  $\varepsilon > 0$ , we have

$$\mathbb{P}(|\hat{p}_n - p| \leq \varepsilon) = \mathbb{P}\left(\left|\frac{\hat{p}_n - p}{\sqrt{p(1-p)/n}}\right| \leq \frac{\varepsilon\sqrt{n}}{\sqrt{p(1-p)}}\right) \quad (72)$$

$$\geq \mathbb{P}\left(\left|\frac{\hat{p}_n - p}{\sqrt{p(1-p)/n}}\right| \leq 2\varepsilon\sqrt{n}\right) \quad (73)$$

$$\approx \mathbb{P}(|Z| \leq 2\varepsilon\sqrt{n}) = 2\mathbb{P}(0 \leq Z \leq 2\varepsilon\sqrt{n}), \quad (74)$$

where for the inequality we have used the fact that  $p(1-p) \leq 1/4$  for all  $0 \leq p \leq 1$ . The last expression is at least 0.95 if and only if

$$\mathbb{P}(0 \leq Z \leq 2\varepsilon\sqrt{n}) \geq 0.475. \quad (75)$$

From the table of standard normal distribution, we know that  $\mathbb{P}(0 \leq Z \leq 1.96) = 0.475$ . Hence (75) holds if and only if  $2\varepsilon\sqrt{n} \geq 1.96$ , or equivalently,

$$n \geq \left(\frac{0.98}{\varepsilon}\right)^2. \quad (76)$$

For instance,  $\varepsilon = 0.01$  gives  $n \geq 9604$ . This is a drastic improvement from  $n \geq 50,000$  via Chebyshev.

**Exercise 5.25.** Let  $X_1, Y_1, \dots, X_n, Y_n$  be i.i.d. Uniform([0, 1]) RVs. Let

$$W_n = \frac{(X_1 + \dots + X_n) - (Y_1 + \dots + Y_n)}{n}. \quad (77)$$

Find a numerical approximation to the quantity

$$\mathbb{P}(|W_{20} - \mathbb{E}[W_{20}]| < 0.001). \quad (78)$$

**5.5. The SLLN and convergence with probability 1.** Let  $(X_n)_{n \geq 1}$  be i.i.d. RVs with finite mean  $\mathbb{E}[X_1] = \mu$  and let  $S_n = X_1 + \dots + X_n$  for all  $n \geq 1$ . The weak law of large numbers states that the sample mean  $S_n/n$  converges to  $\mu$  in probability, that is,

$$\lim_{n \rightarrow \infty} \mathbb{P}\left(\left|\frac{S_n}{n} - \mu\right| > \varepsilon\right) = 0 \quad \forall \varepsilon > 0. \quad (79)$$

On the other hand, the Strong Law of Large Numbers (SLLN) tells us that a similar statement holds where the limit is inside the probability bracket. Namely,

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} \left|\frac{S_n}{n} - \mu\right| > \varepsilon\right) = 0 \quad \forall \varepsilon > 0. \quad (80)$$

If we view the limit on the left hand side as a RV, then (80) in fact states that this limit RV is 0 with probability 1:

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} \left|\frac{S_n}{n} - \mu\right| = 0\right) = 1. \quad (81)$$

This is equivalent to the following familiar form of SLLN in Theorem 5.2:

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} \frac{S_n}{n} = \mu\right) = 1. \quad (82)$$

**Definition 5.26.** Let  $(X_n)_{n \geq 1}$  be a sequence of RVs and let  $a$  be a real number. We say that  $X_n$  converges to  $a$  with probability 1 if

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} X_n = a\right) = 1. \quad (83)$$

**Exercise 5.27.** Let  $(X_n)_{n \geq 1}$  be a sequence of RVs and let  $a$  be a real number. Suppose  $X_n$  converges to  $a$  with probability 1.

(i) Show that

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} |X_n - a| \leq \varepsilon\right) = 1 \quad \forall \varepsilon > 0. \quad (84)$$

(ii) Fix  $\varepsilon > 0$ . Let  $A_k$  be the event that  $|X_n - a| \leq \varepsilon$  for all  $n \geq k$ . Show that  $A_1 \subseteq A_2 \subseteq \dots$  and

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} |X_n - a| \leq \varepsilon\right) \leq \mathbb{P}\left(\bigcup_{k=1}^{\infty} A_k\right). \quad (85)$$

(iii) Show that for each  $\varepsilon > 0$ ,

$$\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - a| \leq \varepsilon) \geq \lim_{n \rightarrow \infty} \mathbb{P}(A_n) = \mathbb{P}\left(\bigcup_{k=1}^{\infty} A_k\right) \geq \mathbb{P}\left(\lim_{n \rightarrow \infty} |X_n - a| \leq \varepsilon\right) = 1. \quad (86)$$

Conclude that  $X_n \rightarrow a$  in probability.

**Example 5.28.** In this example, we will see that convergence in probability does not necessarily imply convergence with probability 1. Define a sequence of RVs  $(X_n)_{n \geq 1}$  as follows. Let  $X_1 = 1$ , and  $X_2 \sim \text{Uniform}(\{2, 3\})$ ,  $X_3 \sim \text{Uniform}(\{4, 5, 6\})$ , and so on. In general,  $X_k \sim \text{Uniform}(\{(k-1)k/2, \dots, (k(k+1)/2\})$  for all  $k \geq 2$ . Let  $Y_n = \mathbf{1}(\text{some } X_k \text{ takes value } n)$ . Then note that

$$\mathbb{P}(Y_1 = 1) = 1, \quad (87)$$

$$\mathbb{P}(Y_2 = 1) = \mathbb{P}(Y_3 = 1) = 1/2, \quad (88)$$

$$\mathbb{P}(Y_4 = 1) = \mathbb{P}(Y_5 = 1) = \mathbb{P}(Y_6 = 1) = 1/3, \quad (89)$$

and so on. Hence it is clear that  $\lim_{n \rightarrow \infty} \mathbb{P}(Y_n = 1) = 0$ . Since  $Y_n$  is an indicator variable, this yields that  $\lim_{n \rightarrow \infty} \mathbb{P}(|Y_n - 0| > \varepsilon) = 0$  for all  $\varepsilon > 0$ , that is,  $Y_n$  converges to 0 in probability. However, always infinitely many  $Y_n$ 's take value 1, so  $Y_n$  cannot converge to 0 with probability 1.

**Exercise 5.28** (A simple fact from analysis). Let  $(a_n)_{n \geq 0}$  be a sequence of real numbers such that  $\sum_{n=1}^{\infty} a_n < \infty$ . Let  $S_n = a_1 + \dots + a_n$  for all  $n \geq 1$ . Show that

$$\lim_{n \rightarrow \infty} a_n = \lim_{n \rightarrow \infty} (S_n - S_{n-1}) = \lim_{n \rightarrow \infty} S_n - \lim_{n \rightarrow \infty} S_n = 0. \quad (90)$$

A typical tool for proving convergence with probability 1 is the following.

**Proposition 5.29** (Borel-Cantelli lemma). *Let  $(X_n)_{n \geq 1}$  be a sequence of nonnegative RVs such that  $\sum_{n=1}^{\infty} \mathbb{E}[X_n] < \infty$ . Then  $X_n \rightarrow 0$  as  $n \rightarrow \infty$  with probability 1.*

*Proof.* By Fubini's theorem (viewing summation as a discrete integral) or applying monotone convergence theorem, we get

$$\mathbb{E} \left[ \sum_{n=1}^{\infty} X_n \right] = \sum_{n=1}^{\infty} \mathbb{E}[X_n] < \infty. \quad (91)$$

It follows that  $\mathbb{P}(\sum_{n=1}^{\infty} X_n < \infty) = 1$ . By Proposition 5.28, we have

$$1 = \mathbb{P} \left( \sum_{n=1}^{\infty} X_n < \infty \right) \leq \mathbb{P} \left( \lim_{n \rightarrow \infty} X_n = 0 \right). \quad (92)$$

Since the last expression is at most 1, we conclude that  $\mathbb{P}(\lim_{n \rightarrow \infty} X_n = 0) = 1$ .  $\square$

Now we prove the strong law of large numbers. The proof of full statement (Theorem 5.2) with finite second moment assumption has extra technicality, so here we prove the result under a stronger assumption of finite fourth moment.

**Theorem 5.30** (SLLN with fourth moment). *Let  $(X_n)_{n \geq 1}$  be a sequence of i.i.d. RVs such that  $\mathbb{E}[X_n^4] < \infty$ . Let  $S_n = X_1 + \dots + X_n$  for all  $n \geq 1$ . Then  $S_n/n$  converges to  $\mathbb{E}[X_1]$  with probability 1.*

*Proof.* Our aim is to show that

$$\sum_{n=1}^{\infty} \mathbb{E}[(S_n/n)^4] < \infty. \quad (93)$$

Then by Borel-Cantelli lemma,  $(S_n/n)^4$  converges to 0 with probability 1. Hence  $S_n/n$  converges to 0 with probability 1, as desired.

For a preparation, we first verify that we have finite first and second moments for  $X_1$ . It is easy to verify the inequality  $|x| \leq 1 + x^4$  for all  $x \in \mathbb{R}$ , so we have

$$\mathbb{E}[|X_1|] \leq 1 + \mathbb{E}[X_1^4] < \infty. \quad (94)$$

Hence  $\mathbb{E}[X_1]$  exists. By shifting, we may assume that  $\mathbb{E}[X_1] = 0$ . Similarly, it holds that  $x^2 \leq c + x^4$  for all  $x \in \mathbb{R}$  if  $c > 0$  is large enough. Hence  $\mathbb{E}[X_1^2] < \infty$ .

Note that

$$\mathbb{E}[S_n^4] = \mathbb{E} \left[ \left( \sum_{k=1}^n X_k \right)^4 \right] = \mathbb{E} \left[ \sum_{1 \leq i, j, k, \ell \leq n} X_i X_j X_k X_{\ell} \right] = \sum_{1 \leq i, j, k, \ell \leq n} \mathbb{E}[X_i X_j X_k X_{\ell}]. \quad (95)$$

Note that by independence and the assumption that  $\mathbb{E}[X_1] = 0$ ,  $\mathbb{E}[X_i X_j X_k X_{\ell}] = 0$  if at least one of the four indices does not repeat. For instance,

$$\mathbb{E}[X_1 X_2^3] = \mathbb{E}[X_1] \mathbb{E}[X_2^3] = 0, \quad (96)$$

$$\mathbb{E}[X_1 X_2^2 X_3] = \mathbb{E}[X_1] \mathbb{E}[X_2^2] \mathbb{E}[X_3] = 0. \quad (97)$$

Hence by collecting terms based on number of overlaps, we have

$$\sum_{1 \leq i, j, k, \ell \leq n} \mathbb{E}[X_i X_j X_k X_\ell] = \sum_{i=1}^n \mathbb{E}[X_i^4] + \binom{4}{2} \sum_{1 \leq i < j \leq n} \mathbb{E}[X_i^2] \mathbb{E}[X_j^2] \quad (98)$$

$$= n \mathbb{E}[X_1^4] + 3n(n-1) \mathbb{E}[X_1^2]^2. \quad (99)$$

Thus for all  $n \geq 1$ ,

$$\mathbb{E}[(S_n/n)^4] = \frac{n \mathbb{E}[X_1^4] + 3n(n-1) \mathbb{E}[X_1^2]^2}{n^4} \leq \frac{n^2 \mathbb{E}[X_1^4] + 3n^2 \mathbb{E}[X_1^2]^2}{n^4} = \frac{\mathbb{E}[X_1^4] + 3\mathbb{E}[X_1^2]^2}{n^2}. \quad (100)$$

Summing over all  $n$ , this gives

$$\sum_{n=1}^{\infty} \mathbb{E}[(S_n/n)^4] \leq (\mathbb{E}[X_1^4] + 3\mathbb{E}[X_1^2]^2) \sum_{n=1}^{\infty} \frac{1}{n^2} < \infty. \quad (101)$$

Hence by Borell-Cantelli lemma, we conclude that  $(S_n/n)^4$  converges to 0 with probability 1. The same conclusion holds for  $S_n/n$ . This shows the assertion.  $\square$