

Lecture 7: Law of Large Numbers and Central Limit Theorem

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EE210: Probability and Introductory Random Processes
KAIST EE

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- Most remarkable two results in probability theory history
- Weak Law of Large Numbers: Result and Meaning
- Central Limit Theorem: Result and Meaning
- Weak Law of Large Numbers: Proof
 - Inequalities: Markov and Chebyshev
- Central Limit Theorem: Proof
 - Moment Generating Function (MGF)
- Strong Law of Large Numbers

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- **Example 1.** n students who decide their presence, depending on their feeling. Each student is happy or sad at random. How many students will show their presence?
- **Example 2.** I am hearing some sound. There are n noisy sources from outside.
- X_1, X_2, \dots, X_n : i.i.d (independent and identically distributed) random variables
- $\mathbb{E}[X_i] = \mu, \text{var}[X_i] = \sigma^2$
- Our interest is to understand how the following sum behaves:

$$S_n = X_1 + X_2 + \dots + X_n$$

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- Challenging if we intend to approach directly. Even just for $Z = X + Y$, finding the distribution, for example, requires the complex **convolution**.

$$p_Z(z) = \mathbb{P}(X + Y = z) = \sum_x p_X(x)p_Y(z - x)$$

- Take a certain **scaling** with respect to n that corresponds to a **new glass**, and investigate the system for large n
- First, consider the sample mean, and try to understand how it behaves:

$$M_n = \frac{X_1 + X_2 + \dots + X_n}{n}$$

$$M_n = \frac{S_n}{n} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

- **Example.** n coin tossing. $X_i = 1$ if head, and 0 otherwise. S_n : total number of heads.
- $\mathbb{E}(M_n) = \mu$, $\text{var}(M_n) = \sigma^2/n$
- For large n , the variance decays. We expect that, for large n , M_n loses its randomness and concentrates around μ .
- Why important? If we take the scaling of S_n by $1/n$, it behaves like a deterministic number. This significantly simplifies how we understand the world.
- We call this **law of large numbers**.

$$M_n = \frac{S_n}{n} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

- What about this? What's wrong?

$$M_n \xrightarrow{n \rightarrow \infty} \mu$$

- Ordinary convergence for the sequence of real numbers: $a_n \rightarrow a$
 - For every $\epsilon > 0$, there exists n_0 , such that for every $n \geq n_0$, $|a_n - a| \leq \epsilon$.
- M_n is a random variable, which is a function from Ω to \mathbb{R} .
- Need to mathematically build up the concept of convergence for the sequence of random variables.

- Consider the sequence of rvs $(Y_n)_{n=1,2,\dots}$, and I want to say they “converge” to a number a .
- Play the game with my friend Lin.
 - Lin, give me any $\epsilon > 0$.
 - OK. Then, let me consider the event $\{|Y_n - a| \geq \epsilon\}$, and compute its probability $a_n = \mathbb{P}(|Y_n - a| \geq \epsilon)$.
 - Now, a_n is just the real number, and I will show that $a_n \rightarrow a$ as $n \rightarrow \infty$.

Convergence in probability

For any $\epsilon > 0$, $\mathbb{P}(|Y_n - a| \geq \epsilon) \xrightarrow{n \rightarrow \infty} 0$.

$$M_n = \frac{S_n}{n} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

Weak law of large numbers

M_n converges to μ in probability.

- Why "Weak"? There exists a stronger version, which we call "strong" law of large numbers.
- Proof requires some knowledge about useful inequalities, which we cover later.

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- Loosely speaking, WLLG says:

$$(M_n - \mu) \xrightarrow{n \rightarrow \infty} 0$$

- However, we don't know **how** $M_n - \mu$ converges to 0. For example, what's the speed of convergence?
- Question.** What should be “something”? Something should what blows up.

$$\boxed{\text{(something)}} \times (M_n - \mu) \xrightarrow{n \rightarrow \infty} \text{meaningful thing}$$

$$\boxed{n^\alpha} \times (M_n - \mu) \xrightarrow{n \rightarrow \infty} \text{meaningful thing}$$

- What's α for our magic?
- The answer is $\frac{1}{2}$

- Reshaping the equation:

$$\sqrt{n} \times (M_n - \mu) = \sqrt{n} \left(\frac{S_n - n\mu}{n} \right) = \frac{S_n - n\mu}{\sqrt{n}}. \quad \text{Let } Z_n = \frac{S_n - n\mu}{\sigma \sqrt{n}}.$$

- $\mathbb{E}[Z_n] = 0$ and $\text{var}(Z_n) = 1$.
 - Z_n is well-centered with a constant variance irrespective of n .
- We expect that Z_n converges to something meaningful, but what?
- Some deterministic number just like WLLG?
- Interestingly, it converges to some **random variable Z** that we know very well.

- $Z_n \xrightarrow{n \rightarrow \infty} Z$, where $Z \sim N(0, 1)$.
- Wait! What kind of convergence? Convergence in probability as in WLLN? No.
- Convergence **in distribution** (another type of convergence of rvs)

Central Limit Theorem

For every z ,

$$\mathbb{P}(Z_n \leq z) \xrightarrow{n \rightarrow \infty} \mathbb{P}(Z \leq z),$$

where $Z \sim N(0, 1)$.

- **Meaning from scaling perspective.**
 - LLN: Scaling S_n by $1/n$, you go to a deterministic world.
 - CLT: Scaling S_n by $1/\sqrt{n}$, you still stay at the random world, but not an arbitrary random world. That's the normal random world, not depending on the distribution of each X_i . Very interesting!

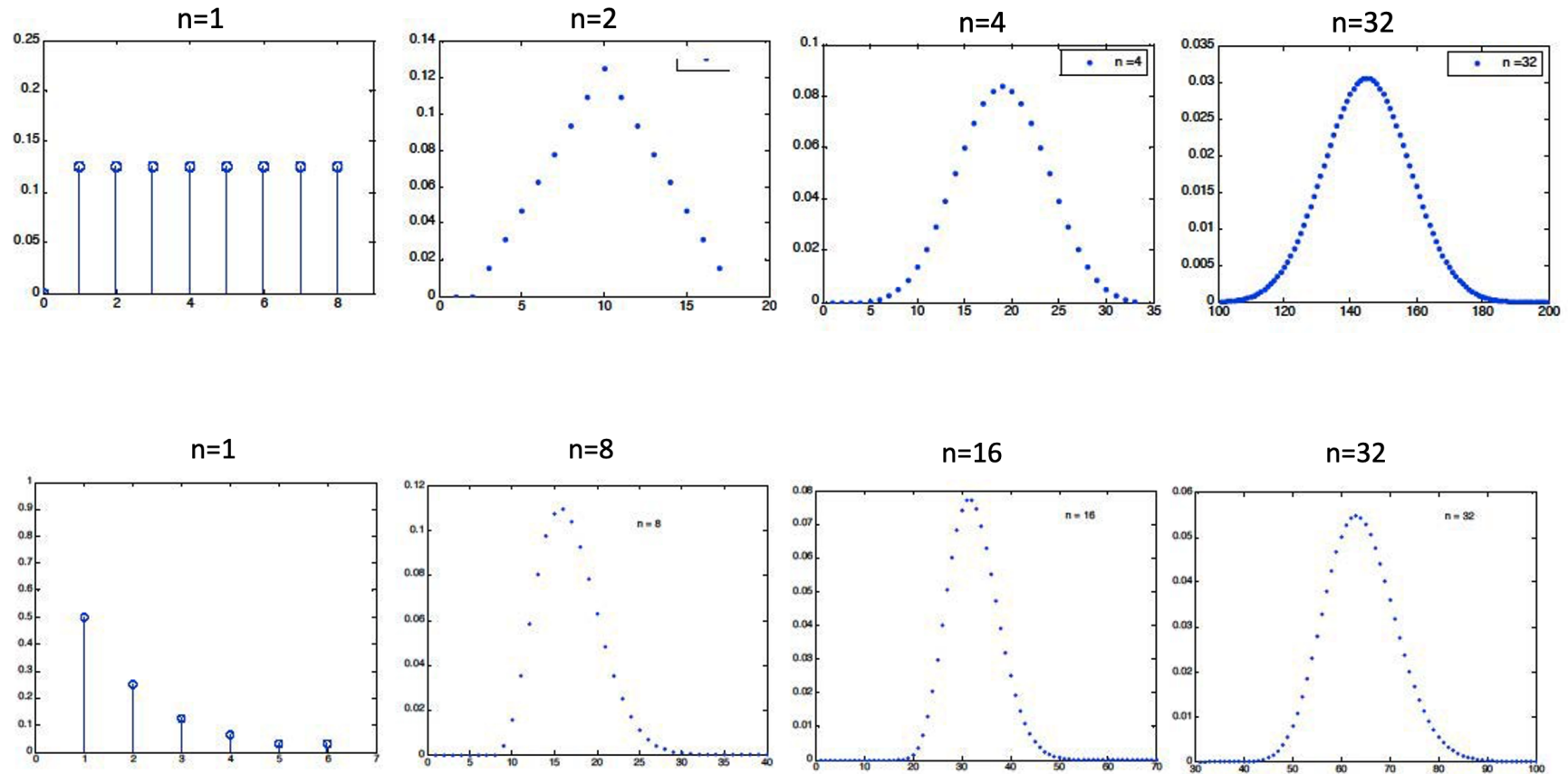
$$Z_n = \frac{S_n - n\mu}{\sigma\sqrt{n}}$$

$$\mathbb{P}(Z_n \leq z) \xrightarrow{n \rightarrow \infty} \mathbb{P}(Z \leq z), \quad Z \sim N(0, 1)$$

- Can approximate Z_n with a standard normal rv
- Can approximate S_n with a normal rv $\sim (n\mu, n\sigma^2)$
 - $S_n = n\mu + Z_n\sigma\sqrt{n}$
- How large should n be?
 - A moderate n (20 or 30) usually works, which the power of CLT.
 - If X_i resembles a normal rv more, smaller n works: symmetry and unimodality¹

¹Only unique mode. A single maximum or minimum.

CLT: Examples of n



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- (Q) Knowing $\mathbb{E}(X)$, can we say something about the distribution of X ?
- Intuition: small $\mathbb{E}(X) \implies$ small $\mathbb{P}(X \geq a)$

Markov Inequality

If $X \geq 0$ and $a > 0$, then $\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}(X)}{a}$.

Proof. For any $a > 0$, define Y_a as:

$$Y_a \triangleq \begin{cases} 0, & \text{if } X < a, \\ a, & \text{if } X \geq a \end{cases}$$

Then, using non-negativity of X , $Y_a \leq X$, which leads to $\mathbb{E}[Y_a] \leq \mathbb{E}[X]$.

Note that we have:

$$\mathbb{E}[Y_a] = a\mathbb{P}(Y_a = a) = a\mathbb{P}(X \geq a).$$

$$\text{Thus, } a \cdot \mathbb{P}(X \geq a) \leq \mathbb{E}[X].$$

□

- (Q) Knowing both $\mathbb{E}(X)$ and $\text{var}(X)$, can we say something about the distribution of X ?
- Intuition: small $\text{var}(X) \implies X$ is unlikely to be too far away from its mean.
- $\mathbb{E}(X) = \mu$, $\text{var}(X) = \sigma^2$.

Chebyshev Inequality

$$\mathbb{P}(|X - \mu| \geq c) \leq \frac{\sigma^2}{c^2}$$

- Proof.

$$\mathbb{P}(|X - \mu| \geq c) = \mathbb{P}((X - \mu)^2 \geq c^2) \leq \frac{\mathbb{E}[(X - \mu)^2]}{c^2} = \frac{\text{var}(X)}{c^2}$$

Example

- $X \sim \exp(1)$. Then, $\mathbb{E}[X] = 1$ and $\text{var}[X] = 1$.

- $\mathbb{E}(X \geq a) = e^{-a}$

- Markov inequality

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}[X]}{a} = \frac{1}{a}$$

- Chebyshev inequality

$$\begin{aligned}\mathbb{P}(X \geq a) &= \mathbb{P}(X - 1 \geq a - 1) \\ &\leq \mathbb{P}(|X - 1| \geq a - 1) \leq \frac{1}{(a - 1)^2}\end{aligned}$$

- For reasonably large a , CI provides much better bound.

- knowing the variance helps

- Both bounds are the ones that bound the probability of rare events.

$$M_n = \frac{S_n}{n} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

Weak law of large numbers

M_n converges to μ in probability.

Proof.

$$\mathbb{P}\left(|M_n - \mu| \geq \epsilon\right) \leq \frac{\text{var}(M_n)}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2} \xrightarrow{n \rightarrow \infty} 0$$

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Moment Generating Function

- For a rv X , we introduce a kind of transform, called **moment generating function (MGF)**.
- A function of a scalar parameter s , defined by

$$M_X(s) = \mathbb{E}[e^{sX}]$$

- If clear, we omit X and use $M(s)$.

$$M(s) = \sum_x e^{sx} p_X(x) \quad (\text{discrete})$$

$$M(s) = \int e^{sx} f_X(x) dx \quad (\text{continuous})$$

Ex1) $X \sim \exp(\lambda)$, $f_X(x) = \lambda e^{-\lambda x}$, $x \geq 0$

$$\begin{aligned} M(s) &= \lambda \int_0^{\infty} e^{sx} e^{-\lambda x} dx \\ &= \lambda \left. \frac{e^{(s-\lambda)x}}{s-\lambda} \right|_0^{\infty} \quad (\text{if } s < \lambda) \\ &= \frac{\lambda}{\lambda - s} \end{aligned}$$

Ex2) $X \sim N(0, 1)$ (homework problem)

$$M(s) = e^{s^2/2}$$

1. $M'(0) = \mathbb{E}[X]$

$$\begin{aligned}\frac{d}{ds}M(s) &= \frac{d}{ds} \int_{-\infty}^{\infty} e^{sx} f_X(x) dx = \int_{-\infty}^{\infty} \frac{d}{ds} e^{sx} f_X(x) dx = \int_{-\infty}^{\infty} x e^{sx} f_X(x) dx \\ &= \left. \frac{d}{ds} M(s) \right|_{s=0} = \mathbb{E}[X]\end{aligned}$$

2. Similarly, $M''(0) = \mathbb{E}[X^2]$

3. $\left. \frac{d^n}{ds^n} M(s) \right|_{s=0} = \mathbb{E}[X^n]$

4. MGF provides a convenient way of generating moments. That's why it is called moment generating function.

Inversion Property

The transform $M_X(s)$ associated with a random variable X uniquely determines the CDF of X , assuming that $M_X(s)$ is finite for all s in some interval $[-a, a]$, where a is a positive number.

- In easy words, we can recover the distribution if we know the MGF.
- Thus, each rv has its own MGF.

- Without loss of generality, assume $\mathbb{E}(X_i) = 0$ and $\text{var}(X_i) = 1$
- $Z_n = \frac{S_n}{\sqrt{n}} = \frac{X_1 + X_2 + \dots + X_n}{\sqrt{n}}$
- Show: MGF of Z_n converges to MFG of $N(0, 1)$ (using inversion property)

Proof.

$$\begin{aligned}\mathbb{E}\left[e^{sS_n/\sqrt{n}}\right] &= \mathbb{E}\left[e^{sX_1/\sqrt{n}}\right] \times \dots \times \mathbb{E}\left[e^{sX_n/\sqrt{n}}\right] \\ &= \left(\mathbb{E}\left[e^{sX_1/\sqrt{n}}\right]\right)^n = \left(M_{X_1}\left(\frac{s}{\sqrt{n}}\right)\right)^n\end{aligned}$$

- For simplicity, let $M(\cdot) = M_{X_1}(\cdot)$
- **Facts:** $M(0) = 1$, $M'(0) = 0$, $M''(0) = 1$
- $\left(M\left(\frac{s}{\sqrt{n}}\right)\right)^n \rightarrow \text{what???$
- Taking log, $n \log M\left(\frac{s}{\sqrt{n}}\right) \rightarrow \text{what???$

For convenience, do the change of variable $y = \frac{1}{\sqrt{n}}$. Then, we have

$$\lim_{y \rightarrow 0} \frac{\log M(ys)}{y^2}$$

- If we apply l'hospital's rule twice (please check), we get

$$\lim_{y \rightarrow 0} \frac{\log M(ys)}{y^2} = \frac{s^2}{2}$$

□

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Questions?

- 1) What's the practical value of LLN and CLT?
- 2) Explain LLN and CLT from the scaling perspective.
- 3) Why are LLN and CLT great?
- 4) Why do we need different concepts of convergence for random variables?
- 5) Explain what is convergence in probability.
- 6) Explain what is convergence in distribution.
- 7) Why is MGF useful?