

# SDS 384 11: Theoretical Statistics

## Lecture 2: Stochastic Convergence

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# Convergence of expectations: exchanging limit and integral

## Theorem (Monotone convergence theorem)

If  $0 \leq X_1 \leq X_2 \leq \dots \leq X_n \uparrow X$ , then

$$E[X_n] \rightarrow E[X]$$

## Lemma (Fatou's lemma)

If  $X_n \geq Y \ \forall n$  for some random variable  $Y$  with  $E|Y| < \infty$  then

$$\liminf_{n \rightarrow \infty} E[X_n] \geq E[\liminf_n X_n]$$

## Theorem (Dominated convergence theorem)

If  $X_n \xrightarrow{a.s.} X$  and  $|X_n| \leq Y$  with  $E[|Y|] < \infty$ , then

$$E[X_n] \rightarrow E[X]$$

## Things you should know

Consider  $n$  i.i.d. random variables  $X_i \sim F$ .

**Definition (Empirical distribution function)**

The empirical distribution function is defined as:

$$F_n(x) = \frac{1}{n} \sum_i 1(X_i \leq x).$$

**Theorem (Glivenko-Cantelli)**

*The random variable  $\sup_x |F_n(x) - F(x)|$  almost surely converges to zero.*

$$P \left( \limsup_n \sup_x |F_n(x) - F(x)| \rightarrow 0 \right) = 1$$

# Things you should know

Let  $X_1, \dots, X_n$  be i.i.d random variables with  $E[|X_1|] \leq \infty$ , mean  $\mu$ .

**Theorem (Weak law of large numbers)**

$$\bar{X}_n \xrightarrow{P} \mu$$

**Theorem (Strong law of large numbers)**

$$\bar{X}_n \xrightarrow{a.s.} \mu$$

**Theorem (Central limit theorem)**

If  $E[X_i^2] = \sigma^2$ ,  $\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{d} N(0, \sigma^2)$ .

## Things you should know

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### Theorem (Berry Esseen)

If  $E[X_i^2] = \sigma^2$ , and  $E[|X_i|^3] = \rho < \infty$ ,

$$\left| P\left(\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \leq x\right) - \Phi(x) \right| \leq \frac{C\rho}{\sigma^3\sqrt{n}} \quad \forall x, \text{ and } n,$$

where  $\Phi(x)$  is the CDF of the standard normal and  $c$  is an universal constant known to be greater than 0.4097 and less than 0.7975.

# Lindeberg-feller CLT for triangular arrays

$$X_{11}$$

$$X_{21}, X_{22}$$

$$X_{21}, X_{22}, X_{23}$$

$$\dots$$

## Theorem

For each  $n$  let  $(X_{ni})_{i=1}^n$  be independent random variables with mean zero

and variance  $\sigma_{ni}^2$ . Let  $Z_n = \sum_{i=1}^n X_{ni}$  and  $B_n^2 = \text{var}(Z_n)$ . Then

$Z_n/B_n \xrightarrow{d} N(0,1)$ , as long as the **Lindeberg condition** holds.

# The Lindeberg condition

## Definition (Lindeberg condition)

For every  $\epsilon > 0$ ,

$$\frac{1}{B_n^2} \sum_{j=1}^n E[X_{nj}^2 1(|X_{nj}| \geq \epsilon B_n)] \rightarrow 0 \text{ as } n \rightarrow \infty \quad (1)$$

**Converse:** If  $\frac{\sigma_{nj}^2}{B_n^2} \rightarrow 0$  as  $n \rightarrow \infty$ , i.e. no one variance plays a significant role in the limit, and if  $Z_n/B_n \xrightarrow{d} N(0,1)$ , then the Lindeberg condition holds.

**Necessary and Sufficient:** If  $\frac{\sigma_{nj}^2}{B_n^2} \rightarrow 0$ , the the Lindeberg condition is necessary and sufficient to show the CLT.

## Example

Let  $X_1, \dots, X_n$  be independent random variables with mean zero and variance one. Do you think  $\sqrt{n}\bar{X}_n \xrightarrow{d} N(0, 1)$ ?



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$$X_{nj} = \begin{cases} 2j & \text{w.p. } \frac{1}{8j^2} \\ 0 & \text{w.p. } 1 - \frac{1}{4j^2} \\ -2j & \text{w.p. } \frac{1}{8j^2} \end{cases}$$

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- $E[X_{nj}] = 0$  and  $\text{var}(X_{nj}) = 1$ .  $B_n^2 = n$ .

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- Lets check the Lindeberg condition with  $\epsilon = 1$ .

$$\frac{1}{n} \sum_j E[X_{nj}^2 1(|X_{nj}| \geq \sqrt{n})] = \frac{1}{n} \sum_j 2 \times 4j^2 1(2j \geq \sqrt{n}) \frac{1}{8j^2} = \frac{1}{n} \sum_{j \geq \sqrt{n}/2} 1 \rightarrow 1$$

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- Since  $\sigma_{nj}^2/B_n^2 = 1/n \rightarrow 0$ , this implies that the CLT does not hold for the sum.

# Permutation Tests

Consider  $2n$  paired experimental units with measurement  $(X_i, Y_i)_{i=1}^n$  in which  $X_j$  is the result of the treatment and  $Y_j$  is the result of control.

- $H_0$  is that the treatment has had no effect, i.e.  $Z_j = X_j - Y_j$  conditioned on the magnitude  $|Z_j|$  is symmetric, i.e.  
 $P(Z_j = |z_j|) = P(Z_j = -|z_j|) = 1/2$ .

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- Thus, under  $H_0$ ,  $(Z_1, \dots, Z_n)$  has  $2^n$  possible values  $(\pm|z_1|, \dots, \pm|z_n|)$ .
- Conditioned on the magnitudes of the differences,  $B_n^2 = \sum_i z_i^2$ .

Assume that  $\max_i z_i^2 / B_n^2 \rightarrow 0$ . Then  $\sum_i Z_i / B_n \xrightarrow{d} N(0, 1)$  using the Lindeberg-feller theorem.

## Permutation tests: proof

### Proof.

- Lets check the Lindeberg condition:

$$\begin{aligned}\frac{\sum_{j=1}^n E[Z_j^2 1(|Z_j| \geq \epsilon B_n) | Z_1, \dots, Z_n]}{B_n^2} &= \frac{\sum_j Z_j^2 1(|Z_j| \geq \epsilon B_n)}{B_n^2} \\ &\leq \frac{(\sum_j Z_j^2) 1(\max_j |Z_j| \geq \epsilon B_n)}{B_n^2} \\ &= 1(\max_j |Z_j| \geq \epsilon B_n)\end{aligned}$$

- Since  $\max_i z_i^2 / B_n^2 \rightarrow 0$ , the above is zero for all sufficiently large  $n$ .





# Tail probabilities

- Most often, we are interested in the question, how far is an empirical quantity from its “population variant”?
- This empirical quantity can be an eigenvalue of a matrix, or the weight vector learned using linear regression and so on.
- For rest of today, and a few more lectures we will brush up on tail inequalities.
- Lets start with the mean?

# Concentration inequalities

- How will you bound  $P(|\bar{X}_n - \mu| \geq t)$ ? Central limit theorem works under regularity conditions, but its only asymptotic.
- We will look at three methods:
  - Moment based:

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  - Moment generating function based bounds: Hoeffding, Chernoff, Bernstein, subgaussian and subexponential random variables
  - Martingale based methods: Azuma-Hoeffding, McDiarmid

