

# Asymptotic theory

## Stochastic convergence

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Let  $x_1, x_2, \dots$  be a sequence of a scalar random variable that converge to a random variable  $x$ . Both  $x_N$  and  $x$  are defined on probability space  $(\Omega, \mathcal{F}, Pr)$ . Let us denote the cumulative distribution functions of  $x_N$  and  $x$  by  $F_N$  and  $F$  respectively.

**Question:** What if  $x$  is a fixed, real number?

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**Question:** What if  $x$  is a fixed, real number?

# Convergence in probability

The sequence  $x_n$  **converges in probability** to  $x$  if for every  $\epsilon > 0$

$$\lim_{n \rightarrow \infty} \Pr(|x_n - x| < \epsilon) = 1$$

It is abbreviated as

$$p \lim x_n = x$$

or

$$x_n \rightarrow^p x$$

# Rules

If  $x_n$  and  $y_n$  are random variables with  $p \lim x_n = c$  and  $p \lim y_n = d$ , then

- **Sum rule:**  $p \lim (x_n + y_n) = c + d$
- **Product rule:**  $p \lim x_n y_n = cd$
- **Ratio rule:**  $p \lim x_n / y_n = c/d$ , if  $d \neq 0$

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If  $X_n$  and  $Y_n$  are random matrices with  $p \lim X_n = A$  and  $p \lim Y_n = B$ , then

- **Inverse rule:** if  $A$  is square and non-degenerated then  $p \lim X_n^{-1} = A^{-1}$
- **Product rule:**  $p \lim X_n Y_n = AB$

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# Convergence almost surely

The sequence  $x_N$  **converges almost surely** or **with a probability one** to  $x$  if for every  $\epsilon > 0$

$$Pr(\lim_{N \rightarrow \infty} |x_N - x| < \epsilon) = 1$$

It is abbreviated as

$$x_N \rightarrow^{a.s.} x$$

Sometimes it is called a **strong convergence**.

# Convergence in distribution

The sequence  $x_N$  **converges in distribution** to  $x$  if for every real number  $c$

$$\lim_{N \rightarrow \infty} F_N(c) = F(c)$$

It is abbreviated as

$$x_N \rightarrow^d x$$

Sometimes it is called a **weak convergence**.

**Remark:** It does not require convergence of p.d.f.s



# Rules

If  $x_n \rightarrow^d x$  and  $\text{plim } y_n = c$ , then

- $x_n + y_n \rightarrow^d x + c$
- $x_n y_n \rightarrow^d cx$
- $x_n / y_n \rightarrow^d x/c$ , if  $c \neq 0$

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# Convergence properties

## Convergence properties

1  $X_N \rightarrow^p X \Rightarrow X_N \rightarrow^d X$

2 Suppose  $x$  is a fixed, real number then

$$X_N \rightarrow^p x \Leftrightarrow X_N \rightarrow^d x$$

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# Convergence properties

## Slutsk'y theorem

If  $g : R \rightarrow R$  is a continuous functions then

- $x_N \rightarrow^p x \Rightarrow g(x_N) \rightarrow^p g(x)$
- $x_N \rightarrow^d x \Rightarrow g(x_N) \rightarrow^d g(x)$
- $x_N \rightarrow^{a.s.} x \Rightarrow g(x_N) \rightarrow^{a.s.} g(x)$

where

$$\lim g(x_N) = g(\lim x_N)$$

# Questions

Suppose  $x_n \rightarrow^d N(\alpha, \sigma^2)$

- if  $\hat{\alpha}_n \rightarrow^d \alpha \in R$ , does  $\hat{\alpha}_n$  converge in probability?
- $p \lim \hat{\alpha} = \alpha$ , what is the asymptotic distribution of  $x_n - \hat{\alpha}$ ?
- $p \lim \hat{\sigma}^2 = \sigma^2$ , what is  $p \lim 1/\sqrt{\hat{\sigma}^2}$  and the asymptotic distribution of  $(x_n - \hat{\alpha})/\sqrt{\hat{\sigma}^2}$ ?



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# Asymptotic theory

## Laws of Large Number and Central Limit Theorem

# Laws of large numbers

## Khinchine's Theorem

Let  $x_n$  be a sequence of i.i.d. random variables with  $E(x_n) = \mu < \infty$ . Then

$$\bar{x}_N := \frac{1}{N} \sum_{n=1}^N x_n \xrightarrow{p} \mu$$

# Laws of large numbers

## Chebyshev's Theorem

Let  $x_n$  be a sequence of independent random variables with  $E(x_i) = \mu_i < \infty$  and  $Var(x_i) = \sigma_i^2 < \infty$ , such that  $\bar{\sigma}_n^2 = 1/n^2 \sum_{i=1}^n \sigma_i^2 \rightarrow 0$ , then

$$\bar{x}_n \rightarrow^p \bar{\mu}_n$$

# Question

Suppose,  $x_n$  is a sequence of independent random variables with  $E(x_n) = \mu < \infty$  and  $Var(x_n) \leq c < \infty$  for some finite constant  $c$ .

- Are the conditions of Chebyshev's Theorem satisfied?
- What is the  $p \lim \bar{x}_N$ ?

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# Central Limit Theorem

## Lindberg-Levy CLT

Suppose  $x_n$  be a sequence of independent random variables with finite means  $\mu_i$  and a finite variances  $\sigma_i^2$ . If no single element dominates

$$\lim_{n \rightarrow \infty} \max(\sigma_i^2)/(n^2 \bar{\sigma}_n^2) = 0$$

and there exists a finite constant  $\bar{\sigma}^2$

$$\bar{\sigma}^2 = \lim_{n \rightarrow \infty} \bar{\sigma}_i^2 < \infty$$

then

$$\sqrt{n}(\bar{x}_n - \bar{\mu}_n) \rightarrow^d N(0, \bar{\sigma}^2)$$



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Suppose  $x_n$  is a sequence of i.i.d. random variables with a mean  $\mu$  and a finite variance  $\sigma^2$ .

- Are the conditions of Lindberg-Levy CLT satisfied?
- Formulate the CLT.

$$\sqrt{n}(\bar{x}_n - \mu) \rightarrow^d N(0, \sigma^2)$$

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# Question

Suppose  $x_n \sim N(\mu, \sigma^2)$  is a sequence of i.i.d. random variables.  
Let  $\hat{\mu}_n = 1/n \sum_{i=1}^n x_i$ .

- What is the asymptotic distribution of  $\hat{\mu}_n$  (use CLT)?
- Does it matter, if  $x_n$  does not have a normal distribution?

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# Limiting distribution of a function

Suppose  $\sqrt{n}(x_n - \mu) \rightarrow^d N(0, \sigma^2)$  and if  $g(z)$  is a continuous and continuously differentiable function with  $g'(z) \neq 0$ , then

$$\sqrt{n}(g(x_n) - g(\mu)) \rightarrow^d N(0, g'(\mu)^2 \sigma^2)$$

# Question

Suppose  $\sqrt{n}(x_n - 1) \rightarrow^d N(0, 5)$ . What is the asymptotic distribution of  $g(x_n)$ , when

- $g(z) = z + 2$
- $g(z) = z^2$



# Central Limit Theorem

## Lindberg-Levy CLT

Let  $x_n$  be a sequence of  $K$ -dimensional i.i.d random variables with a mean  $\mu$  and a covariance matrix  $\Sigma$ . Then

$$\sqrt{N}(\bar{x}_N - \mu) \rightarrow^d N(0, \Sigma)$$

# Limiting distribution of a function

Suppose  $\sqrt{n}(x_n - \mu) \rightarrow^d N(0, \Sigma)$  and if  $g(z)$  is a  $J$  continuous and continuously differentiable function with  $G(z) = g'(z) \neq 0$ , then

$$\sqrt{n}(g(x_n) - g(\mu)) \rightarrow^d N(0, G(\mu)' \Sigma G(\mu))$$

# Question

Suppose  $\sqrt{n}x_n \rightarrow^d N(0, I_2)$ . What is the asymptotic distribution of  $g(x_n)$ , when

- $g(z) = z_1 + z_2$
- $g(z) = [z_1, z_1 - z_2 + 1]'$

# Asymptotic theory

## Asymptotic properties of estimators

# Properties of estimators

Properties of an estimator  $\hat{\beta}$ :

- $\hat{\beta}$  is **unbias** estimator of  $\beta$  if  $E(\hat{\beta}) = \beta$
- $\hat{\beta}$  is **(weakly) consistent** if  $\hat{\beta}_N \rightarrow^p \beta$
- $\hat{\beta}$  is **strongly consistent** if  $\hat{\beta}_N \rightarrow^{a.s.} \beta$
- $\hat{\beta}$  is asymptotically normal if

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# Linear combination of estimators

Suppose  $\hat{\beta}$  is an estimator of a  $(K \times 1)$  vector  $\beta$  with

$$\sqrt{N}(\hat{\beta} - \beta) \rightarrow^d N(0, \Sigma)$$

- Let  $A \neq 0$ . What is the asymptotic distribution of  $\sqrt{N}A(\hat{\beta} - \beta)$ ?
- Suppose,  $p \lim \hat{A} = A$ . Does it change the previous result?

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# Example 1

Suppose  $K = 2$  and  $\beta = (2, 2)'$  and

$$\Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 3 \end{bmatrix}$$

What is the asymptotic distribution of  $\hat{\beta}_1 - \hat{\beta}_2$ ?

$$\sqrt{N}(\hat{\beta}_1 - \hat{\beta}_2) \rightarrow^d N(0, 3)$$



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# Delta method

Suppose  $g(\beta) = (g_1(\beta), \dots, g_m(\beta))'$  is a vector-valued continuously differentiable function with  $\partial g(\beta)/\partial \beta' \neq 0$  at  $\beta$ , then

$$\sqrt{N}(g(\hat{\beta}) - g(\beta)) \rightarrow^d N(0, \frac{\partial g(\beta)}{\partial \beta'} \Sigma \frac{\partial g(\beta)'}{\partial \beta})$$

**Remark:** if  $\partial g(\beta)/\partial \beta' = 0$  then

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**Remark:** if  $\partial g(\beta)/\partial \beta' = 0$  then

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## Example 2

Suppose the true parameter  $\beta = 1$  is a single valued scalar and  $\sqrt{N}(\hat{\beta} - \beta) \rightarrow^d N(0, 2)$

What is an asymptotic distribution of  $g(\hat{\beta}) = \hat{\beta}^3 + \hat{\beta}^2 - 2$ ?

$$\sqrt{N}(g(\hat{\beta}) - g(\beta)) = \sqrt{N}g(\hat{\beta}) \rightarrow^d N(0, 50)$$

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# Quadratic form

Suppose,  $\Sigma$  is nonsingular,  $(K \times K)$  matrix and

$$\sqrt{N}(\hat{\beta} - \beta) \rightarrow^d N(0, \Sigma)$$

- What is the asymptotic distribution of  $N(\hat{\beta} - \beta)' \Sigma^{-1}(\hat{\beta} - \beta)$ ?
- Suppose,  $p \lim \hat{\Sigma} = \Sigma$ . Does it change the previous result?

$$N(\hat{\beta} - \beta)' \Sigma^{-1}(\hat{\beta} - \beta) \rightarrow^d \chi^2(K)$$

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## Example 3

Suppose,  $\sqrt{N}(\hat{\beta} - \beta) \rightarrow^d N(0, \Sigma)$ , with a nonsingular,  $(K \times K)$  matrix  $\Sigma$ .

- Find a matrix  $M$  such that a quadratic form of  $A(\hat{\beta} - \beta)$  will converge to  $\chi^2(K)$

What is the asymptotic distribution of a quadratic form of  $A(\hat{\beta} - \beta)$ , where  $A$  is a quadratic, nonsingular matrix?

$$N(\hat{\beta} - \beta)' A' (A \Sigma A')^{-1} A (\hat{\beta} - \beta) \rightarrow^d \chi^2(K)$$

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## Example 4

What happens if the matrix  $A$  is not quadratic, but has dimension  $(M \times K)$ , where  $M < K$  and  $\text{rank}(A) = M$ ?

Similarly to the previous example, the quadratic form will have a  $\chi^2$  distribution. It will have  $M$  degrees of freedom.

$$N(\hat{\beta} - \beta)' A' (A \Sigma A')^{-1} A (\hat{\beta} - \beta) \rightarrow^d \chi^2(M)$$

## Example 4

What happens if the matrix  $A$  is not quadratic, but has dimension  $(M \times K)$ , where  $M < K$  and  $\text{rank}(A) = M$ ?

Similarly to the previous example, the quadratic form will have a  $\chi^2$  distribution. It will have  **$M$  degrees of freedom**.

$$N(\hat{\beta} - \beta)' A' (A \Sigma A')^{-1} A (\hat{\beta} - \beta) \rightarrow^d \chi^2(M)$$