

Convergence of Random Variables

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Outline

- ▶ convergence definitions
- ▶ continuous mapping and Slutsky's theorems
- ▶ big-O notation
- ▶ major convergence theorems

Reading: van der Vaart Chapter 2

Basics of convergence

Definition

Let X_n be a sequence of random vectors. Then X_n *converges in probability to* X ,

$$X_n \xrightarrow{p} X$$

if for all $\epsilon > 0$,

$$\mathbb{P}(\|X_n - X\| \geq \epsilon) \rightarrow 0 \text{ as } n \rightarrow \infty$$

Convergence in distribution / weak convergence

Definition

For random variables $X_n \in \mathbb{R}$ and $X \in \mathbb{R}$, X_n converges in distribution to X ,

$$X_n \xrightarrow{d} X \quad \text{or} \quad X_n \rightsquigarrow X$$

if for all x such that $x \mapsto \mathbb{P}(X \leq x)$ is continuous,

$$\mathbb{P}(X_n \leq x) \rightarrow \mathbb{P}(X \leq x) \quad \text{as } n \rightarrow \infty$$

Convergence in distribution / weak convergence

Definition

For metric space-valued random variables X_n, X , X_n converges in distribution to X if for all bounded continuous f

$$\mathbb{E}[f(X_n)] \rightarrow \mathbb{E}[f(X)] \text{ as } n \rightarrow \infty$$

Convergence in p th mean

Definition

Vector-valued random variables X_n converge in L^p (or converge in p th mean) to X ,

$$X_n \xrightarrow{L^p} X$$

if $\mathbb{E}[\|X_n - X\|^p] \rightarrow 0$ as $n \rightarrow \infty$.

Almost sure convergence

Definition

Random variables *converge almost surely*, $X_n \xrightarrow{a.s.} X$, if

$$\mathbb{P}\left(\lim_n X_n \neq X\right) = 0 \quad \text{or} \quad \mathbb{P}\left(\lim_n \|X_n - X\| \geq \epsilon\right) = 0$$

for all $\epsilon > 0$.

Standard implications

An example (the central limit theorem)

Portmanteau Lemma

Theorem

Let X_n, X be random vectors. The following are all equivalent.

- (1) $X_n \xrightarrow{d} X$
- (2) $\mathbb{E}[f(X_n)] \rightarrow \mathbb{E}[f(X)]$ for all bounded continuous f
- (3) $\mathbb{E}[f(X_n)] \rightarrow \mathbb{E}[f(X)]$ for all 1-Lipschitz f with $f(x) \in [0, 1]$
- (4) $\liminf_n \mathbb{E}[f(X_n)] \geq \mathbb{E}[f(X)]$ for all continuous nonnegative f
- (5) $\liminf_n \mathbb{P}(X_n \in O) \geq \mathbb{P}(X \in O)$ for all open sets O
- (6) $\limsup_n \mathbb{P}(X_n \in C) \leq \mathbb{P}(X \in C)$ for all closed sets C
- (7) $\lim \mathbb{P}(X_n \in B) = \mathbb{P}(X \in B)$ for all sets B such that $\mathbb{P}(X \in \text{bd}B) = 0$

A few remarks on the Portmanteau Lemma

- ▶ A collection \mathcal{F} is a *convergence determining class* if

$$\mathbb{E}[f(X_n)] \rightarrow \mathbb{E}[f(X)] \text{ for all } f \in \mathcal{F} \text{ if and only if } X_n \xrightarrow{d} X$$

- ▶ Characteristic functions of the form $f(x) = \exp(it^T x)$ for $i = \sqrt{-1}$ and $t \in \mathbb{R}^d$ are convergence determining
- ▶ Boundedness of f in the Portmanteau lemma is important

Proof sketches of the Pormanteau lemma

Continuous mapping theorems

Theorem (Continuous mapping)

Let g be continuous on a set B such that $\mathbb{P}(X \in B) = 1$. Then

(1) $X_n \xrightarrow{P} X$ implies $g(X_n) \xrightarrow{P} g(X)$

(2) $X_n \xrightarrow{d} X$ implies $g(X_n) \xrightarrow{d} g(X)$

(3) $X_n \xrightarrow{a.s.} X$ implies $g(X_n) \xrightarrow{a.s.} g(X)$

Slutsky's theorems

Theorem (Slutsky)

(1) $X_n \xrightarrow{d} c$ if and only if $X_n \xrightarrow{P} c$

(2) $X_n \xrightarrow{d} X$ and $d(X_n, Y_n) \xrightarrow{P} 0$ implies that $Y_n \xrightarrow{d} X$

(3) $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{P} c$ implies

$$\begin{pmatrix} X_n \\ Y_n \end{pmatrix} \xrightarrow{d} \begin{pmatrix} X \\ c \end{pmatrix}$$

Proof sketches

Consequences of Slutsky's theorems

Corollary

If $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{d} c$, then

(1) $X_n + Y_n \xrightarrow{d} X + c$

(2) $X_n Y_n \xrightarrow{d} cX$

(3) If $C \in \mathbb{R}^{d \times d}$ with $\det(C) \neq 0$, and $Y_n \xrightarrow{d} C$, then

$$Y_n^{-1} X_n \xrightarrow{d} C^{-1} X$$

Example: t -type statistics

Example

Let $X_i \stackrel{\text{iid}}{\sim} P$ with $\text{Cov}(X_i) = \Sigma \succ 0$, set

$$\mu_n := \frac{1}{n} \sum_{i=1}^n X_i \quad S_n := \frac{1}{n} \sum_{i=1}^n (X_i - \mu_n)(X_i - \mu_n)^T.$$

Then

$$T_n := \frac{1}{\sqrt{n}} S_n^{-1/2} \sum_{i=1}^n (X_i - \mu_n) \text{ satisfies } T_n \xrightarrow{d} \mathcal{N}(0, I).$$

Big-O Notation

Let X_n be random vectors, $R_n \in \mathbb{R}$ be random variables. We write

$$X_n = o_P(R_n) \text{ if } X_n = Y_n R_n, \text{ where } Y_n \xrightarrow{P} 0$$

and

$$X_n = O_P(R_n) \text{ if } X_n = Y_n R_n \text{ where } Y_n = O_P(1)$$

and $Y_n = O_P(1)$ means that Y_n is *uniformly tight*, that is,

$$\limsup_{M \rightarrow \infty} \sup_n \mathbb{P}(\|Y_n\| \geq M) = 0.$$

Some consequences of big-O notation

Lemma

We have $o_P(1) + o_P(1) = o_P(1)$, $O_P(1) + O_P(1) = O_P(1)$, and $o_P(R_n) = O_P(R_n)$

Lemma

Let $R : \mathbb{R}^d \rightarrow \mathbb{R}^k$ satisfy $R(0) = 0$ and let $X_n \xrightarrow{P} 0$. Then

- (1) If $R(h) = o(\|h\|^p)$ as $h \rightarrow 0$, then $R(X_n) = o_P(\|X_n\|^p)$
- (2) If $R(h) = O(\|h\|^p)$ as $h \rightarrow 0$, then $R(X_n) = O_P(\|X_n\|^p)$

Compactness and distributional convergence

Definition

A collection of random vectors $\{X_\alpha\}_{\alpha \in \mathcal{A}}$ is *uniformly tight* if for all $\epsilon > 0$, there exists $M < \infty$ such that

$$\sup_{\alpha \in \mathcal{A}} \mathbb{P}(\|X_\alpha\| \geq M) \leq \epsilon.$$

Remark: A single random vector is tight

Remark: if $X_n \xrightarrow{d} X$ then $\{X_n\}_{n \in \mathbb{N}}$ is uniformly tight

Prohorov's Theorem

Theorem (Prohorov)

A collection $\{X_\alpha\}_{\alpha \in \mathcal{A}}$ is uniformly tight if and only if it is sequentially compact for convergence in distribution, that is, for all sequences $\{X_n\} \subset \{X_\alpha\}_{\alpha \in \mathcal{A}}$, there is a subsequence $n(k)$ such that $X_{n(k)} \xrightarrow{d} X$ as $k \rightarrow \infty$ for some random vector X .

A final useful convergence theorem

Theorem (Scheffe)

For a measure μ , let $f_n \rightarrow f$ μ -almost everywhere and assume $\limsup_n \int |f_n|^p d\mu \leq \int |f|^p d\mu < \infty$. Then

$$\|f_n - f\|_{L^p(\mu)}^p = \int |f_n - f|^p d\mu \rightarrow 0$$