

Session 26

Convergence of Sequences of RVs

26.1

$$X_1, X_2, \dots, X_n, \dots$$

Example: Suppose I make a sequence of measurements:

$$X_k = a + W_k, \quad k = 1, 2, 3, \dots$$

a = parameter of interest.

X_k = k -th measurement.

W_k = experimental error in the k -th measurement

$$E[W_k] = 0 \quad (\text{unbiased measurement})$$

If we consider X_1, \dots, X_n, \dots to be measurements, we typically estimate the value of a by

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$$\bar{X}_n = \frac{1}{n} [X_1 + X_2 + \dots + X_n]$$

Is this a good estimate of a ?

Hopefully, $\bar{X}_n \rightarrow a$, as $n \rightarrow \infty$.

Is this true? Is it always true?

Is it ever true?

What does $\bar{X}_n \rightarrow a$ mean?

Note that

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$$\bar{X}_n = \frac{1}{n} [X_1 + \dots + X_n]$$

is itself a random variable, so

$$\bar{X}_1, \bar{X}_2, \bar{X}_3, \dots, \bar{X}_n, \dots$$

is also a sequence of random variables
(i.e., a random sequence.)

Q: What does it mean to ask if

$$\bar{X}_n \rightarrow a \text{ as } n \rightarrow \infty ?$$

Defn: A random sequence or a

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discrete-time stochastic process

is a sequence of random variables

X_1, \dots, X_n, \dots defined on (Ω, \mathcal{F}, P)

(If X_i is a R.V. for each $i \in \mathbb{N}$, then measurability is not an issue.)

• We often write a random sequence as $\{X_n\}$ or $\{X_n\}_{n \in \mathbb{N}}$ or $\{X_n\}_{n \geq 1}$

• For any specific $\omega_0 \in \Omega$ of (Ω, \mathcal{F}, P)
 $X_1(\omega_0), X_2(\omega_0), \dots, X_n(\omega_0), \dots$

is a sequence of real numbers.

Defn: A sequence of real numbers x_1, \dots, x_n, \dots is said to converge to a limit x if, for $\forall \varepsilon > 0$, there exists a number $n_\varepsilon \in \mathbb{N}$ such that

$$|x_n - x| < \varepsilon, \quad \forall n \geq n_\varepsilon.$$

" $x_n \rightarrow x$ as $n \rightarrow \infty$ "

Given a random sequence

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$X_1(\cdot), X_2(\cdot), \dots, X_n(\cdot), \dots$

for any particular $\omega \in \Omega$, we have

$X_1(\omega), X_2(\omega), \dots, X_n(\omega), \dots$

is a sequence of real numbers

- It may converge to a number $X(\omega)$
- or, it may not converge.

note The $X(\omega)$ that the random sequence converges to is itself a function of ω ($X(\omega)$ is a R.V.).

Given a random sequence

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$X_1(\cdot), X_2(\cdot), \dots, X_n(\cdot), \dots$

for any particular $\omega \in \Omega$, we have

$X_1(\omega), X_2(\omega), \dots, X_n(\omega), \dots$

is a sequence of real numbers

- It may converge to a number $X(\omega)$
- or, it may not converge.

note The $X(\omega)$ that the random sequence converges to is itself a function of ω ($X(\omega)$ is a R.V.).

Given a random sequence

$$X_1(\omega), \dots, X_n(\omega), \dots$$

most likely it will converge for some $\omega \in \Omega$, and not converge for other $\omega \in \Omega$.

When we study convergence of random sequences (Stochastic Convergence) we study the set $A \subset \Omega$ for which

$$X_1(\omega), \dots, X_n(\omega), \dots$$

is a convergent sequence for all

$$\omega \in A.$$

Defn: We say that a sequence of RVs converges everywhere (e) if the sequences

$$X_1(\omega), X_2(\omega), \dots, X_n(\omega), \dots$$

each converge to a number $X(\omega)$ for each $\omega \in \Omega$.

n.b.

- The number $X(\omega)$ that each sequence converges to for each $\omega \in \Omega$ is a function of ω .
 $X(\omega)$ is a RV.

- Convergence everywhere is too strong or restrictive to be useful.

Defn: A random sequence $\{X_n\}$
converges almost everywhere (a.e.)

if the set of outcomes $A \subset \Omega$ such
 that $X_n(\omega) \xrightarrow{n \rightarrow \infty} X(\omega)$, $\omega \in A$
 exists and has probability 1:

$$P(A) = 1.$$

Other names for convergence almost everywhere.

- also sure convergence (a.s.)
- convergence with probability one.

We write this as

$$"X_n \xrightarrow{\text{a.e.}} X"$$

$$"P(\{X_n \rightarrow X\}) = 1"$$

Defn:

A random sequence $\{X_n\}$
converges in mean-square (m.s.)
to a RV X if

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$$E[|X_n - X|^2] \rightarrow 0 \text{ as } n \rightarrow \infty.$$

n.b.

If we have the j. pdf of X_n and X ,
we can compute

$$E[|X_n - X|^2] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x_n - x)^2 f_{X_n, X}(x_n, x) dx_n dx$$

So in principle, it is easy to
determine mean-square convergence

Defn: A random sequence $\{X_n\}$
converges in probability (p)
to a random variable X if,
 $\forall \varepsilon > 0$

$$P(\{|X_n - X| > \varepsilon\}) \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Defn: A random sequence $\{X_n\}$
converges in distribution (d) to
 a RV X if

$$F_{X_n}(x) \rightarrow F_X(x) \text{ as } n \rightarrow \infty \quad (*)$$

at every point $x \in \mathbb{R}$ where

$F_X(x)$ is continuous.

(*): i.e. $\forall \varepsilon > 0$, $\exists n_\varepsilon \in \mathbb{N}$ such that

$$|F_{X_n}(x) - F_X(x)| < \varepsilon, \quad \forall n \geq n_\varepsilon$$

for all $x \in \mathbb{R}$ where $F_X(x)$ is continuous.

Defn: A random sequence $\{X_n\}$
converges in density (den)
to a R.V. X if

$$f_{X_n}(x) \rightarrow f_X(x) \text{ as } n \rightarrow \infty$$

at every point $x \in \mathbb{R}$ where $F_X(x)$
is continuous.

Aren't convergence in density and convergence in distribution equivalent?

No!

Example: Let $\{X_n\}$ be a sequence of RVs having p.d.f's

$$f_{X_n}(x) = [1 + \cos(2\pi nx)] \cdot \mathbb{1}_{[0,1]}(x).$$

n.b. (i) $f_{X_n}(x) \geq 0, \forall x$

(ii) $= \int_{-\infty}^{\infty} f_n(x) dx = \int_0^1 (1 + \cos(2\pi nx)) dx = \left(x + \frac{1}{2\pi n} \sin(2\pi nx) \right) \Big|_0^1 = 1, n = 1, 2, 3, \dots$

Now define

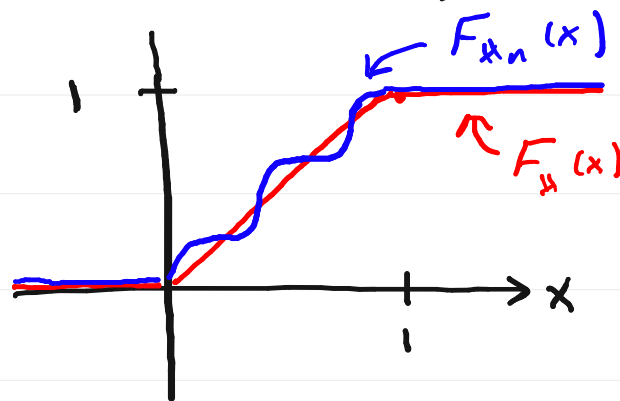
$$F_{\#}(x) = \begin{cases} 0, & x < 0, \\ x, & x \in [0, 1], \\ 1, & x > 1. \end{cases}$$

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Note that

$$F_{\#_n}(x) = \int_{-\infty}^x f_n(\alpha) d\alpha = \begin{cases} 0, & x < 0 \\ x + \frac{1}{2\pi n} \sin(2\pi n x), & x \in [0, 1] \\ 1, & x > 1 \end{cases}$$

Clearly $F_{\#_n}(x) \rightarrow F_{\#}(x), \forall x \in \mathbb{R}$



$$F_{\#_n}(x) \rightarrow F_{\#}(x)$$

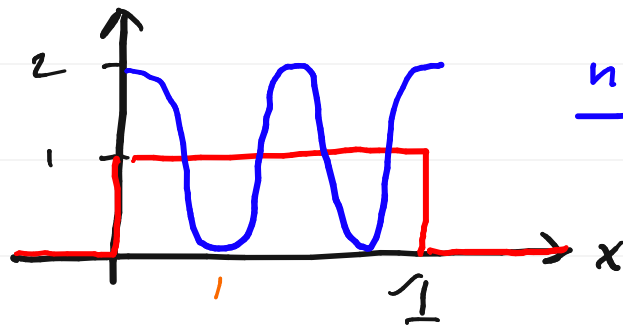
as $n \rightarrow \infty$.

But $f_{F_n}(x) \not\rightarrow f_{F^*}(x)$

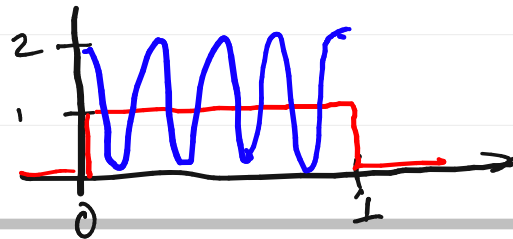
$$f_{F^*}(x) = \frac{dF_{F^*}(x)}{dx} = \mathbb{1}_{[0,1]}(x)$$

and

$$f_n(x) = [1 + \cos 2\pi n x] \cdot \mathbb{1}_{[0,1]}(x)$$



As $n \rightarrow \infty$



$$f_{F_n}(x) \not\rightarrow f_{F^*}(x)$$

as $n \rightarrow \infty$

\therefore Convergence (d)

$\not\Rightarrow$ convergence (Den)

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However

convergence (den) \implies convergence (d).

(n.b. The integration that converts $f_{h_n}(x)$
into $F_{h_n}(x)$ smoothes things out.)

Cauchy Criterion for Convergence

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Recall that a sequence of real numbers x_1, \dots, x_n, \dots converges to a limit x if $\forall \varepsilon > 0, \exists n_\varepsilon \in \mathbb{N}$ such that

$$|x_n - x| < \varepsilon, \quad \forall n \geq n_\varepsilon.$$

To use this definition to determine if x_1, \dots, x_n, \dots converges, we have to know the limit x .

The Cauchy Criterion gives us a way to test for convergence without knowing the limit x .

Cauchy Criterion: If $\{X_n\}$ is a sequence of real numbers and

$$|X_{n+m} - X_n| \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

for all $m \in \mathbb{N}$, then the sequence converges to a real number.

n.b. The Cauchy criterion can be applied to various forms of stochastic convergence.

e.g. $E[|X_{n+m} - X_n|^2] \rightarrow 0$ as $n \rightarrow \infty$ for all $m = 1, 2, 3, 4, \dots$

then $\{X_n\}$ converges in mean-square.

Comparison of Modes of Convergence

