

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:

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

a = parameter of interest.

X_k = k -th measurement.

w_k = experimental error in the k -th measurement

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

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

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

Is this a good estimate of a ?

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

Is this true? Is it always true?

Is it ever true?

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

Note that

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

is itself a random variable, so

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

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

Q: What does it mean to ask if

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

Defn: A random sequence or a 26.4
 discrete-time stochastic process
 is a sequence of random variables
 $\{X_1, X_2, \dots, X_n, \dots\}$ 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 26.5
 $\{x_1, x_2, \dots, x_n, \dots\}$ is said to converge
to a limit x if, for $\forall \epsilon > 0$,
 there exists a number $n_\epsilon \in \mathbb{N}$
 such that
 $|x_n - x| < \epsilon, \forall n \geq n_\epsilon$.
 " $x_n \rightarrow x$ 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.

n.b 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

26.7

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

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.

n.b 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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$$X_1(\omega), \dots, X_n(\omega), \dots$$

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

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RVs converges everywhere (\mathcal{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 $\{\mathbb{X}_n\}$ 26.10

converges almost everywhere (a.e.)

if the set of outcomes $A \subset \Omega$ such

that $\mathbb{X}_n(\omega) \xrightarrow{n \rightarrow \infty} \mathbb{X}(\omega)$, $\omega \in A$

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

$$\text{" } \mathbb{X}_n \xrightarrow{\text{a.e.}} \mathbb{X} \text{"}$$

$$\text{" } P(\{\mathbb{X}_n \rightarrow \mathbb{X}\}) = 1 \text{"}$$

Defn: A random sequence $\{\mathbb{X}_n\}$ 26.11

converges in mean-square (m.s.)

to a RV \mathbb{X} if

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

n.b. If we have the j-pdf of \mathbb{X}_n and \mathbb{X} ,
we can compute

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

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

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

$$\forall \varepsilon > 0$$

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

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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

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

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

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

$$f_{\hat{X}_n}(x) \rightarrow f_{\hat{X}}(x) \text{ as } n \rightarrow \infty$$

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

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

No!

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

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

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

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

Now define

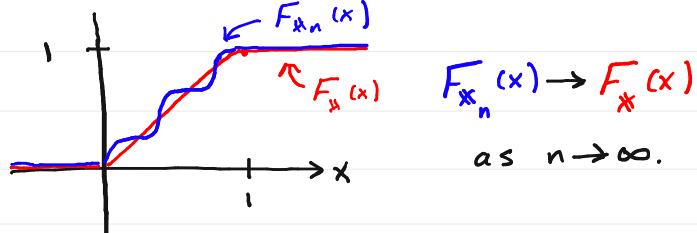
$$F_x(x) = \begin{cases} 0, & x < 0, \\ x, & x \in [0, 1], \\ 1, & x > 1. \end{cases}$$

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Note that

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

Clearly $F_{x_n}(x) \rightarrow F_x(x)$, $\forall x \in \mathbb{R}$



But $f_{x_n}(x) \not\rightarrow f_x(x)$

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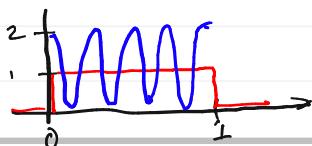
$$f_x(x) = \frac{d F_x(x)}{dx} = \underset{[0,1]}{1}$$

and

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



As $n \rightarrow \infty$



$f_{x_n}(x) \not\rightarrow f_x(x)$
as $n \rightarrow \infty$,
 \therefore Convergence (d)
 $\not\Rightarrow$ convergence (den).

However

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Convergence (den) \Rightarrow convergence (d).

(n.b. The integration that converts $f_{x_n}(x)$ into $F_{x_n}(x)$ 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 .

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

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

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. $E[|X_{n+m} - X_n|^2] \rightarrow 0 \text{ as } n \rightarrow \infty \text{ for all } m = 1, 2, 3, 4 \dots$
 then $\{X_n\}$ converges in mean-square

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Comparison of Modes of Convergence

