

Statistical Sciences

DoSS Summer Bootcamp Probability Module 7

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July 24, 2022

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Recap

Learnt in last module:

• Covariance

- $\,\triangleright\,$ Covariance as an inner product
- \triangleright Correlation
- Cauchy-Schwarz inequality
- $\,\triangleright\,$ Uncorrelatedness and Independence

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- Concentration
 - ▷ Markov's inequality
 - ▷ Chebyshev's inequality
 - Chernoff bounds



Outline

- Stochastic convergence
 - $\,\triangleright\,$ Convergence in distribution
 - ▷ Convergence in probability
 - Convergence almost surely
 - \triangleright Convergence in L^p
 - ▷ Relationship between convergences



Recall: Convergence

Convergence of a sequence of numbers

A sequence a_1, a_2, \cdots converges to a limit *a* if

$$\lim_{n\to\infty}a_n=a.$$

That is, for any $\epsilon > 0$, there exists an $N(\epsilon)$ such that

$$|a_n-a|<\epsilon,\quad\forall n>N(\epsilon).$$



a, a2 a, ... a NEE, (a NEE)+1

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Example: $a_n = \frac{1}{n}$, $\forall \epsilon > 0$, take $N(\epsilon) = \lceil \frac{1}{\epsilon} \rceil$, then for $n > N(\epsilon)$,

$$|\underline{a_n - 0}| = a_n < \epsilon, \quad \lim_{n \to \infty} a_n = 0.$$

$$\frac{1}{n} < \varepsilon \quad \frac{1}{n'} < \frac{1}{n'' < \varepsilon}, \quad \leq \varepsilon.$$

$$\mathcal{V}(\varsigma) = \int \frac{1}{\varepsilon} \int z \frac{1}{\varepsilon} \quad \text{and } \varepsilon \in \varepsilon.$$

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- Capture the property of a series as $n \to \infty$;
- The limit is something where the series concentrate for large *n*;
- $|a_n a|$ quantifies the closeness of the series and the limit.



$$X_i$$
; $X_1 \times 2 \cdots \times n \cdots$

Observation: closeness of random variables

Sample mean of i.i.d. random variables

For i.i.d. random variables X_i , $i = 1, \dots, n$ with $\mathbb{E}(X_i) = \mu$, $Var(X_i) = \sigma^2$, then for the sample mean $\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$,

$$\mathbb{E}(\bar{X}) = \mu, \quad Var(\bar{X}) = \frac{\sigma^2}{n}.$$

Proof:

$$E(\bar{x}) = E(\frac{1}{n}\sum_{i=1}^{n} x_i) = \frac{1}{n}\sum_{i=1}^{n} E(x_i) = M.$$

$$Var(\bar{x}) = Var(\frac{1}{n}\sum_{i=1}^{n} x_i) = (\frac{1}{n}\sum_{i=1}^{n} Var(x_i)$$

$$= \frac{1}{n^2} \times n\sigma^2 = \frac{\sigma^2}{n}.$$



Example:

Further suppose X_i , $i = 1, \dots, n$ i.i.d. with distribution $\mathcal{N}(\mu, \sigma^2)$, then $\bar{X} \sim \mathcal{N}(\mu, \frac{\sigma^2}{n})$, so we can draw the probability density plot of \bar{X} .



Example:

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Figure: Probability density curve of sample mean of normal distribution



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Intuition:

- Series of numbers $a_n \Rightarrow$ Series of random variables X_n ;
- Limit $a \Rightarrow$ Limit X; (an a)
- How to quantify the closeness? $(|X_n X|?)$



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Pointwise convergence / Sure convergence

Suppose random variables X_n and X are defined over the same probability space, then we say X_n converges to X pointwise if

$$\lim_{n\to\infty}X_n(\omega)=X(\omega), \ \forall \omega\in\Omega.$$



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Remark:

Incorporate probability measure in some sense.

Alternatives of describing the closeness:

- Utilize CDF: $F_{X_n}(x) F_X(x)$; $P(x \leq y) = P((-y, y)) = F_x(x)$
- Utilize probability of an event: $\mathbb{P}(|X_n X| > \epsilon);$ $|X_n X| > \epsilon$.
- Utilize the probability over all ω : $\mathbb{P}(\lim_{n\to\infty} X_n(\omega) = X(\omega))$;
- Utilize mean/moments: $\mathbb{E}|X_n X|^p$.



Convergence in distribution

A sequence X_1, X_2, \cdots of real-valued random variables is said to converge in distribution, or converge weakly to a random variable X if $X \quad \mathcal{B}ernem(1) \quad (0) \quad 1$ $\lim_{n \to \infty} F_n(x) = F(x),$ for every number $x \in \mathbb{R}$ at which $F(\cdot)$ is continuous. Here, $F_n(\cdot)$ and $F(\cdot)$ are the cumulative distribution functions of the random variables X_n and X, respectively.

Notation: $X_n \xrightarrow{d} X, \quad X_n \xrightarrow{\mathcal{D}} X, \quad X_n \Rightarrow X.$



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Notation:

 $X_n \xrightarrow{d} X, \quad X_n \xrightarrow{\mathcal{D}} X, \quad X_n \Rightarrow X.$

Remark:

$$F_{n(x)} = P(x \in x)$$



 X_n and X do not need to be defined on the same probability space.



Convergence in probability

A sequence X_n of random variables converges in probability towards the random variable X if for all $\epsilon > 0$, $|a_n - a| < \epsilon$ $n \rightarrow \infty$

$$\lim_{n\to\infty}\mathbb{P}\big(|X_n-X|>\epsilon\big)=0$$

Notation: $X_n \xrightarrow{P} X$, $X_n \xrightarrow{P} X$.

Remark: $\{w: | \times_n (w) - \times (w) | \ge \xi\}$ X_n and X need to be defined on the same probability space.

 $\lim_{n \to \infty} \frac{f_{xn}(x) - f_{x}(x)}{p(x - x)} p(x - x)$

 $P(\{w: X_n(w) \leq x\})$



Examples: $X_n(w) = Z(w) + \frac{1}{n}$. • Let $X_n = Z + \frac{1}{n}$, where $Z \sim \mathcal{N}(0, 1)$, then $X_n \xrightarrow{P} Z$. lim P(1xn-21>E)=0 N-10 V & 20. 4570 **Proof:** $P(|X_n-2| > \varepsilon) = P(\frac{1}{n} > \varepsilon) \longrightarrow o$ $n \rightarrow \infty$. $\left\{\frac{1}{n} > \varepsilon\right\}$ • Let $X_n = Z + Y_n$, where $Z \sim \mathcal{N}(0,1)$, $\mathbb{E}(|Y_n|) = \frac{1}{n}$, then $X_n \xrightarrow{P} Z$. **Proof:** ∀ *ξ* > *o* $P(|Xn-z|z\epsilon)$ $= P(|Y_n| > \varepsilon) \leq \frac{E^{1/n}}{s} = \frac{1}{n\varepsilon}$ 1-100 3 ▲ E ▶ ▲ E ▶ E • ○ Q ○

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Convergence almost surely

A sequence X_n of random variables converges almost surely or almost everywhere or with probability 1 or strongly towards X means that

$$\mathbb{P}\left(\lim_{n\to\infty}X_n=X\right)=\mathbb{P}\left(\omega\in\Omega:\lim_{n\to\infty}X_n(\omega)=X(\omega)\right)=1.$$

Xn(W) X(W)

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Notation: $X_n \xrightarrow{a.s.} X_{\cdot}$

Remark: X_n and X need to be defined on the same probability space.



Examples:

• Let
$$X_n = Z + \frac{1}{n}$$
, where $Z \sim \mathcal{N}(0, 1)$, then $X_n \xrightarrow{a.s.} Z$.
Proof: $P(\{w: \lim_{n \to \infty} X_n; w) = Z(w)\}$
 $= P(\{w: \lim_{n \to \infty} Z(w) + \frac{1}{n} = Z(w)\})$
 $= P(\{w: \lim_{n \to \infty} \frac{1}{n} = 0\}) = 1$.



Convergence in L^p

A sequence $\{X_n\}$ of random variables converges in L_p to a random variable X, $p \ge 1$, if

$$\lim_{n\to\infty} \mathbb{E}|X_n - X|^p = 0$$

Notation: $X_n \xrightarrow{L^p} X_{\cdot}$

Remark: X_n and X need to be defined on the same probability space.



Examples:

• Let
$$X_n = Z + \frac{1}{n}$$
, where $Z \sim \mathcal{N}(0, 1)$, then $X_n \xrightarrow{L^p} Z$.
Proof: $\mathcal{E} / \times n - 2 / = \mathcal{E} / \frac{1}{n} / = (\frac{1}{n})^n \longrightarrow \mathcal{O}$.

• Let
$$X_n = Z + Y_n$$
, where $Z \sim \mathcal{N}(0,1)$, $\mathbb{E}(|Y_n|^p) = \frac{1}{n}$, then $X_n \xrightarrow{L^p} Z$.
Proof:
 $\mathcal{E}/|X_n - 2|^p = \mathcal{E}/|Y_n|^p = \frac{1}{n} \xrightarrow{P} \mathcal{O}$



Relationship between convergences (on complete probability space):



Figure: relationship between convergences



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$$\int w : |xn - c| \ge i$$

= $\int w : |xn - c| \ge i$
= $\int w : |xn - c \ge i > 0 \int w : |xn - c| \le i$

Highlights:

• Almost sure convergence implies convergence in probability:

$$X_n \xrightarrow{\text{a.s.}} X \Rightarrow X_n \xrightarrow{P} X;$$

• Convergence in probability implies convergence in distribution:

$$X_n \xrightarrow{P} X \Rightarrow X_n \xrightarrow{d} X;$$

• If X_n converges in distribution to a constant c, then X_n converges in probability to $c: \qquad \downarrow w: \mid \times n - \times \iota > \varepsilon$ $X_n \xrightarrow{d} c \Rightarrow X_n \xrightarrow{P} c$, provided c is a constant. X = c

Problem Set

Problem 1: Prove that on a complete probability space, if $X_n \xrightarrow{L^p} X$, then $X_n \xrightarrow{P} X$. (Hint: use Markov's inequality)

Problem 2: Let X_1, \dots, X_n be i.i.d. random variables with Bernoulli(p) distribution, and $X \sim Bernoulli(p)$ is defined on the same probability space, independent with X_i 's. Does X_n converge in probability to X?

Problem 3: Give an example where X_n converges in distribution to X, but not in probability.

