

Monday December 07th 2020

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Lecture 23

Convergence in probability to a constant

$X_n \xrightarrow{P} c$. This means $\forall \epsilon > 0 \lim_{n \rightarrow \infty} P(|X_n - c| \geq \epsilon) = 0$

Thm: If X_n has expectation μ_n for all n and variance σ_n^2 which is finite for all n , then $\lim_{n \rightarrow \infty} \sigma_n^2 = 0 \Rightarrow X_n \xrightarrow{P} \mu$.

Recall Chebyshev's Inequality:

$$P(|X_n - \mu| \geq \epsilon) \leq \frac{\sigma_n^2}{\epsilon^2} \quad \left(\text{Now take the limit both side} \right)$$

$$\lim_{n \rightarrow \infty} P(|X_n - \mu| \geq \epsilon) \leq \lim_{n \rightarrow \infty} \frac{\sigma_n^2}{\epsilon^2} = \frac{1}{\epsilon^2} \lim_{n \rightarrow \infty} \sigma_n^2 = 0$$

Because probabilities are between 0 and 1, if you know the probability is ≤ 0 , that means the probability is 0.

$$\Rightarrow \lim_{n \rightarrow \infty} P(|X_n - \mu| \geq \epsilon) = 0 \Rightarrow X_n \xrightarrow{P} \mu$$

$$\text{e.g. } X_n \sim \left(-\frac{1}{n}, \frac{1}{n}\right) \quad \text{Prove } X_n \xrightarrow{P} 0$$

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$$E[X_n] = 0 = \mu \quad \forall n, \quad \sigma_n^2 = \left(\frac{1}{n} - \left(-\frac{1}{n}\right)\right)^2 = \frac{4}{12n^2} = \frac{1}{3n^2}$$

$$\lim_{n \rightarrow \infty} \sigma_n^2 = \lim_{n \rightarrow \infty} \frac{1}{3n^2} = 0 \quad \xrightarrow{\text{Thm}} X_n \xrightarrow{P} 0$$

$$\text{e.g. } X_n \sim N\left(0, \frac{1}{n}\right) \quad \text{Prove } X_n \xrightarrow{P} 0$$

$$E[X_n] = 0 = \mu \quad \forall n, \quad \sigma_n^2 = \frac{1}{n}, \quad \lim_{n \rightarrow \infty} \sigma_n^2 = \lim_{n \rightarrow \infty} \frac{1}{n} = 0$$

$$\Rightarrow X_n \xrightarrow{P} 0$$

Let X_1, X_2, \dots be i.i.d with mean μ and variance $\sigma^2 < \infty$.
infinity. $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$, $E[\bar{X}_n] = \mu$, $\text{Var}[\bar{X}_n] = \frac{\sigma^2}{n}$

Prove $\bar{X}_n \xrightarrow{P} \mu$, $\lim \text{Var}[\bar{X}_n] = \lim \frac{\sigma^2}{n} = 0 \Rightarrow \bar{X}_n \xrightarrow{P} \mu$ ②
 this is a very famous thm. it's called the "weak" weak
 law of large # (WLLN)

The last type of convergence we'll study is called
 Convergence in law or Convergence in L^r norm to a
 constant. where $r \geq 1$ denoted: $X_n \xrightarrow{L^r}$, & which
 means by definition:

$$\lim E[|X_n - c|^r] = 0,$$

eg: $r=1$ $\lim E[|X_n - c|] = 0$

$r=2$ $\lim E[(X_n - c)^2] = 0$

Convergence in mean"
 "mean square Convergence"

eg $X_n \sim U(0, \frac{1}{n})$

Prove $X_n \xrightarrow{L^r} 0$ $\lim E[|X_n - 0|^r] = \lim E[X_n^r]$

$$= \lim \int_{\mathbb{R}} x^r n \mathbb{1}_{x \in [0, \frac{1}{n}]} dx = \lim \int_0^{\frac{1}{n}} x^r dx$$

$$= \lim n \left[\frac{x^{r+1}}{r+1} \right]_0^{\frac{1}{n}} = \frac{1}{r+1} \lim n \frac{1}{n^{r+1}} = \frac{1}{r+1} \lim \frac{1}{n^r} = 0 \quad \checkmark$$

Law. proof for $X_n \xrightarrow{L^r} \Rightarrow X_n \xrightarrow{P} c$

$$\lim P[|X_n - c| \geq \varepsilon] = \lim P(|X_n - c|^r \geq \varepsilon^r) \leq \lim \frac{E[|X_n - c|^r]}{\varepsilon^r} = 0$$