Law of Large Numbers

Tuesday, November 29, 2022

Definition:

Given independent and Identically Distribited iid random variables X, X2, ..., Xn, the <u>sample</u> mean denoted X is defined as

$$X = X_1 + X_2 + \dots + X_N$$

We can also write Mu.

Since X: s are random variables, the sample mean X = Mn(x) is also a random variable.

Expected yelve: $E[X] = \underbrace{E[X_1] + E[X_2] + \cdots + E[X_n]}_{N} \rightarrow \text{(by linearity of Expectation)}$ $= \underbrace{nE[X]}_{N} \rightarrow \text{Since } E[X_1] = E[X]$ E[X] = E[X]

Variance:

$$V_{\partial r}(\overline{X}) = \underbrace{V_{\partial r}(X_1 + X_2 + \dots + X_N)}_{N^2} \longrightarrow \text{ since } Y_{\partial r}(x) = z^2 V_{\partial r}(x)$$

$$= \underbrace{V_{\partial r}(X_1) + V_{\partial r}(X_2) + \dots + V_{\partial r}(X_N)}_{N^2} \longrightarrow \text{ since } X_1' \text{ s are ind.}$$

$$= \underbrace{N_{\partial r}(X_1) + V_{\partial r}(X_2) + \dots + V_{\partial r}(X_N)}_{N^2} \longrightarrow \text{ since } V_{\partial r}(X_1) = V_{\partial r}(X_1)$$

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West law of large numbers.

Let X_1, X_2, \dots, X_n be iid rv with finite expected value $E[X_i] = \mathcal{M} < \infty$. Then, for any $\epsilon > 0$

Proof: Assume that
$$Var(x) = \sigma^2$$
 is finite.

Vising chebyshov's inegonity

$$P(|X - u|Z \in) \leq \frac{Var(X)}{\varepsilon^2}$$

$$= \frac{Var(X)}{\varepsilon^2}.$$

So, $\lim_{n\to\infty} \frac{Var(X)}{n\varepsilon^2} = 0.$

Thus, $\lim_{n\to\infty} P(|X - u|Z \in) = 0.$

Strong Lew of large inhors

Suppose that the first moment $E[X]$ of X is finite.

Thus, $\lim_{n\to\infty} P(|X - E[X]|Z \in) = 0$

Thus $\lim_{n\to\infty} P(|X - E[X]|Z \in) = 0$ for every $E \neq 0.$

Chaeloughness inequality

Let X be $E = rendom variable and $E[X] = 0$.

E[X^2] = $\int_{X} x^2 f_X(x) dx$
 $\lim_{n\to\infty} E[X^2] = \int_{X} x^2 f_X(x) dx$
 $\lim_{n\to\infty} \frac{x^2 f_X(x)}{x^2 f_X(x)} dx = \frac{x^2 f_X(x)}{x^2 f_X(x)} dx$
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In general,
$$P(|X| = 2) \leq \frac{1}{2^p} E(|X|^p)$$
 for any $p=1,2,...$

$E(1\times1^p)$ is finite
E(IXI') is finite