

Theory of Probability

Dec 2

Weak Law of Large Numbers (WLLN)

Let X_1, X_2, \dots be IID random variables with $E[X_i] = \mu < \infty$ and $\text{Var}[X_i] = \sigma^2 < \infty$.

Then for any $\epsilon > 0$,

$$P\left[\left|\frac{1}{n} \sum_{i=1}^n X_i - \mu\right| \geq \epsilon\right] \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

To prove WLLN, we first need some inequalities:

Markov Inequality

If $X \geq 0$ is a random variable, then for any $a > 0$,

$$P[X \geq a] \leq \frac{E[X]}{a}.$$

Proof:

$$\begin{aligned} a P[X \geq a] &= \int_a^{\infty} a f(x) dx \\ &\leq \int_a^{\infty} x f(x) dx \\ &\leq \int_0^{\infty} x f(x) dx = E[X] \end{aligned}$$

$$\Rightarrow a P[X \geq a] \leq E[X]$$

$$\Rightarrow P[X \geq a] \leq \frac{E[X]}{a}.$$

□

Chebyshev's Inequality

Let X be a random variable with $E[X] = \mu < \infty$
and $\text{Var}[X] = \sigma^2 < \infty$.

Then for any $k > 0$,

$$P[|X - \mu| \geq k] \leq \frac{\sigma^2}{k^2}$$

Proof: By Markov's Inequality,

$$P[(X - \mu)^2 \geq k^2] \leq \frac{E[(X - \mu)^2]}{k^2}$$

$$\Leftrightarrow P[|X - \mu| \geq k] \leq \frac{\sigma^2}{k^2} .$$

Proof of WLLN:

$$\text{Note that } E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \mu$$

$$\text{and } \text{Var}\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{\sigma^2}{n} .$$

Using Chebyshev's Inequality, we have that

$$P\left[\left|\frac{1}{n} \sum_{i=1}^n X_i - \mu\right| \geq \epsilon\right] \leq \frac{\sigma^2/n}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2}$$

$$\lim_{n \rightarrow \infty} P\left[\left|\frac{1}{n} \sum_{i=1}^n X_i - \mu\right| \geq \epsilon\right] = 0 \quad \checkmark$$

The Central Limit Theorem

Let X_1, X_2, \dots be IID with $E[X_i] = \mu < \infty$
 $\text{Var}[X_i] = \sigma^2 < \infty$.

Then

$$\frac{\frac{1}{n} \sum_{i=1}^n X_i - \mu}{\sigma/\sqrt{n}} = \frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n}\sigma} \rightsquigarrow N(0,1) \text{ as } n \rightarrow \infty.$$

I.e.,

$$\lim_{n \rightarrow \infty} P \left[\frac{\frac{1}{n} \sum_{i=1}^n X_i - \mu}{\sigma/\sqrt{n}} \leq a \right] = \Phi(a).$$

This theorem can be extended to many more general cases where X_i are independent, and

$$E[X_i] = \mu_i < \infty$$

$$\text{and } \text{Var}[X_i] = \sigma_i^2 < \infty$$

and if (a) $P[|X_i| < M] = 1$ (bounded)

$$(b) \sum_{i=1}^{\infty} \sigma_i^2 = \infty$$

$$\text{Then } \lim_{n \rightarrow \infty} P \left[\frac{\sum_{i=1}^n (X_i - \mu_i)}{\sqrt{\sum_{i=1}^n \sigma_i^2}} \leq a \right] = \Phi(a).$$