

# Weak Law of Large Numbers Proof

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## 1 Weak Law of Large Numbers Theorem

Let  $X_1, X_2, \dots, X_n$  be a random sample from the same distribution  $\tilde{X}$  with  $E(\tilde{X}) = \mu$  and  $Var(\tilde{X}) = \sigma^2$ . Let  $\bar{X}_n = \frac{X_1 + X_2 + \dots + X_n}{n}$ . Then for any  $\epsilon > 0$ :

$$\lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| \geq \epsilon) = 0$$

### 1.1 Chebyshev's Inequality

If  $X$  has finite mean  $\mu$  and variance  $\sigma^2$ , and  $k > 0$ , then:

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

### 1.2 Proof of Weak Law of Large Numbers

Let  $X_1, X_2, \dots, X_n$  be a random sample from the same distribution  $\tilde{X}$ . Assume that  $E(\tilde{X}) = \mu$  and  $Var(\tilde{X}) = \sigma^2$  are both finite.

Let  $S_n = X_1 + \dots + X_n$  and let  $\bar{X}_n = \frac{S_n}{n}$ . By the Central Limit Theorem, we know that as  $n \rightarrow \infty$ ,  $S_n$  has a Normal distribution with  $Var(S_n) = n\sigma^2$ . By theorem,  $Var(\frac{S_n}{n}) = \left(\frac{1}{n}\right)^2 Var(S_n) = \frac{\sigma^2}{n} = Var(\bar{X}_n)$ . In addition, we know from CLT that  $E(S_n) = n\mu$ . This implies that  $E(\frac{S_n}{n}) = \mu$  by theorem.

By Chebyshev's Inequality, for any  $\epsilon > 0$ , we have that:

$$P(|\bar{X}_n - \mu| \geq \epsilon) = \frac{Var(\bar{X}_n)}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2}$$

Thus, for a fixed  $\epsilon$ ,

$$\lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| \geq \epsilon) = 0$$

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