

Law of Large Numbers

Consider i.i.d. random variables $X_1, X_2, \dots$, where $E[X_i] = \mu < \infty$ and $\text{Var}(X_i) = \sigma^2 < \infty$.

Defn: The sample mean of the first n of these is $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$. Each X_i is called a sample.

$$\begin{aligned} E[\bar{X}_n] &= E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{1}{n} E\left[\sum_{i=1}^n X_i\right] = \frac{1}{n} \sum_{i=1}^n E[X_i] \\ &= \frac{1}{n} \sum_{i=1}^n \mu = \frac{1}{n} \cdot n\mu = \mu. \end{aligned}$$

$$\begin{aligned} \text{Var}(\bar{X}_n) &= \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right) \\ &= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{1}{n^2} \sum_{i=1}^n \sigma^2 = \frac{1}{n^2} \cdot n\sigma^2 = \frac{\sigma^2}{n} \end{aligned}$$

Recall CLT: As $n \rightarrow \infty$, $\bar{X}_n \rightarrow N\left(\mu, \frac{\sigma^2}{n}\right)$.

Defn: μ is the population mean, σ^2 is the population variance.

Since $E[\bar{X}_n] = \mu$ and $\text{Var}(\bar{X}_n) = \frac{\sigma^2}{n}$, as n increases, $\bar{X}_n$ more likely to be close to μ .

Theorem (Weak Law of Large Numbers):

For any $\varepsilon > 0$, as $n \rightarrow \infty$,

$$P(|\bar{X}_n - \mu| > \varepsilon) \rightarrow 0.$$

Proof: By Chebyshev's Inequality,

$$P(|\bar{X}_n - \mu| > \varepsilon) \leq \frac{\sigma^2}{n\varepsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Strong Law of Large Numbers: $P\left(\lim_{n \rightarrow \infty} \bar{X}_n = \mu\right) = 1$.

Maximum Likelihood Estimators

Given independent samples $x_1, x_2, \dots, x_n$ from some distribution $f(x|\theta)$, estimate θ .

Ex: Given samples HHTHH of independent flips of a coin, estimate $\theta = P(\text{heads})$.

$P(x|\theta)$: Probability of event x given model θ .

Viewed as a function of x (θ fixed), it's a probability.
 " " " " " θ (x fixed), it's a likelihood
 and often written $L(x|\theta)$.

What θ makes HHTHH most likely? I.e.,
 what θ maximizes $L(\text{HHTHH}|\theta)$?

Approach: $\frac{\partial}{\partial \theta} L(\vec{x}|\theta) = 0$ and solve for $\hat{\theta} = \theta$.