

ST102 Week 12

I. Introduction

II. Course structure

(i) attendance

(ii) assignment (check your submission)

(iii) office hours 12:00 - 13:00 Thu
Workspace 3, LSE Life

Assumption. Quite often, I.I.D. is assumed for a random sample $\{X_i\}_{i=1}^n$, with each $X_i \sim f(x_i; \theta)$.

Under such assumption, a sample has joint pf/p.d.f.
$$f(x_1, x_2, \dots, x_n) = \prod_{i=1}^n f(x_i; \theta)$$

Notation. Random sample v.s. realized sample
 $\{X_i\}_1^n$ $\{x_i\}_1^n$

Def. A statistic is a known function of r.v.'s $\{X_i\}_1^n$ in a random sample.

Def. A sampling distribution is a probability distribution in the value of a statistic.

The case of i.i.d. r.v.'s

Recall, for any seq. of independent r.v.'s,

$$1) E\left(\sum_i a_i X_i\right) = \sum_i a_i E(X_i) \quad \text{Linearity}$$

$$2) \text{Var}\left(\sum_i a_i X_i\right) = \sum_i a_i^2 \text{Var}(X_i)$$

Then for any i.i.d. sample $\{X_i\}_1^n$ with sample mean $\bar{X} = \frac{1}{n} \sum_i X_i$, we immediately know:

$$E(\bar{X}) = E\left(\frac{\sum_{i=1}^n X_i}{n}\right) = \sum_i \frac{1}{n} E(X_i) = E(X_1)$$

$$\text{Var}(\bar{X}) = \text{Var}\left(\sum_i \frac{1}{n} X_i\right) = \sum_i \frac{1}{n^2} \text{Var}(X_i) = \frac{1}{n} \text{Var}(X_1)$$

The case of i.i.d. Normal

Assume i.i.d. $X_i \sim N(\mu, \sigma^2)$:

It can be shown (like using the uniqueness of mgf) that

$$\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

Thm. (Central Limit Thm (CLT))

Given i.i.d. r.v.s $\{X_i\}_1^n$, $E(X_i) = \mu < \infty$, and $\text{Var}(X_i) = \sigma^2 < \infty$, then

$$\lim_{n \rightarrow \infty} P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \leq z\right) = \Phi(z), \quad \forall z \in \mathbb{R},$$

where Φ is the cdf. of $N(0, 1)$.

PK. For any $n \in \mathbb{Z}_+$, the above is always an approximation. Need large n for good approximation.