

LLN and CLT (Ch 4.2.1/4.4.2 in ER)

In the last lectures we saw that if

$S \sim \text{Binomial}(N, p)$ (remember this means $S = \sum_{i=1}^N X_i$, $X_i \sim \text{Bernoulli}(p)$)

Just to remind us this is bin.

then $P(S=k)$ has a bell curve shape which becomes narrower as N becomes large

this implies for large N

$$\bar{X} = \frac{S}{N} \approx E[X_i] = p \text{ for large } N$$

In other words, the sample avg. tends towards the expected value.

This is true for (almost) any r.v. and is made precise by the LLN:

Law of Large Numbers (Thm 4.2.1)

Let X_1, X_2, \dots, X_N be iid and $E[X_i] < \infty$

then for any $\epsilon > 0$

$$P(|\bar{X} - E[X_i]| > \epsilon) \rightarrow 0 \text{ as } N \rightarrow \infty$$

Note in the textbook they call \bar{X} , M_N

We also saw that the distribution of the standardized variable
(or z-score)

$$Z = \frac{S - \mathbb{E}[S]}{\sqrt{\text{Var}(S)}} = \frac{S - Nq}{\sqrt{Nq(1-q)}}$$

looks the same for any value of N .

The limiting behavior of Z is given by
an example of a continuous distribution, so
we need to take a detour into ch 2.4

Detour (Continuous distributions)

Def 2.4.3 a continuous (or technically absolutely continuous)
r.v. is one that can take on real # values
and hence can not be described by a probability
function $P(X=x)$. Instead we define
a curve $f_X(x)$ called a density and
define the probabilities by $\int_a^b f_X(x) dx$ see def 2.3.2

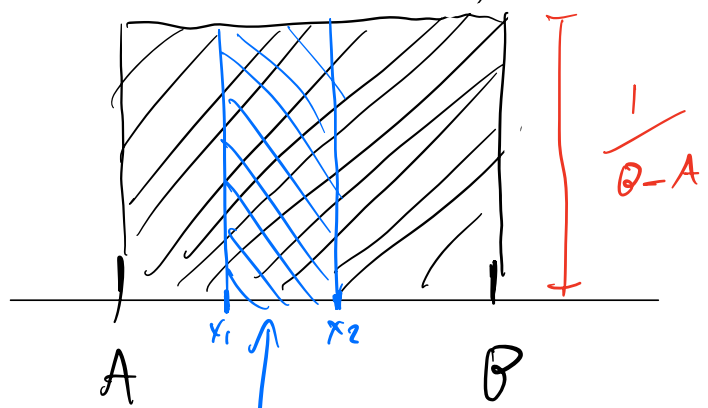
$$P(a < X < b) = \int_a^b f_X(x) dx$$

Note that $P(-\infty < X < \infty) = 1$

Example The r.v. $U \sim \text{Uniform}(A, B)$

has density $f_U(x) = \begin{cases} \frac{1}{B-A} & \text{if } x \in [A, B] \\ 0 & \text{if } x \notin [A, B] \end{cases}$

This means any value of $x \in [A, B]$ is equally likely likely (also $P(U=x) = 0$ for all x , which may seem odd)



Note that the density is the mathematical idealization of a histogram

$$\begin{aligned} \text{Area} &= (x_2 - x_1) \times \frac{1}{B-A} \\ &= P(x_1 < U < x_2) \end{aligned}$$

Back to the CLT

The CLT says that the standardized variable Z approaches a special random variable called a standard Normal random variable which has density (Example 2.4.7)

$$\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

Central Limit Theorem (from 4.4.3)

Let X_1, \dots, X_N be iid w/ $\mu = E[X_i] < \infty$

and $\sigma^2 = \text{var}(X) < \infty$, let $S = \sum_{i=1}^N X_i$

and $Z = \frac{S - N\mu}{\sigma\sqrt{N}}$, then

$$P(a < Z < b) \rightarrow \int_a^b \phi(x) dx$$

Basically the histogram becomes normal

Examples to focus on: 4.4.7, 4.4.9, 4.4.10

I will also cover general Normal random variables and properties of Normal r.v.
If time permits