

## Class Notes 3-4-2019

- **The Law of Large Numbers (LLN):**

Although the LLN can/will be proved without using the CLT we give here a first look at it. The LLN states that for any  $p \in [0, 1]$  that for any  $\epsilon > 0$  we have

$$P\left(\left|\frac{S_n}{n} - p\right| < \epsilon\right) \rightarrow 1 \quad \text{as } n \rightarrow \infty$$

For  $p = 0$  and  $p = 1$  this is trivially true since  $P(S_n/n = 0) = 1$  for  $p = 0$  and  $P(S_n/n = 1) = 1$  for  $p = 1$ . For  $0 < p < 1$  we have from the CLT

$$\begin{aligned} P\left(\left|\frac{S_n}{n} - p\right| < \epsilon\right) &= P\left(\left|\frac{\frac{S_n}{n} - p}{\sqrt{p(1-p)/n}}\right| < \frac{\epsilon}{\sqrt{p(1-p)/n}}\right) \approx P\left(|Z| < \frac{\sqrt{n}\epsilon}{\sqrt{p(1-p)}}\right) \\ &= 2\Phi\left(\frac{\sqrt{n}\epsilon}{\sqrt{p(1-p)}}\right) - 1 \rightarrow 1 \quad \text{as } n \rightarrow \infty \end{aligned}$$

HW 7, Problem 2 lets you work out a specific example case.

- **Sampling with and without Replacement:**

Suppose we have a large population of size  $N$  from which we sample at random  $n$  items without replacement, either one by one or as a single unordered grab of  $n$ . Then the outcome  $\omega$  is either an ordered  $n$ -tuple, denoted by  $\omega$ , each with probability

$$P(\omega) = \frac{1}{N \cdot (N-1) \cdot (N-2) \cdots (N-n+1)} = \frac{1}{(N)_n}$$

or an unordered set of  $n$  items representing all  $n!$  permutations of the previous  $\omega$ . We will denote this set by  $\{\omega\}$  and it has probability

$$P^*(\{\omega\}) = \frac{n!}{N \cdot (N-1) \cdot (N-2) \cdots (N-n+1)} = \frac{1}{\binom{N}{n}}$$

Suppose now that our population consists of two types of items, say  $M$  red balls and  $N - M$  blue balls. We are interested in the random variable  $X$  that counts the number of red balls in  $\omega$  or in  $\{\omega\}$ . We can find  $P(X = k) = P(\omega : X(\omega) = k)$  or  $P^*(X = k) = P^*(\{\omega\} : X(\{\omega\}) = k)$ . Any  $n$ -tuple  $\omega$  with  $k$  red balls in specified position and with blue balls in the other positions can be obtained in

$$M \cdot (M-1) \cdots (M-k+1) \cdot (N-M) \cdot (N-M-1) \cdots (N-M-(n-k-1)) = (M)_k (N-M)_{n-k}$$

ways. As far as  $P(X = k) = P(\omega : X(\omega) = k)$  is concerned there are  $\binom{n}{k}$   $n$ -tuples  $\omega$  which have  $k$  red balls and  $n - k$  blues balls in one of the chosen  $\binom{n}{k}$  positions of the  $n$ -tuple. Thus

$$P(X = k) = \frac{\binom{n}{k} (M)_k (N-M)_{n-k}}{(N)_n} = \frac{\binom{M}{k} \cdot \binom{N-M}{n-k}}{\binom{N}{n}} = P^*(X = k)$$

where the  $= P^*$  derives from the fact that in order to get a set  $\{\omega\}$  with exactly  $k$  red balls I have to grab  $k$  from  $M$  red balls in one of  $\binom{M}{k}$  ways and combine that with a grab of  $n - k$

blue balls from  $N - M$  in  $\binom{N-M}{n-k}$  possible ways. This equality  $P(X = k) = P^*(X = k)$  should have been made clear in the beginning of this class and it is predicated on the fact that the event  $X = k$  does not involve any order. This common distribution of  $X$  is referred to as the hypergeometric distribution and we write  $X \sim \text{Hypergeom}(N, M, n)$ . See HW 4, Problem 4.

Let us next consider sampling  $n$  items with replacement from the same population and let  $X$  again denote the number of red balls. Then we are dealing with  $n$  independent trials and with success (red ball chosen in a given trial) probability  $p = M/N$  and we have  $X \sim \text{Bin}(n, p)$ . We write

$$\tilde{P}(X = k) = \binom{n}{k} \left(\frac{M}{N}\right)^k \left(\frac{N-M}{N}\right)^{n-k} = \binom{n}{k} p^k (1-p)^{n-k}$$

Let  $A$  denote the set of all  $n$ -tuples with distinct elements, assuming all  $N$  items are labeled  $1, 2, \dots, N$ . Then

$$\tilde{P}(A) = \frac{N \cdot (N-1) \cdot (N-2) \cdot \dots \cdot (N-n+1)}{N^n} \rightarrow 1 \quad \text{as } N \rightarrow \infty, n \text{ staying fixed}$$

and since  $\tilde{P}(A^c) \rightarrow 0$  as  $N \rightarrow \infty$  we then have

$$\tilde{P}(X = k) = \tilde{P}(X = k|A)\tilde{P}(A) + \tilde{P}(X = k|A^c)\tilde{P}(A^c) \approx \tilde{P}(X = k|A)$$

For  $n$ -tuples  $\omega \in A$  we have

$$\tilde{P}(\omega|A) = \frac{\tilde{P}(\omega)}{\tilde{P}(A)} = \frac{\frac{1}{N^n}}{\frac{N \cdot (N-1) \cdot (N-2) \cdot \dots \cdot (N-n+1)}{N^n}} = \frac{1}{(N)_n} = P(\omega)$$

and thus

$$\tilde{P}(X = k) \approx \tilde{P}(X = k|A) = \tilde{P}(\{\omega : X(\omega) = k\}|A) = P(\omega : X(\omega) = k) = P(X = k) = P^*(X = k)$$

Thus the “two sampling without replacement” schemes give approximately the same distribution to  $X$  as the sampling with replacement, provided  $N$  is large. In order for the binomial distribution  $\text{Bin}(n, p = M/N)$  to stay stable we would also need to assume that  $p = M/N$  stay stable and stay away from zero or one. In that case the CLT applied to the binomial distribution ( $\tilde{P}$ ) equally applies to the nonreplacement schemes, where the sequential selections (if we sample one by one) are certainly no longer independent.

- **The Poisson Distribution and Poisson Approximation to the Binomial:**

If  $S_n \sim \text{Bin}(n, p)$  with  $p \approx 0$  or  $p \approx 1$  presents a problem for the CLT, at least for moderate  $n$ . In that case the Poisson distribution provides a very useful alternative for  $p \approx 0$  and for  $p \approx 1$  we switch to  $\tilde{S}_n = n - S_n \sim \text{Bin}(n, 1 - p)$ , counting the number of failures instead.

A random variable  $X$  has a Poisson distribution with parameter  $\lambda > 0$ , and we write  $X \sim \text{Poisson}(\lambda)$  or  $X \sim \text{Pois}(\lambda)$ , when

$$P(X = k) = \frac{e^{-\lambda} \lambda^k}{k!} \quad \text{for } k = 0, 1, 2, \dots$$

Its mean and variance are given by

$$E(X) = \lambda \quad \text{and} \quad \text{var}(X) = \lambda$$

$$E(X) = \sum_{k=0}^{\infty} k \frac{e^{-\lambda} \lambda^k}{k!} = \sum_{k=1}^{\infty} k \frac{e^{-\lambda} \lambda^k}{k!} = \lambda \sum_{k=1}^{\infty} \frac{e^{-\lambda} \lambda^{k-1}}{(k-1)!} = \lambda \sum_{k=0}^{\infty} \frac{e^{-\lambda} \lambda^k}{k!} = \lambda$$

$$E(X(X-1)) = \sum_{k=0}^{\infty} k(k-1) \frac{e^{-\lambda} \lambda^k}{k!} = \sum_{k=2}^{\infty} k(k-1) \frac{e^{-\lambda} \lambda^k}{k!} = \lambda^2 \sum_{k=2}^{\infty} \frac{e^{-\lambda} \lambda^{k-2}}{(k-2)!} = \lambda^2 \sum_{k=0}^{\infty} \frac{e^{-\lambda} \lambda^k}{k!} = \lambda^2$$

Thus  $\text{var}(X) = E(X(X-1)) + E(X) - [E(X)]^2 = \lambda^2 + \lambda - \lambda^2 = \lambda$

• **Law of Rare Events Or Law of Small Numbers**

Let  $\lambda > 0$  and consider positive integer  $n$  with  $\lambda/n < 1$ . Let  $S_n \sim \text{Bin}(n, \lambda/n)$ . Then

$$\lim_{n \rightarrow \infty} P(S_n = k) = e^{-\lambda} \frac{\lambda^k}{k!} \quad \text{for } k = 0, 1, 2, \dots$$

Proof:

$$\begin{aligned} P(S_n = k) &= \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} = \frac{n(n-1) \cdots (n-k+1) \lambda^k}{n^k} \frac{1}{k!} \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-k} \\ &\rightarrow \frac{\lambda^k}{k!} e^{-\lambda} \quad \text{as } n \rightarrow \infty \text{ for any fixed } k \quad \square \end{aligned}$$