

# 3/13 Central Limit Theorem (cont).

If  $X_1, \dots, X_n$  iid from population with mean  $\mu$  and std. deviation  $\sigma$ ,

•  $\bar{X} \sim^{\text{approx}} N\left(\mu, \frac{\sigma^2}{n}\right)$  more so as  $n \rightarrow \infty$

•  $\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} = Z \sim N(0, 1)$  " "

$$S_n = \sum_{i=1}^n X_i$$

(Sample sum)

where  $X_1, \dots, X_n$  iid from pop with mean  $\mu$  and std dev  $\sigma$  (ie var is  $\sigma^2$ )

$$E(S_n) = E(X_1 + \dots + X_n) \\ = \sum_{i=1}^n E(X_i) = n \cdot \mu$$

$$\text{Var}(S_n) = \text{Var}(X_1 + \dots + X_n) \\ = \sum_{i=1}^n \text{Var}(X_i) = n \cdot \sigma^2$$

so SD  $(S_n) = \sqrt{n} \cdot \sigma$

CLT says  $S_n \sim N(n\mu, n\sigma^2)$  approx

$$\bar{X} = \frac{S_n}{n} = \frac{\sum_{i=1}^n X_i}{n} \Leftrightarrow n\bar{X} = S_n$$

Say you have 2 populations with means  $\mu_1, \mu_2$  and variances  $\sigma_1^2, \sigma_2^2$

take samples of sizes  $n_1, n_2$

$$\bar{X}_1 - \bar{X}_2 \sim N\left(\mu_1 - \mu_2, \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)$$

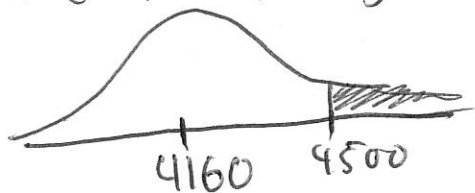
$$\mu = 104 \text{ sec}, \sigma = 10 \text{ sec.}$$

sample size  $n = 40$

$$P(S_n > 75 \text{ min} = 4500_{\text{sec}})$$

$$\text{CLT: } S_n \sim N(n \cdot \mu, n\sigma^2) \quad \leftarrow 40 \cdot 10^2$$
$$\Rightarrow N(4160, 4000) \quad \leftarrow \begin{matrix} \sigma_{S_n}^2 \\ \sigma_{S_n} = \sqrt{4000} \end{matrix}$$

$$P(S_n > 4500) = \text{normalcdf}(4500, 100000, 4160, \sqrt{4000})$$



$\approx 0$

$\downarrow$   
 $\approx 63 \text{ sec}$

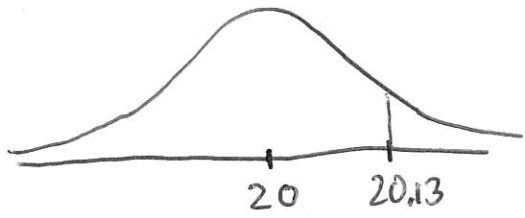
same as asking

$$P(\bar{X} > \frac{4500}{40})$$

$\downarrow 112.5$

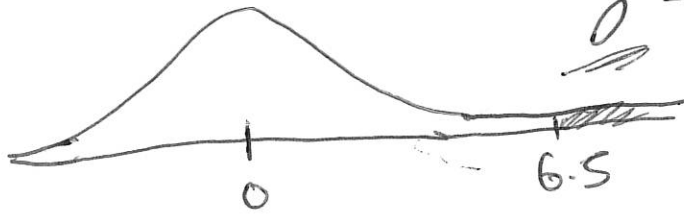
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if  $\mu=20$ ,  $\bar{X} \sim N\left(20, \frac{.2^2}{100}\right)$  or  $\sigma_{\bar{x}} = \frac{.2}{\sqrt{100}} = \frac{.2}{10} = .02$



~~What is~~

$$z = \frac{20.13 - 20}{.02} = 6.5$$



empirical rule  
99.7% within  $3\sigma$

within

$$P(Z > 6.5) \approx 0$$

An estimator is called consistent if  $T_n$  of  $\theta$

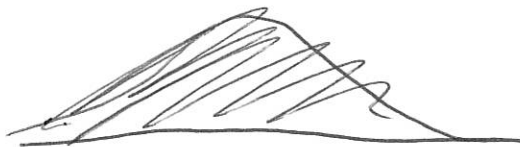
if  $T_n \rightarrow \theta$  as  $n \rightarrow \infty$

eg.  $\bar{X}$  to estimate  $\mu$

Say in May avg temp is  $70^\circ$  with  $\sigma = 5^\circ$   
in Dec avg temp is  $30^\circ$  with  $\sigma = 7^\circ$

May 12 it was  $78^\circ$ , Dec 15 it was  $40^\circ$   
Which is a more rare event?

$$z_{\text{May}} = \frac{78 - 70}{5} = 1.6 \quad z_{\text{Dec}} = \frac{40 - 30}{7} = 1.429$$



$$E(\bar{X}_1 - \bar{X}_2) = E(\bar{X}_1) - E(\bar{X}_2) = \mu_1 - \mu_2$$

$$\text{Var}(\bar{X}_1 - \bar{X}_2) = \text{Var}(\bar{X}_1) + \text{Var}(\bar{X}_2) = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$$

(ex) Apples from orchard 1 ~~supposedly~~ have ~~mean~~ weight of ~~15 oz~~ with std. dev. of .8 oz,  
 From orchard 2, ~~sup~~ ~~mean~~ ~~supposed~~ stdev of .9 oz.

We want to see whether they apples in orchard 1 have a greater mean weight.

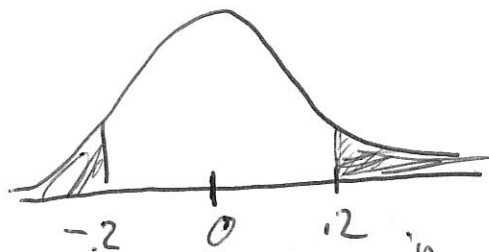
Sample randomly 37 from 1 get  $\bar{X}_1 = 15.3 \text{ oz}$   
 sample 45 from 2 get  $\bar{X}_2 = 15.1 \text{ oz}$

$$\bar{X}_1 - \bar{X}_2 = .2 \text{ oz}$$

Suppose  $\mu_1 = \mu_2$

$$\bar{X}_1 - \bar{X}_2 \sim N\left(\mu_1 - \mu_2, \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right) = N(0, .03529)$$

$$\sigma_{\bar{X}_1 - \bar{X}_2} = .1879$$



$$P(\bar{X}_1 - \bar{X}_2 > .2) = .1436$$

inconclusive - assume equal mean weights.

$$\text{normal cdf}(.2, 1000, 0, .1879)$$