

# Chapter 7 - Normal Probability Approximations

STAT 251

## Lecture 22

### Central Limit Theorem (CLT)

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# Chapter 7 - Learning Outcomes

- Statistic and parameter
- Sampling distribution
- Central Limit Theorem (CLT)
- Normal Approximation to the Binomial distribution
- Normal Approximation to the Poisson distribution

# Population and Sample

- **Population** is the entire collection of individuals we want to study
- **Sample** is a subset of individuals selected from the population

\*\* Statistics techniques are used to make conclusions about the population based on the sample.

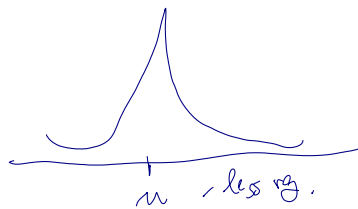
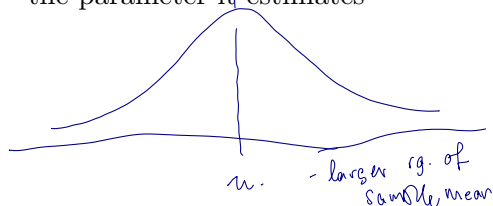
Random sample → unbiased, representative population

# Statistic and Parameter

- A **statistic** is a numerical summary of the sample
    - e.g. sample mean ( $\bar{x}$ )
    - sample standard deviation ( $s$ )
  - A **parameter** is a numerical summary of a population
    - e.g. population mean ( $\mu$ ) → unknown - how to estimate.
    - population standard deviation ( $\sigma$ )
- just use sample val.
- Value of the parameter is unknown in practice.
  - Due to sampling variability, a statistic takes on different values for different samples. → Many sample means / s.d.
  - Parameters are estimated using sample data. We use statistics to estimate parameters.

# Sampling Distributions

- The sampling distribution of a statistic is the probability distribution that specifies probabilities for the possible values the statistic can take
- Sampling distribution describes the variability that occurs from study to study using statistics to estimate population parameters.
- Sampling distributions help to predict how close a statistic falls to the parameter it estimates



# Results from Ch 4 & 5: Linear combination of Normal rvs

*IID: Independent & Identical.*

- If  $X_1, X_2, \dots, X_n$  is a random sample from a normal population with mean  $= \mu$  and variance  $= \sigma^2$  then,

$$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

- often, however, we have to deal with non-normal populations

# Mean and Variance of the Sampling distribution of sample mean

Suppose a random sample of  $n$  observations is taken from a population with mean  $= \mu$  and variance  $= \sigma^2$  then,

- the mean of the of the Sampling distribution of sample mean is  $\mu$  (same as the population mean)
- the standard deviation of the Sampling distribution of sample mean is  $\frac{\sigma}{\sqrt{n}}$  (i.e. standard error  $= \frac{\sigma}{\sqrt{n}}$ ) *estimate.*  
?

\*\* To distinguish the standard deviation of a sampling distribution from the standard deviation of an ordinary probability distribution, we refer it to as a standard error.

# Central Limit Theorem (CLT)

- Let  $X_1, X_2, \dots, X_n$  be a random sample from an arbitrary population/distribution with mean  $\mu$  and variance  $\sigma^2$ . When  $n$  is large (book says  $n \geq 20$ ), <sup>30 (good rule)</sup> then  $\bar{X}$  is approximately normal with mean  $\mu$  and variance  $\frac{\sigma^2}{n}$  regardless of the actual shape of the population distribution

$$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n} \sim N\left(\mu, \frac{\sigma^2}{n}\right), \text{ approximately}$$

- \*\* How the population mean and standard deviation are related to the mean and standard deviation of the sampling distribution of the sample mean

Explain this using applets



## CLT for sum of rvs when $n$ is large

- Consider a random sample  $X_1, X_2, \dots, X_n$  from a distribution with mean  $\mu$  and variance  $\sigma^2$ .

**When  $n$  is large, by CLT**

$$\bar{X} = \frac{\sum_i X_i}{n} \sim N\left(\mu, \frac{\sigma^2}{n}\right), \quad \text{approximately}$$

- If a question is about sum instead an average, still we can use CLT

$$T = X_1 + X_2 + \dots + X_n = \sum_i^n X_i$$

$$\begin{aligned} \text{then, } \bar{X} = \frac{\sum_i X_i}{n} &\Rightarrow \bar{X} = \frac{T}{n} \\ &\Rightarrow T = n\bar{X} \end{aligned}$$

$$E(T) = E(n\bar{X}) = nE(\bar{X}) = n\mu$$

$$Var(T) = Var(n\bar{X}) = n^2 Var(\bar{X}) = n^2 \frac{\sigma^2}{n} = n\sigma^2$$

- Therefore,  $T \sim N(n\mu, n\sigma^2)$ , approximately

# Online Resources to Learn CLT

- **Video: Sampling distribution of the mean** - UBC Flexible Learning Introductory Statistics Project

This video explores the concept of a sampling distribution of the mean. It highlights how we can draw conclusions about a population mean based on a sample mean by understanding how sample means behave when we know the true values of the population.

<https://vimeo.com/196027417>

# Applet: Sampling from a non-Normally distributed population (CLT)

- **Applet: Sampling from a non-Normally distributed population (CLT)** - UBC StatSpace

This web visualization explores the sampling distribution of the mean when the data do not necessarily follow a Normal distribution.

<http://www.zoology.ubc.ca/~whitlock/Kingfisher/CLT.htm>

- Also notice that when  $n$  is increasing, the standard deviation of the sampling distribution of sample mean is decreasing.

# Applet: Sampling from a normally distributed population

- **Applet: Sampling from a normally distributed population**
  - UBC StatSpace

This web visualization demonstrates the concept of a sampling distribution of an estimate, using the example of a mean of a Normally distributed variable. It also reinforces the idea of a histogram.

<http://www.zoology.ubc.ca/~whitlock/Kingfisher/SamplingNormal.htm>

# Before the next class ...

Visit the course website at [canvas.ubc.ca](https://canvas.ubc.ca)

- Review Lecture 22 and related sections in the text book
- Topic of next class: **CLT Examples and Normal approximation to Binomial and Poisson distributions**