ECON10005 Quantitative Methods 1

Tutorial in Week 7

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Introduction

Zheng Fan

- Ph.D student in Economics at Unimelb. Research interest in Bayesian Econometrics
- Personal website: zhengfan.site for some details

Don't be shy if you need help

- Discuss on Ed Discussion Board
- Attend consultation sessions: see Canvas for time and location
- Consult Stop 1, in case of special considerations,
- Contact QM-1@unimelb.edu.au for admin issues
- Send me an email: fan.z@unimelb.edu.au

Section: Introduction

Agenda

Today's focus

- Understanding sampling distributions
- Central Limit Theorem (CLT)
- Practice with normal probability calculations

Section: Introduction

Agenda

- **Next week** (Mid-semester break):
 - No tutorial
- Following week: We will spend time discussing your group report.
 - Overall, a strong start—well done!
 - Remember: this is your first report, and the goal is to learn and improve.
 - Losing marks here is expected and useful—it highlights where you can focus your attention for the next report.

Section: Introduction

Answer the following questions.

- 1. Define a sampling distribution in your own words. How does it differ from a population distribution?
- 2. Explain how the mean and standard deviation of a sampling distribution are related to the population parameters. What happens to the standard deviation of the sampling distribution as the sample size increases?
- 3. State the Central Limit Theorem (CLT). Why is the CLT important for inferential statistics, especially in business decision-making?

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- The distribution shows all possible statistics values that could be obtained from all possible samples of a certain size taken from the population.

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What values can \hat{p} take?

• \hat{p} can be $0, \frac{1}{n}, \frac{2}{n}, \dots, \frac{n-1}{n}, 1$ where n is the sample size.

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- i is the index for each sample, $1, 2, \ldots, n$.

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- A sampling distribution shows how sample statistics (like the mean income \bar{X} of randomly selected groups) would distribute across many samples X_i
- Recall that $\bar{X} = \frac{X_1 + \dots + X_n}{n}$

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• As sample size n increases, SE decreases \rightarrow more precise estimates

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- Allows use of normal distribution for inference.
- Critical for applications in business where underlying data is not normal.

A business school announces that their graduates are among the top earners in the industry and earn an impressive **average** salary of \$2,000 per week just one year after graduation, with a **standard deviation** of \$100 per week.

A group of statistics students decided to investigate this claim using a random sample of **25 graduates** from this business school a year after they completed their degree. Assuming that the claims of the business school about the average salary is true, answer the following questions.

- 1. Find the probability that the students will find a sample mean of the weekly earnings:
 - a. less than \$2,000.
 - b. greater than \$2,000.
 - c. greater than \$2,200. How do you interpret this probability?
 - d. between \$1980 and \$2010.

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 - How to calculate standard deviation of a data?
 - We collect a bunch of \bar{X}_1 , \bar{X}_2 ... and \bar{X}_n .
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- Standard error = $\frac{100}{\sqrt{25}}$ = 20, which is $\sigma_{\bar{X}}$.

Q1 a b: Probabilities at Mean

- $P(\bar{X} < 2000) = 0.5$
- $P(\bar{X} > 2000) = 0.5$
- Follows from symmetry of normal distribution

Q1 c:
$$P(\bar{X} > 2200)$$

•
$$Z = \frac{\bar{X} - \mu}{\sigma_{\bar{X}}} = \frac{2200 - 2000}{20} = 10$$

- $P(Z > 10) \approx 0$
- Sample mean of \$2200 is extremely unlikely

Q1 d: $P(1980 < \bar{X} < 2010)$

•
$$Z_1 = \frac{\bar{X} - \mu}{\sigma_{\bar{X}}} = \frac{1980 - 2000}{20} = -1$$

•
$$Z_2 = \frac{\bar{X} - \mu}{\sigma_{\bar{X}}} = \frac{2010 - 2000}{20} = 0.5$$

•
$$P(-1 < Z < 0.5) = P(Z < 0.5) - P(Z < -1) = 0.5328$$

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A group of statistics students decided to investigate this claim using a random sample of 25 graduates from this business school a year after they completed their degree. Assuming that the claims of the business school about the average salary is true, answer the following questions.

2. Based on your understanding of random variables and income distributions, you hypothesize that the weekly earnings of business graduates might not follow a normal distribution. How would this affect your previous findings? Use the Central Limit Theorem to support your explanation.

Q2: What If Population is Not Normal?

- CLT holds for large n (rule of thumb: $n \ge 30$)
- For n = 25, approximation still reasonable unless heavy skew/outliers
- For extreme cases, larger *n* needed to ensure (approximately distributed as) normality.

Some Discussion and Thoughts

Why is CLT powerful in real-world data?

- It allows inference even when data is not normally distributed.
- Applicable to various fields: economics, finance, health, etc.

When might the approximation break down?

- When sample size is small (n < 30) and population is skewed.
- Presence of extreme outliers or heavy tails.

Examples where sample size matters:

- Income distributions (often skewed)
- Customer spending behavior
- Hospital wait times

Any final questions?

Thanks for your attention! 😂

Let me know if you have any questions.

No tutorial next week!

Section: End 20