

STATISTICS WITH APPLIED PROBABILITY

Custom eBook for STA258

Nishan Mudalige

Nurlana Alili

Bryan Su

CANADA

Statistics with Applied Probability

Custom eBook for STA258

Nishan Mudalige

Department of Mathematical and Computational Sciences
University of Toronto Mississauga

Nurlana Alili

University of Toronto Mississauga

Bryan Xu

University of Toronto Mississauga

© 2025 N. Mudalige, N. Alili, B. Xu
All rights reserved.

This work may not be copied, translated, reproduced or transmitted in any form or by any means — graphic, electronic or mechanical including but not limited to photocopying, scanning, recording, microfilming, electronic file sharing, web distribution or information storage systems — without the explicit written permission of the authors.

Every effort has been made to trace ownership of all copyright material and to secure permission from copyright holders. In the event of any question arising as to the use of copyright material, we will be pleased to make necessary corrections in future publications.

First edition: August 2025

Mudalige, M.; Alili, N.; Xu, B.

University of Toronto Mississauga,
Mississauga, Ontario, Canada

Contents

0	Overview	1
1	Descriptive Statistics and an Introduction to R	2
1.1	Introduction	2
1.2	Descriptive Statistics	4
1.3	Graphical Techniques	10
1.3.1	Histograms	10
1.3.2	Box-Plots	12
1.4	Introduction to R	13
2	Sampling Distributions Related to a Normal Population	16
2.1	Normal Distribution	16
2.2	Gamma and Chi-square Distribution	17
2.3	Student's t-Distribution and F-Distribution	20
3	The Central Limit Theorem	23
4	Normal Approximation to the Binomial Distribution	26
4.1	Introduction	26
4.2	Bernoulli Distribution	27
4.3	Sampling Distribution of the Sum and MGF Derivation	29
4.4	Binomial Distribution	29
4.4.1	Visualizing the PMF of Binomial Distributions	30
4.5	Sampling Distribution of a Sample Proportion and the Normal Approximation	33
4.6	Normal Approximation to Binomial	37
4.7	Continuity Correction	37
5	Law of Large Numbers	40
5.1	Convergence in Probability	40
5.2	Weak Law of Large Numbers (WLLN)	41
6	One Sample Confidence Intervals on a Mean When the Population Vari- ance is Known	45
6.1	Introduction	45
6.2	Interpretation	47
6.3	Confidence Interval for μ (Known Variance)	48
6.4	APPENDIX	55

7	One-Sample Confidence Intervals on a Mean When the Population Vari- ance is Unknown	56
7.1	CIs for μ	56
8	One Sample Confidence Intervals On a Proportion	66
9	Sample Size Selection using Confidence Intervals	69
9.0.1	Empirical Rule	69
9.1	Calculating Sample Size for a Confidence Interval on a Mean	69
9.2	Calculating Sample Size for a Confidence Interval on a Proportion	71
10	Two Sample Confidence Interval	74
10.1	Two Sample Confidence Interval on a Difference of Mean	74
10.2	Two Sample Confidence Interval on Paired Data	79
10.3	Two Sample Confidence Interval on Proportions	81
10.4	Two Sample Confidence Interval on Variances	83
11	Introduction to Hypothesis Testing	85
11.1	Test of Hypothesis for One Mean	85
11.2	Test of Hypothesis for One Proportion	99
11.3	Test of Hypothesis for One Variance	114
12	Statistical Power	118

Chapter 0

Overview

Uncertainty is an inherent part of everyday life. We all face questions regarding uncertainty such as whether classes will go ahead as planned on any given day; will a flight leave on time; will a student pass a certain course? Uncertainties might also change depending on other factors, such as whether classes will still go ahead as planned when there is a snow warning in effect; if a flight is delayed can a person still manage to make their connection; will a student pass their course considering that the instructor is known to be a tough grader?

The ability to quantify uncertainty using rigorous mathematics is a powerful and useful tool. Calculating uncertainty on an intuitive level is something that is hard-wired in our DNA, such as the decision to fight or flight depending on a given set of circumstances. However we cannot always make such intuitive decisions based purely on hunches and gut feelings. Fortunes have been lost based on someone having a good feeling about something. If we have information available, we should make the best prediction possible using this information. For instance if we wanted to invest a lot of money in a company, we should use all available data such as past sales, market and industry trends, leadership ability of the CEO, forward looking statements etc. and with all this information we can then predict whether our investment will be profitable.

In order for companies to survive and remain competitive in today's environment it is essential to monitor industry trends and read markets properly. Companies that don't adapt and stick to an outdated business model tend to pay the price. At the other end of the spectrum, companies that understand the needs of the consumer, build their product around the consumer and keep evolving their product offerings based on consumer trends tend to perform well and remain competitive.

Statistics is the science of uncertainty and it is clearly a very useful subject for business. In this book you will be given an introduction to statistics and you will learn the framework as well as the language required at the introductory level. The material may be daunting at times, but the more you get familiar with the subject the more comfortable you will become with it. As business students, doing well in a statistics course will give you a competitive edge since the ability to interpret and perform quantitative analytics are skills that are highly desired by many employers.

Chapter 1

Descriptive Statistics and an Introduction to R

1.1 Introduction

Intuitively, statistics can be considered the science of uncertainty. Formally,

Definition 1.1 (Statistics).

Statistics is the science of collecting, classifying, summarizing, analyzing and interpreting data.

Population, Sample, Parameter

In statistics, researchers need to observe behavior, pattern, trends and other types of data to give a conclusion. To make the conclusion more persuasive, researchers require huge amount of data to support them, that's why study statistics need population.

Definition 1.2 (Population).

In statistics, a population is a set of similar observations which is of interest for some experimental questions. It can be a set of existing objects such as all people in Canada, or hypothetical group of existing objects such as the set of all possible hands in a game of poker.

However, data collection from population is a lot work. Usually, researchers select a finite number of observations to study.

Definition 1.3 (Sample).

It refers to a selection of a subset from population that researchers use it to estimate population characteristics.

Now, we have already chosen a sample, but how do we use it to estimate population characteristics? This is the point where parameter comes to play.

Definition 1.4 (Parameter Statistics).

A parameter is a quantity of statistical population which summerizes characteristics of the population. For example, mean, variance and standard deviation.

Descriptive and Inferential Statistics

Now, we have set everything we need. A population, a chosen sample in that population with its parameters. Next step is studying. There are two major types of analysis: descriptive and Inferential statistics. In this section, we are only going to give you a rough idea about what they are, more detailed materials will be introduced in later chapters.

Definition 1.5 (Descriptive Statistics).

It refers to the summation of all quantitive values that describe characteristics of the population. Usually, we use descriptive statistics to summerize characteristics of a data set.

Furthermore, we use inferential statistics to do statistical analysis.

Definition 1.6 (Inferential Statistics).

It refers to the process of using data analysis to indicate properties of a population. For example, testing hypothesis and confidence interval (both will be introduced in later chapters).

Qualitative and Quantitative Data

At this point, assume that we have finished all procedures such as obtaining parameters and analyzing properties. Now, another important thing is illustrating all the discovery.

Definition 1.7 (Qualitative Data).

This type of illustration refers to showing categorical data. For example, lecture notes from a course, open-question survey.

To illustrate numerical data, we use quantitative data.

Definition 1.8 (Quantitative Data).

Unless the previous type of illustration, quantitative data is represented numerically, including anything that can be counted, measured, or given a numerical value. For example, STA258 final mark score range from 100 different students who have taken this course.

1.2 Descriptive Statistics

Previously, we defined descriptive statistics. Now, let's introduce what exact they are.

Sample Mean, Variance and Standard Deviation

Sample mean (or sample average) is the average value of a sample which is selected from an interested population of an experiment. Usually, the sample mean is used to estimate population mean. In other words, we say that the sample mean is an estimator of population mean.

Definition 1.9 (Sample Mean).

Let $x_1, x_2, x_3, \dots, x_n$ be a sample of data points. We define sample mean of the sample data points (\bar{x}) as the following:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i.$$

Also, we define sample variance of the sample data points (s^2) as:

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2.$$

Moreover, the standard deviation of the sample of data points (s) is:

$$s = \sqrt{s^2}, \quad \text{for } s > 0.$$

Now, let's move to variance. It refers to the expected value of the squared deviation from the mean of a random variable in a population. Similarly, we do have sample variance as well, which is the expected value of the squared deviation from the mean of a random variable in a selected sample. At this point, we can still use sample variance to estimate population variance with adjustment, because the sample variance may differ significantly based on what data points are chosen from that population.

Definition 1.10 (Sample Variance).

Let $x_1, x_2, x_3, \dots, x_n$ be a sample of data points, we define sample variance of the sample data points (s^2) as:

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2, \quad \text{where } \bar{x} \text{ is the sample mean of the data points.}$$

Next is standard deviation. It is a measure of the amount of variation of the values of a variable about its mean. If standard deviation is relatively larger, then data points are

widely spread out from the mean. Otherwise, data points stay close from the mean. Also, standard deviation is obtained by taking squared root from variance which is dependent on the choices of data points as well. To use sample standard deviation as an estimator to population standard deviation, we still need to adjust it.

Definition 1.11 (Sample Standard Deviation).

Let $x_1, x_2, x_3, \dots, x_n$ be a sample of data points. The standard deviation of the sample of data points (s) is:

$$s = \sqrt{s^2}, \quad \text{for } s > 0.$$

Median and Mode

The median and mode are two important measures of central tendency used in statistics to summarize and understand data. The median represents the middle value in a sorted dataset, giving a sense of the center that is not affected by extreme values or outliers. In contrast, the mode is the value that appears most frequently in a dataset, making it useful for identifying common or repeated observations.

Definition 1.12 (Median).

Let: $x_1, x_2, x_3, \dots, x_n$ be a collection of data points which is arranged in ascending order from the smallest value to the largest value (or descending order from the largest value to the smallest value in that collection). The median of the given collection of data points is the middle value in that collection, which equally spreads the collection into two parts. Half of all the collection values are above the median value and the rest of the values in the collection is below the median value.

- *Case 1: when n is an odd number. (i.e. 1, 3, 11, 237, ...). Then, the median M is defined as:*

$$M = \frac{n+1}{2}, \text{ where } n \text{ represents the } n^{\text{th}} \text{ position.}$$

- *Case 2: when n is an even number (i.e. 2, 6, 100, 500, ...). Then, the median M is: the average value of $\frac{n}{2}$'s and $\frac{n+2}{2}$'s position, where n represents the n^{th} position.*
-

Now, let's introduce mode.

Definition 1.13 (Mode).

It refers to a value that appears the most frequent than the appearance of all other values in a given dataset.

Percentile and Quartile

Percentiles and quartiles are statistical measures used to describe the distribution of data. A percentile indicates the value below which a given percentage of observations fall, helping to understand relative standing within a dataset. Quartiles, a specific type of percentile, divide the data into four equal parts (Q1, Q2/median, and Q3), providing insights into the spread and central tendency.

Definition 1.14 (Percentile and Quartile).

Let: x_1, x_2, \dots, x_n be a collection of data points in either ascending order. Percentile is denoted as: p^{th} , which indicates $p\%$ of observations are below to a such value. Quartiles, are special cases of percentile which equally spread the collection of data into four parts. Each part contains 25% of the entire collection. More specifically, we define quartiles as the following:

- Q_1 : the 25 percentile (or 25^{th}), which shows that 25% of the data points are below the value Q_1 .
- Q_2 : the 50 percentile (or 50^{th}), which shows that 50% of the data points are below the value Q_2 .
- Q_3 : the 75 percentile (or 75^{th}), which shows that 75% of the data points are below the value Q_3 .
- Q_2 is qual to median.

Moreover, we use $Q_3 - Q_1$ to calculate interquartile range (I.P.R), which shows the spread of the whole data set.

Skewness and Symmetry

The two terms 'skewness' and 'symmetry' are used to describe the shape of probability distribution. There are two types of skewness: left (or negative) skew and right (or positive) skew. In real life, a famous distribution highly used in hypothesis testing which is χ_n^2 with n degrees of freedom, is right skewed probability distribution function. Another example regarding to symmetry is normal distribution such that its probability under its curve greater than μ is same as the probability below than μ . Now let's introduce the proper definition of skewness and symmetry.

Definition 1.15 (Skewness).

Skewness refers to such a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The skewness value can be positive, zero, negative or undefined.

Now, let's break down the main definition of skewness and symmetry:

Definition 1.16 (Left (or Negative) Skew).

By observing given probability distribution curve, if the left tail of the curve is longer than the right tail the mass of the distribution is concentrated on the right of the figure, then we say that probability distribution is left skew or negative skew. (See figure below)

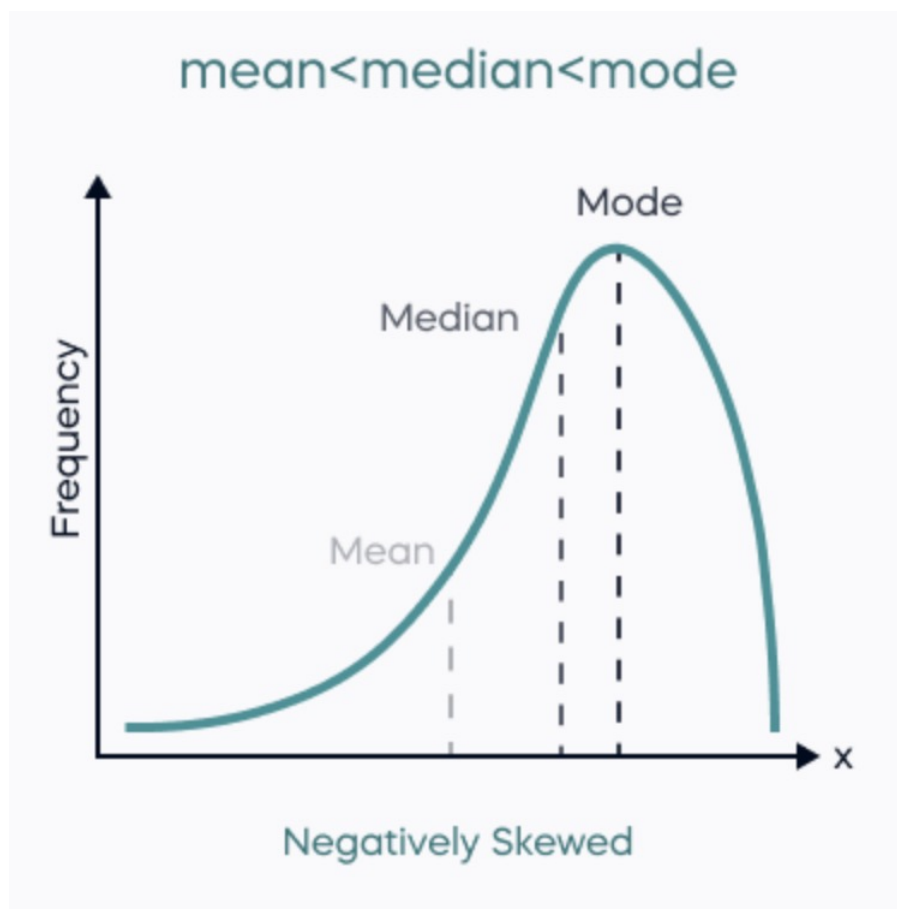


Figure 1.1: Visualization of left skew probability distribution

Definition 1.17 (Right (or Positive) Skew).

By observing given probability distribution curve, if the right tail of the curve is longer than the left tail the mass of the distribution is concentrated on the left of the figure, then we say that probability distribution is right skew or positive skew. (See figure below)

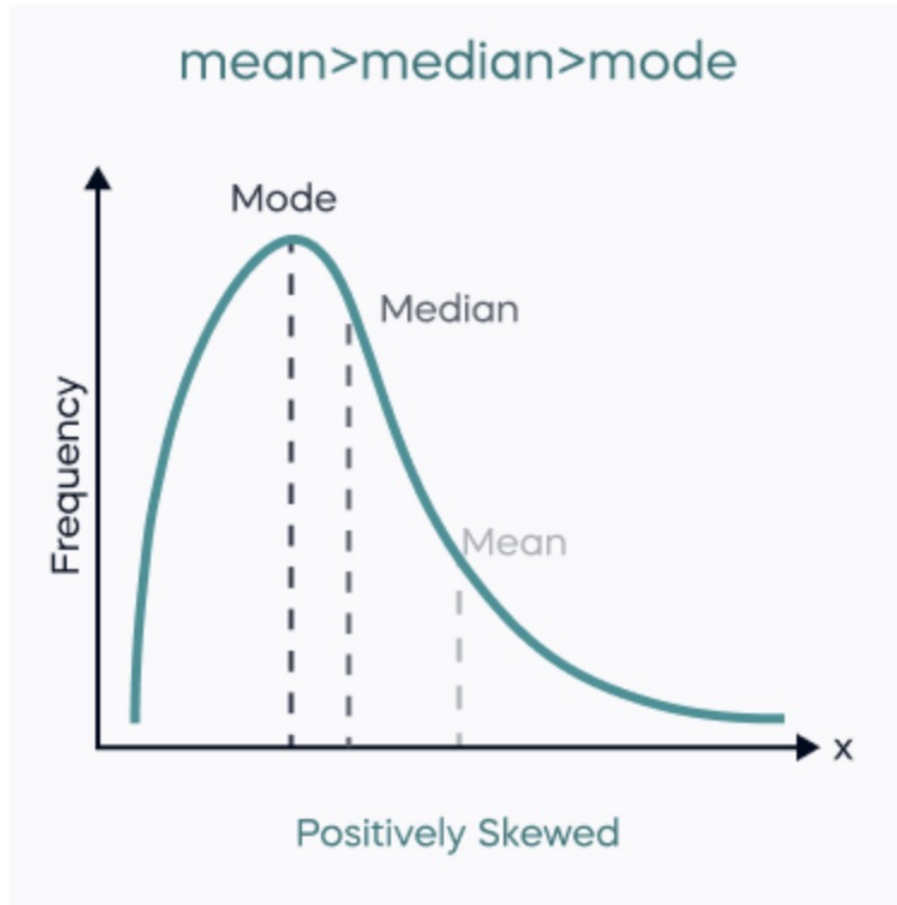


Figure 1.2: Visualization of right skew probability distribution

Symmetry is a special case of skewness when the value of skewness is 0.

Definition 1.18 (Symmetry).

In statistics, symmetry is a probability distribution is reflected around a vertical line at some value of the random variable represented by the distribution. Probability under the curve below that value is equal to probability under the curve greater than that value. (see figure below)

Since symmetry is a special case, so that it has a unique property as the following:

Theorem 1.1 (Empirical Rule (or 68 – 95 – 99.7 Rule)). *For any symmetric (bell-shaped) curve, let μ be its mean and σ be its standard deviation, the following probability set function is true:*

- 1. $P(\mu - \sigma < X < \mu + \sigma) = 68.27\%$;
- 2. $P(\mu - 2\sigma < X < \mu + 2\sigma) = 95.45\%$;
- 3. $P(\mu - 3\sigma < X < \mu + 3\sigma) = 99.73\%$.



Figure 1.3: Visualization of symmetric probability distribution

Practice Example

Example 1.1.

[Calculating Sample Mean, Variance and Standard Deviation] Let: $x_1 = 1, x_2 = 3$ and $x_3 = 7$. Calculate the sample mean, sample variance and sample standard deviation for this collection of data points.

Solution (all results are kept in four digits):

By Definition 1.9, 1.10, 1.11, sample mean:

$$\bar{x} = \frac{1 + 3 + 7}{3} \approx 3.6667.$$

Then, we use sample mean to calculate sample variance:

$$s^2 = \frac{1}{3-1} \times [(1 - 3.6667)^2 + (3 - 3.6667)^2 + (7 - 3.6667)^2] \approx 9.3333.$$

Finally, we take the square root of sample variance to get sample deviation, and remember that $s > 0$:

$$s = \sqrt{s^2} \approx 3.0551.$$

Example 1.2.

[Median Calculation] Given two distinct collections of data points: $S_1 = \{2, 4, 6\}$ and $S_2 = \{1, 5, 16, 28\}$. Calculate the median of both two sets.

Solution:

For S_1 , since $n = 3$ which is an odd number, so by *Definition* 1.3, $M_{S_1} = 4$. For S_2 , $n = 4$ in this case, so that we need to calculate the average of $\frac{n}{2}$ and $\frac{n+1}{2}$. Then,

$$M_{S_2} = \frac{5 + 16}{2} = 10.5.$$

Example 1.3.

Consider the data set $S = \{4, 25, 30, 30, 30, 32, 32, 35, 50, 50, 50, 55, 60, 74, 110\}$. Calculate its median and Q_1 (25^{th}).

Solution:

Simply counting the number of data points, $n = 15$, such that $M_S = \frac{15+1}{2} = 8$. Thus, the 8^{th} value in the set which is 35.

Since we know the median of this collection of data points, we just need to find the median of the lower half of this data, which is exactly going to be 25 percentile (25^{th}). In the lower half of the given collection (all values below the median), $n_{lower} = 7$. By *Definition 1.3*, then median of the lower half (25^{th}) is going to be:

$$25^{th} = \frac{7+1}{2} = 4, \text{ the } 4^{th} \text{ position in the data set.}$$

Thus, Q_1 (25^{th}) = 30. To find Q_3 (75^{th}), apply the same strategy will guide you to find the correct answer, and we leave this as an exercise to you.

1.3 Graphical Techniques

In statistics, there are lots of types of graph to illustrate data, for example histograms and box-plots. This technique is used in the field of statistics for data visualization. Our objective is to both be able to identify some classical types of graph and interpret key statistical values (descriptive statistical values) from it.

1.3.1 Histograms

Introduction to Histograms

Histogram is a graphical representation of data that uses bars to display the frequency distribution of a dataset. Unlike bar graphs, which represent categorical data, histograms group numerical data into intervals (bins) and show how many values fall into each range. This makes histograms ideal for visualizing the shape, spread, and central tendency of continuous data, helping identify patterns such as symmetry, skewness, and outliers.



Figure 1.4: Visualization of histograms

Advantages and Disadvantages of Histograms

- Advantages of Histograms:
 1. Histograms are easily to used for visualise data (relatively). It allows us to get the idea of the "shape" of distribution (i.e. skewness which will be discussed late in this section).
 2. It is also flexible that people are able to modify bin widths.
- Disadvantages of Histograms:
 1. It is not suitable for small data sets.
 2. The values from histograms close to breaking points are likely similar, in fact they need to be classified into different bins (i.e. Student A and B scores 79 and 80 respectively in STA258, we consider a breaking point between 79 and 80. The two students have similar score, but student A is *B+* and student B is *A-* in GPA from).

Histograms with Skewness and Symmetry

A histogram visually represents the distribution of numerical data, making it a useful tool for assessing skewness and symmetry. It is quite straightforward to estimate the skewness of histograms by simply drawing a curve above bins on the histogram.

For a histogram to have a left (or negative) skew probability distribution:

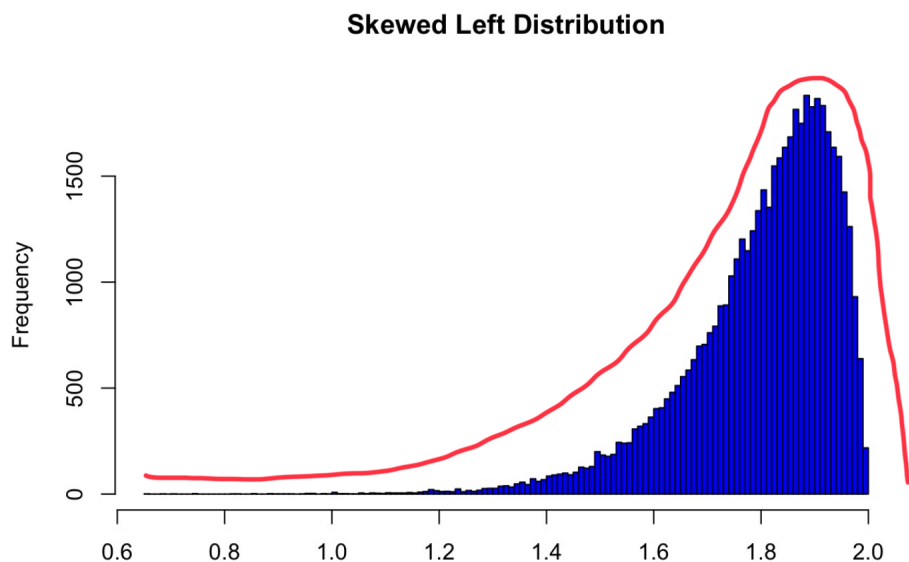


Figure 1.5: Visualization of a histogram has a left (or negative) skew probability distribution

For a histogram to have a right (or positive) skew probability distribution:

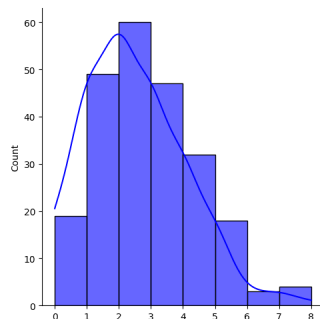


Figure 1.6: Visualization of a histogram has a right (or positive) skew probability distribution

For a histogram to have a symmetric probability distribution:

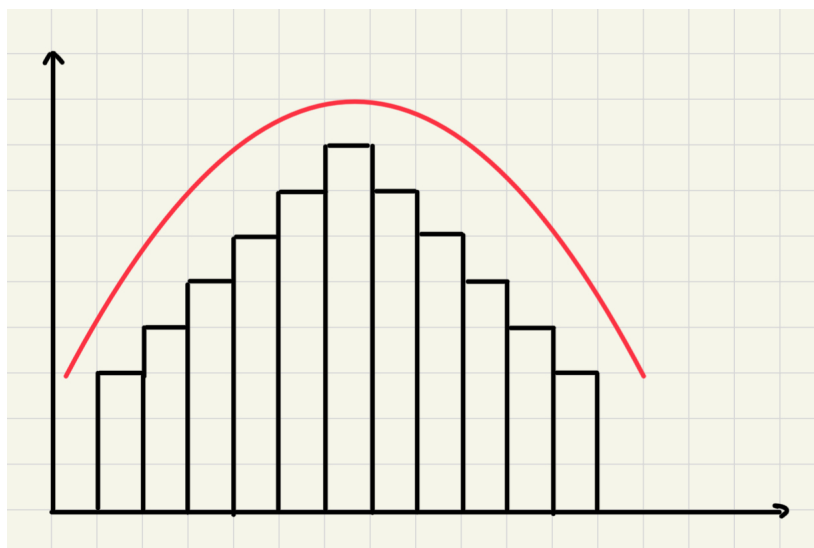


Figure 1.7: Visualization of a histogram has a symmetric probability distribution

1.3.2 Box-Plots

A boxplot (or box-and-whisker plot) is a standardized way to display data distribution based on a five-number summary: minimum, first quartile (Q1), median (Q2), third quartile (Q3), and maximum. The box represents the interquartile range (IQR), while the whiskers show variability outside Q1 and Q3. Outliers are plotted as individual points. Boxplots efficiently compare distributions and highlight skewness, spread, and outliers. (See figure below)

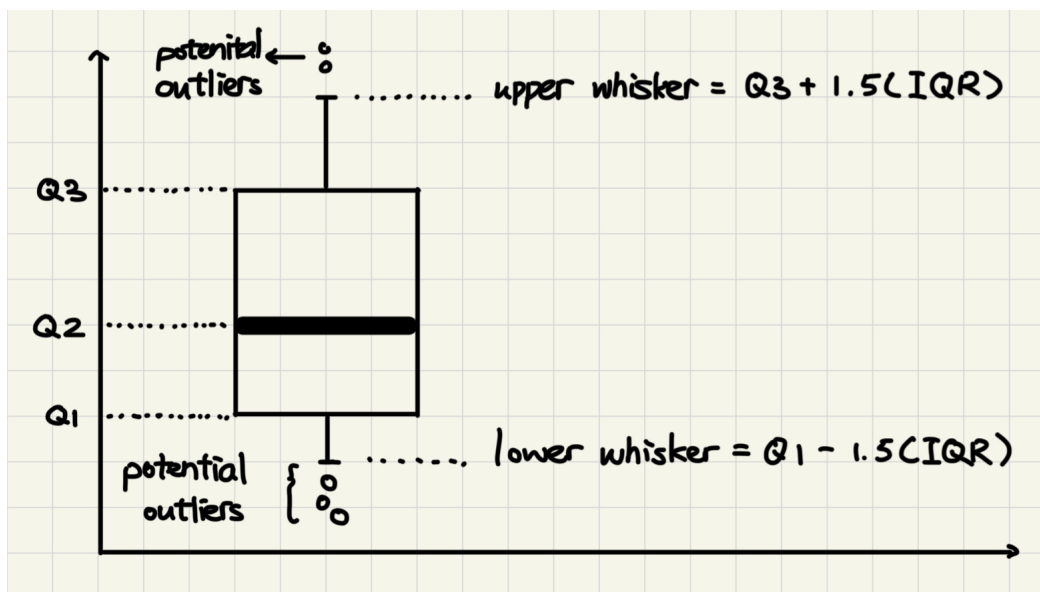


Figure 1.8: Visualization of a box-plot

Similar to histograms, we can still obtain information about skewness and symmetry, by observing the cut from the line of Q_2 .

If the median (Q_2) cuts the box with upper area smaller than lower area, then we say that box-plot with left skew probability distribution. Or, if the median (Q_2) cuts the box with upper area larger than lower area, then we say that box-plot with right skew probability distribution.

Otherwise, if the median (Q_2) cuts the box with upper area equal to lower area, then we say that box-plot with symmetric probability distribution.

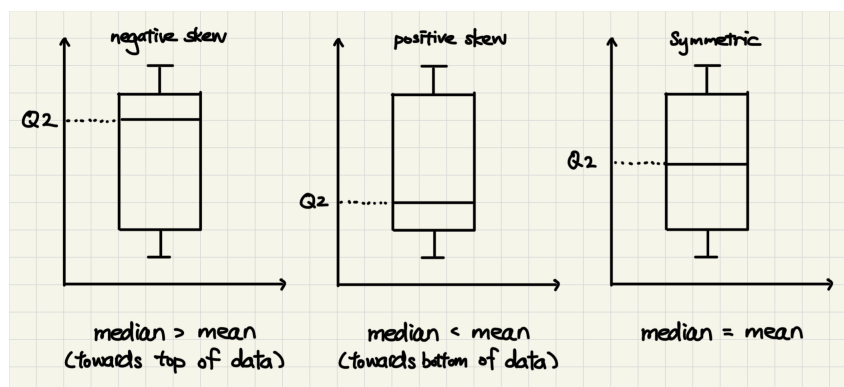


Figure 1.9: Visualization of a box-plot with skew and symmetric probability distribution

1.4 Introduction to R

R is used for data manipulation, statistics, and graphics. It is made of: operations (+, -, <) which is for calculations on vectors, arrays and matrices; a huge collection of functions; fa-

cilities for making unlimited types quality graphs; user contributed packages (sets of related functions); the ability to interface with procedures written in C, C+, or FORTRAN and to write additional primitives. R is also an open-source computing package which has seen a huge growth in popularity in the last few years (Please use this website: <https://cran.r-project.org>, to download R).

What is R-studio?

RStudio is a relatively new editor specially targeted at R. RStudio is cross-platform, free and open-source software (Please use: <https://www.rstudio.com>, to download Rstudio).

Make a Histogram Using R-studio

This is just a demonstration of how to start and use R-studio.

1. First of all, we need to know which dataset are we going to make into a histogram. In this case, as an example, we are going to use the waiting time in faithful in R-studio.
2. For any dataset, use the code: `names(faithful)` to get it. (inside the parentheses, type the names of variables you want in faithful dataset)
3. Then, we proceed with the code: `hist(faithful$waiting)` to get a basic plot.



Figure 1.10: R-studio first three steps (by following the instructions, you should get this histogram)

4. Furthermore, we can also get more information. For example, by keep proceeding with the code: `hist(faithful$waiting, plot=FALSE)$breaks`, R-studio will show you all the breaking points between histogram cells.

```
> hist(faithful$waiting)
> hist(faithful$waiting,plot=FALSE)$breaks
[1] 40 45 50 55 60 65 70 75 80 85 90 95 100
```

Figure 1.11: R-studio the forth step(by following the instructions, you should get this histogram)

Chapter 2

Sampling Distributions Related to a Normal Population

Previously, we have introduced lots of definitions and given you a rough idea about what really statistics it and what people do in statistics. Now, we are going to proceed statistical distributions.

2.1 Normal Distribution

In probability theory and statistics, normal distribution also called Gaussian distribution which is discovered by a famous German mathematician Johann Carl Friedrich Gauss in 1809. It is one of the most important distribution that used to approximate other types of probability distribution, such as binomial, hypergeometric, inverse (or negative) hypergeometric, negative binomial and Poisson distribution. Generally, it is denote as $N(\mu, \sigma^2)$ with probability density function as the following:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}.$$

Formally, let's begin with its definition:

Definition 2.1 (Normal Distribution).

Suppose a random variable $X \sim N(\mu, \sigma^2)$, then $E(X) = \mu$ and $Var(X) = \sigma^2$. And $-\infty < \mu < \infty, \sigma^2 > 0$. Moreover, X has probability density function as:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \text{ for } -\infty < x < \infty \text{ (same as above).}$$

The only special case of normal distribution is standard normal distribution, such that a random variable $Y \sim N(\mu = E(Y) = 0, \sigma^2 = Var(Y) = 1)$, then Y has probability density function as:

$$f(y) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{y^2}{2}}.$$

2.2 Gamma and Chi-square Distribution

The Chi-square and Gamma distributions are two fundamental probability distributions widely used in statistical theory and applications. The Gamma distribution is a continuous distribution characterized by its shape and scale parameters, making it versatile for modeling waiting times and various positively skewed data. The Chi-square distribution, a special case of the Gamma distribution, arises naturally in the context of hypothesis testing and confidence interval estimation, especially in tests involving variance and categorical data.

Gamma Distribution

Definition 2.2 (Gamma Distribution).

Suppose a random variable X is Gamma distributed with $\alpha > 0$ (shape parameter) and $\beta > 0$ (scale parameter) if and only if the probability density function of X is

$$f(x) = \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\beta^\alpha \Gamma(\alpha)}, \text{ for } 0 < x < \infty.$$

Then, $E(X) = \alpha\beta$, $\text{Var}(X) = \alpha\beta^2$ and its moment generating function is $M_X(t) = \frac{1}{(1-\beta t)^\alpha}$, for $t < \frac{1}{\beta}$.

Now, let's introduce some properties of Gamma function:

- Gamma function (**not a distribution**):

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt, \text{ for } x > 0.$$

- Properties

- 1. $\Gamma(x) = x \cdot \Gamma(x-1)$;
- 2. For all $n \in \mathbb{N}$, $\Gamma(n) = (n-1)!$;
- 3. $\Gamma(\frac{1}{2}) = \sqrt{\pi}$.

Chi-square Distribution

Here is its formal definition:

Definition 2.3 (Chi-square Distribution).

A random variable X has a Chi-squared distribution with n degrees of freedom (χ_n^2) if and only if X is a random variable with a Gamma distribution with parameters $\alpha = \frac{n}{2}$ and $\beta = 2$. Then, the probability density function of X is given by

$$f(x) = \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} x^{\frac{n}{2}-1} e^{-\frac{x}{2}}.$$

Moreover, $E(X) = n$, $Var(X) = 2n$ and moment generating function of X is $M_X(t) = (1 - 2t)^{-\frac{n}{2}}$, for $t < \frac{1}{2}$.

We claim that Chi-square distribution is a special case of Gamma distribution with $\alpha = \frac{n}{2}$ and $\beta = 2$. Now, let's prove it by using moment generating function.

The proof is quite straightforward as the following shows:

Proof. Suppose $X \sim \text{Gamma}(\alpha = \frac{n}{2}, \beta = 2)$.

Then the following moment generating function holds for X :

$$M_X(t) = (1 - 2t)^{-\frac{n}{2}}, \text{ for } t < \frac{1}{2}.$$

Compare the moment generating function of X under Gamma distribution with Chi-square distribution, we can conclude that $X \sim \chi_n^2$. \square

Obtaining Chi-square Distribution by Normal Distribution

Previously, we showed how to use Gamma distribution to get Chi-square distribution by moment generating function method. Now, let's do something interestingly, to use normal distribution to get Chi-square distribution. We will begin with a theorem, then prove it.

Theorem 2.1.

Suppose a random variable Z is standard normally distributed, such that $Z \sim N(0, 1)$. Then, Z^2 is Chi-square distributed with 1 degree of freedom, so that $Z^2 \sim \chi_1^2$.

The proof of Theorem 2.1 isn't that trivial to see. We still need moment generating function, but in a different way. Before we get into the proper proof, let's grab everything we need:

- 1. Recall STA256 about how to get moment generating function for a given continuous random variable that:

$$M_Z(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx.$$

- 2. We also need Gaussian integral:

$$\int_{-\infty}^{\infty} e^{-x^2} dx = \sqrt{\pi}; \tag{2.2.1}$$

$$\int_{-\infty}^{\infty} e^{-kx^2} dx = \sqrt{\frac{\pi}{k}}, \text{ for } k > 0; \tag{2.2.2}$$

$$\int_{-\infty}^{\infty} e^{kx^2} dx = \sqrt{\frac{\pi}{-k}}, \text{ for } k < 0. \tag{2.2.3}$$

Proof. Suppose that $Z \sim N(0, 1)$, then $f_Z(z) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{z^2}{2}}$.

The moment generating function (MGF) of Z^2 is:

$$\begin{aligned} M_{Z^2}(t) &= \mathbb{E} \left(e^{tZ^2} \right) \\ &= \int_{-\infty}^{\infty} e^{tz^2} f_Z(z) dz \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{tz^2} e^{-\frac{z^2}{2}} dz \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{1}{2}-t\right)z^2} dz. \end{aligned}$$

Apply substitution with $u = z\sqrt{\frac{1}{2}-t}$, $dz = \frac{du}{\sqrt{\frac{1}{2}-t}}$:

$$\begin{aligned} M_{Z^2}(t) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-u^2} \cdot \frac{1}{\sqrt{\frac{1}{2}-t}} du \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sqrt{\frac{1}{2}-t}} \int_{-\infty}^{\infty} e^{-u^2} du \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sqrt{\frac{1}{2}-t}} \cdot \sqrt{\pi} \\ &= \frac{1}{\sqrt{1-2t}}. \end{aligned}$$

This is the MGF of a chi-squared distribution with 1 degree of freedom, $Z^2 \sim \chi_1^2$. □

Now, we can do another proof by using Theorem 2.1.

Theorem 2.2.

Suppose $Z_1, Z_2, \dots, Z_n \stackrel{i.i.d.}{\sim} N(0, 1)$, then the sum of n independent Z^2 is going to be Chi-square distributed with n degrees of freedom, as the following:

$$\sum_{i=1}^n Z_i^2 \sim \chi_n^2.$$

We need Theorem 2.1 to prove this, but it going to be easier.

Proof. Suppose $Z \sim \mathcal{N}(0, 1)$, then its probability density function is:

$$f_Z(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}.$$

Let $\delta = \sum_{i=1}^n Z_i^2$, where $Z_1, \dots, Z_n \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$. The moment generating function (MGF) of δ is:

$$\begin{aligned} M_\delta(t) &= \mathbb{E} \left[e^{t\delta} \right] \\ &= \mathbb{E} \left[e^{t(Z_1^2 + \dots + Z_n^2)} \right] \\ &= \mathbb{E} \left[\prod_{i=1}^n e^{tZ_i^2} \right]. \end{aligned}$$

Since Z_1, \dots, Z_n are independent and identically distributed:

$$\begin{aligned} M_\delta(t) &= \prod_{i=1}^n \mathbb{E} \left[e^{tZ_i^2} \right] \\ &= \prod_{i=1}^n M_{Z_i^2}(t). \end{aligned}$$

From Theorem 2.1, we know $Z_i^2 \sim \chi_1^2$ with MGF $(1 - 2t)^{-1/2}$, therefore:

$$\begin{aligned} M_\delta(t) &= \prod_{i=1}^n (1 - 2t)^{-1/2} \\ &= (1 - 2t)^{-n/2}. \end{aligned}$$

This is exactly the MGF of a chi-squared distribution with n degrees of freedom, proving that $\delta \sim \chi_n^2$ as required. \square

Here is the last theorem for Chi-square and normal distribution, but we won't show you the proof due to its complexity. For people who are interested in that, please see STA260 lecture notes or power point slide to figure out.

Theorem 2.3.

Let n be sample size, s^2 be sample variance and σ^2 be population variance, then $\frac{(n-1)s^2}{\sigma^2}$ is Chi-square distributed with $n - 1$ degrees of freedom. As the following:

$$\frac{(n-1)s^2}{\sigma^2} \sim \chi_{n-1}^2.$$

2.3 Student's t-Distribution and F-Distribution

The t-distribution and F-distribution are essential tools in inferential statistics, particularly in the context of hypothesis testing and variance analysis. The t-distribution, which resembles the normal distribution but with heavier tails, is primarily used when estimating

population means in situations where the sample size is small and the population standard deviation is unknown. On the other hand, the F-distribution is used to compare variances between two populations and plays a central role in analysis of variance (ANOVA) and regression analysis.

Student's t-Distribution

Definition 2.4 (Student's t-Distribution).

Suppose X is t -distributed with n degrees of freedom, then the probability density function of X is given by:

$$f_X(x) = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{\pi n} \Gamma(\frac{n}{2})} \left(1 + \frac{x^2}{n}\right)^{-\frac{n+1}{2}}.$$

Alternatively, define a new variable T is the following:

$$T = \frac{W}{\sqrt{\frac{V}{r}}}, \text{ for } W \sim N(0, 1) \text{ and } V \sim \chi_r^2.$$

Or suppose $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} N(\mu, \sigma^2)$, then $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$. Thus,

$$T = \frac{\bar{x} - \mu}{\left(\frac{s}{\sqrt{n}}\right)}.$$

Same as normal distribution, student's t -distribution is also symmetric. Also, as the degrees of freedom of t -distribution getting larger, the curve of student's t -distribution getting closer to standard normal distribution.

F-Distribution

Definition 2.5.

We define a new variable F as the following shows:

$$F = \frac{\left(\frac{W_1}{v_1}\right)}{\left(\frac{W_2}{v_2}\right)} \sim F_{v_1, v_2}; \text{ for } W_1 \sim \chi_{v_1}^2 \text{ and } W_2 \sim \chi_{v_2}^2; \text{ also both } W_1 \text{ and } W_2 \text{ are independent.}$$

Alternatively, we select two samples (with same population variance) with size n and m , and also sample variance s_x and s_y respectively. Then, F -distribution is:

$$F = \frac{\left[\frac{\left(\frac{n-1}{2}\right)s_x^2}{n-1}\right]}{\left[\frac{\left(\frac{m-1}{2}\right)s_y^2}{m-1}\right]} \sim F_{n-1, m-1}.$$

Both student's t-distribution and F-distribution are highly used in inferential statistics, until confidence interval, testing hypothesis and ANOVA analysis, these two distributions will come to play a lot. At this point, just guarantee that you know how to obtain those distribution from random given information is sufficient.

Chapter 3

The Central Limit Theorem

The Central Limit Theorem (CLT) is one of the most important results in probability and statistics. It states that, given a sufficiently large sample size, the distribution of the sample mean of independent and identically distributed (i.i.d.) random variables approaches a normal distribution, regardless of the shape of the original distribution. Real-life Application of Central Limit Theorem in Financial Analysis. The CLT is often used by financial experts to examine stock market results.

Now, let's discuss Central Limit Theorem with more details. Suppose we have a finite number of populations and each population follows a distribution with population mean μ and population variance σ^2 . Then we take samples of same size n from each population, such that we have $\bar{x}_1, \bar{x}_2, \dots, \bar{x}_m$ from population group 1 to m , respectively. Next, we make a histogram using the large collection of sample taken from each population group. Then, what we are doing right now is sampling distribution of \bar{x} . As a result, \bar{x} follows a normal distribution with mean $\mu_{\bar{x}} = \mu$ and variance $\sigma_{\bar{x}}^2 = \frac{\sigma^2}{n}$, which is denoted as the following:

$$\bar{x} \sim N(\mu_{\bar{x}} = \mu, \sigma_{\bar{x}}^2 = \frac{\sigma^2}{n}).$$

Figure 3.1 below shows the entire procedure about the Central Limit Theorem.

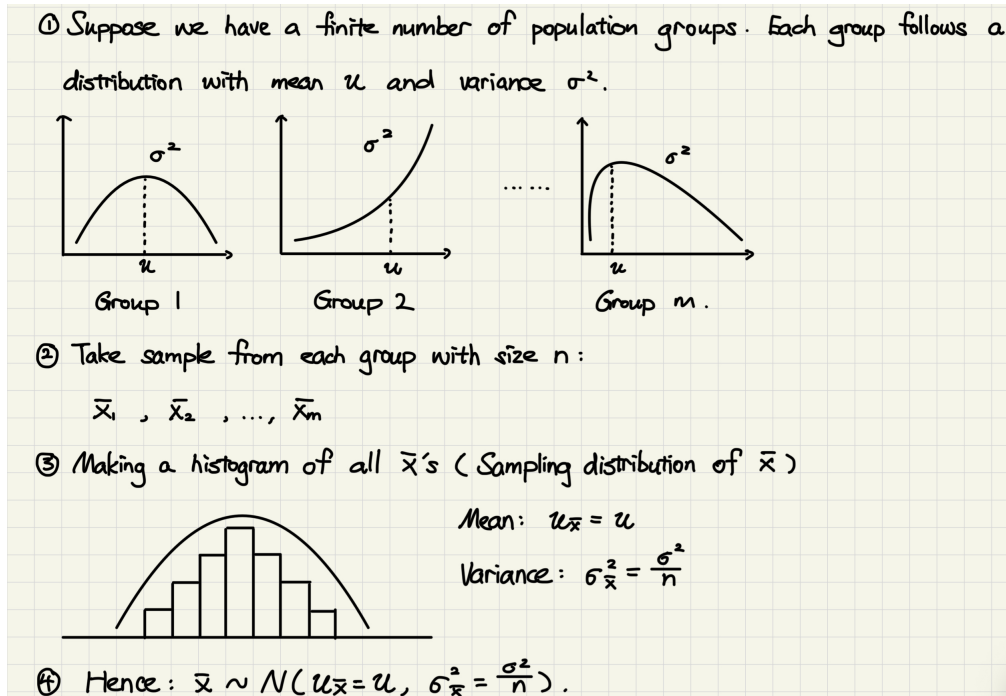


Figure 3.1: Procedure of the Central Limit Theorem

Now, let's begin with the proper definition of Central Limit Theorem.

Definition 3.1 (Central Limit Theorem). —————

Let X_1, X_2, \dots, X_n be independent and identically distributed random variables with $E(X_i) = \mu$ and $\text{Var}(X_i) = \sigma^2 < \infty$. Then, we define the following:

$$U_n = \frac{\bar{X} - \mu}{\left(\frac{\sigma}{\sqrt{n}}\right)} \sim N(\mu = 0, \sigma^2 = 1), \text{ where } \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i.$$

Then the distribution function of U_n converges to the standard Normal distribution function as $n \rightarrow \infty$. That is,

$$\lim_{n \rightarrow \infty} P(U_n \leq u) = \int_{-\infty}^u \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt; \text{ for all } u.$$

For this course in particular, we do not need to pay that much attention to the proving part of the definition above. However, we use Central Limit Theorem to approximate distributions. Here are the two important approximations:

- $\bar{X}_n \approx N\left(\mu, \frac{\sigma^2}{n}\right)$;
- $T = \sum_{i=1}^n X_i \approx N(n\mu, n\sigma^2)$.

A reminder that the distribution of U_n in definition 3.1 and the two approximation of distribution above are extremely important in this course, until later chapters you may see some materials that are similar.

Chapter 4

Normal Approximation to the Binomial Distribution

4.1 Introduction

Definition 4.1 (Statistic).

A statistic is a function of the observable random variables in a sample and known constants. Since statistics are functions of the random variables observed in a sample, they themselves are random variables. As such, all statistics have a corresponding probability distribution, which we refer to as their sampling distribution.

Review from STA256**Bernoulli Distribution:**

A Bernoulli trial is a single experiment with two outcomes:

- Success: $X = 1$ with probability p
- Failure: $X = 0$ with probability $1 - p$

$X = x$	0	1
$P(X = x)$	$1 - p$	p

The probability mass function (PMF) is:

$$f(x) = p^x(1 - p)^{1-x}, \quad x \in \{0, 1\}$$

Binomial Distribution:

A binomial distribution arises from n independent Bernoulli trials. Let:

X = number of successes in n trials

Then:

$$X \sim \text{Binomial}(n, p)$$

where:

- Each trial results in either success (with probability p) or failure (with probability $1 - p$)
- $X \in \{0, 1, \dots, n\}$

The PMF is:

$$P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$$

Moment Generating Function (MGF):

The moment generating function (MGF) of a random variable X is defined as:

$$M_X(t) = \mathbb{E}[e^{tX}]$$

The MGF uniquely characterizes the distribution of X (if it exists in an open interval around 0), and it can be used to compute moments such as the mean and variance.

4.2 Bernoulli Distribution

Bernoulli random variable is a discrete random variable that has exactly two possible outcomes which are either a **success** or a **failure**. An experiment in which there are exactly 2 outcomes (which are success or failure) is called a **Bernoulli trial**.

When $x = 1$ we have a success and when $x = 0$ we have a failure. The term success and failure are relative to the problem being studied.

TIP: “success” need not be something positive

We chose to label a person who refuses to administer the worst shock a “success” and all others as “failures”. However, we could just as easily have reversed these labels. The mathematical framework we will build does not depend on which outcome is labeled a success and which a failure, as long as we are consistent.

Consider the random experiment of rolling a die once. Define the random variable:

$$X_i = \begin{cases} 1 & \text{if the } i\text{-th roll is a six,} \\ 0 & \text{otherwise} \end{cases}$$

Then $X_i \sim \text{Bernoulli}(p)$, where $p = P(\text{rolling a six})$.

Let $X \sim \text{Bernoulli}(p)$. The mass function of X is

$$P(X = x) = p^x(1 - p)^{1-x}, \quad x = 0, 1$$

where p represents the probability of success.

Definition 4.2 (Mean and Variance of a Bernoulli Random Variable). —————

Let $X \sim \text{Bernoulli}(p)$. The mean of X is

$$E(X) = \mu = p$$

and the variance of X is

$$\text{Var}(X) = \sigma^2 = p(1 - p)$$

To support the earlier result, we now provide a derivation of the mean, variance, and standard deviation of a Bernoulli random variable.

Let X be a Bernoulli random variable with the probability of a success as p . Then

$$\begin{aligned} E[X] &= \mu = \sum_{i=1}^n x_i \cdot P(X = x_i) \\ &= 0 \cdot P(X = 0) + 1 \cdot P(X = 1) \\ &= 0 \cdot (1 - p) + 1 \cdot p \\ &= p \end{aligned}$$

Similarly, the variance of X can be computed:

$$\begin{aligned} V(X) &= \sigma^2 = \sum_{i=1}^k (x_i - \mu)^2 \cdot P(X = x_i) \\ &= (0 - p)^2 \cdot P(X = 0) + (1 - p)^2 \cdot P(X = 1) \\ &= p^2(1 - p) + (1 - p)^2 p \\ &= p(1 - p) \end{aligned}$$

The standard deviation is

$$\begin{aligned} \sigma &= \sqrt{\sigma^2} \\ &= \sqrt{p(1 - p)} \end{aligned}$$

4.3 Sampling Distribution of the Sum and MGF Derivation

Consider determining the sampling distribution of the sample total:

$$T_n = X_1 + X_2 + \cdots + X_n$$

Suppose $X_i \stackrel{iid}{\sim} \text{Bernoulli}(p)$. Then the moment-generating function of T_n is:

$$\begin{aligned} M_{T_n}(t) &= \mathbb{E}[e^{tT_n}] \\ &= \mathbb{E}\left[e^{t(X_1+X_2+\cdots+X_n)}\right] \\ &= \mathbb{E}\left[e^{tX_1}e^{tX_2}\cdots e^{tX_n}\right] \quad (\text{independence}) \\ &= \mathbb{E}[e^{tX_1}] \cdot \mathbb{E}[e^{tX_2}] \cdots \mathbb{E}[e^{tX_n}] \\ &= M_{X_1}(t) \cdot M_{X_2}(t) \cdots M_{X_n}(t) \\ &= \left[pe^t + (1-p)\right]^n \end{aligned}$$

Since this is the MGF of a binomial random variable with parameters n and p , we conclude:

$$T_n \sim \text{Binomial}(n, p)$$

Example: Binomial Distribution from Die Rolls

We can think of rolling a die n times as an example of the binomial setting. Each roll gives either a six (a “success”) or a number different from six (a “failure”).

Knowing the outcome of one roll doesn’t tell us anything about the others, so the n rolls are independent.

If we call a six a success, then:

- The probability of success on each trial is $p = P(\text{rolling a six}) = \frac{1}{6}$
- The probability of failure is $1 - p = \frac{5}{6}$

Let Y be the number of sixes rolled in n trials. Then $Y \sim \text{Binomial}(n, p)$, and the distribution of Y is called a **binomial distribution**.

4.4 Binomial Distribution

In section 4.2 we learnt about Bernoulli random variables in which we were interested in the outcome of just a single trial. A **binomial random variable** is a generalization of several independent Bernoulli trials. Instead of performing just a single Bernoulli trial and observing whether we have a success or not, we are now performing several Bernoulli trials and observing whether we have a certain number of successes and failures. The **binomial distribution** describes the probability of having exactly k successes in n independent Bernoulli

trials with probability of a success p .

Let $X \sim \text{Bin}(n, p)$. The probability of observing x successes in these n independent trials is given by

$$P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$$

where

- n represents the number of trials,
- x represents the number of successes,
- p represents the probability of success on any given trial,

$$\binom{n}{x} = \frac{n!}{x!(n-x)!} \quad \text{is the binomial coefficient.}$$

Definition 4.3 (Mean and Variance of a Binomial Random Variable). —————

Let $X \sim \text{Bin}(n, p)$. The mean of X is

$$E(X) = \mu = np$$

and the variance of X is

$$\text{Var}(X) = \sigma^2 = np(1 - p)$$

4.4.1 Visualizing the PMF of Binomial Distributions

R code:

```
## Pmf of Binomial with n=10 and p=1/6.

x <- seq(0, 10, by=1)
y <- dbinom(x, 10, 1/6)

plot(x, y, type="p", col="blue", pch=19)
```

Probability Mass Functions (PMFs) for increasing n :

The following plots display the probability mass functions (PMFs) for a binomial distribution with $p = \frac{1}{6}$ and increasing values of n . As n increases, the binomial distribution begins to resemble a normal distribution.

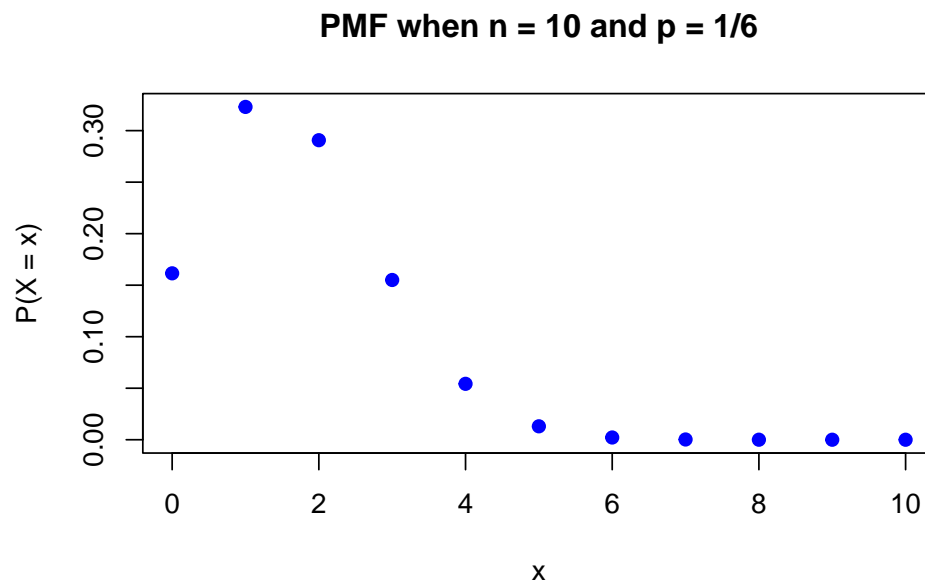


Figure 4.1: PMF of Binomial distribution with $n = 10$ and $p = \frac{1}{6}$.

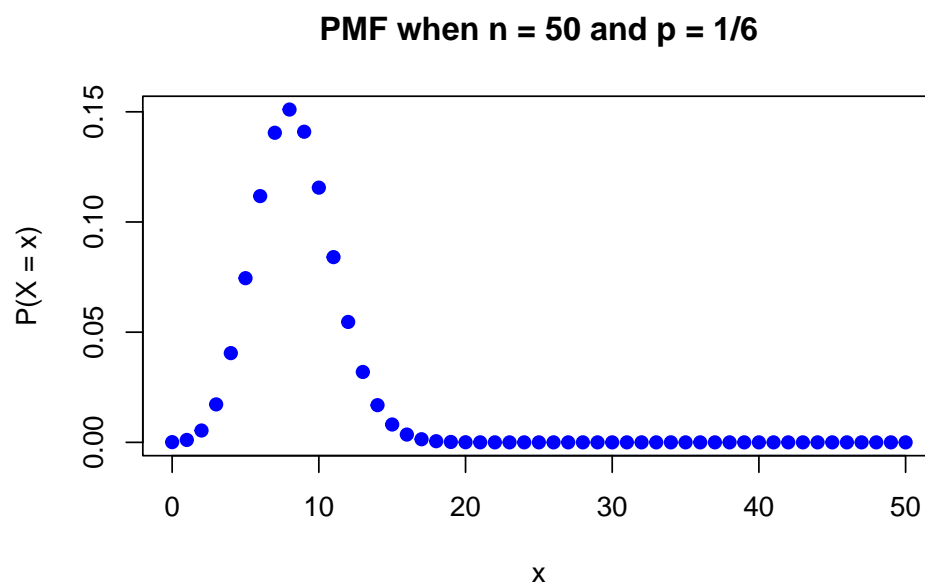


Figure 4.2: PMF of Binomial distribution with $n = 50$ and $p = \frac{1}{6}$.

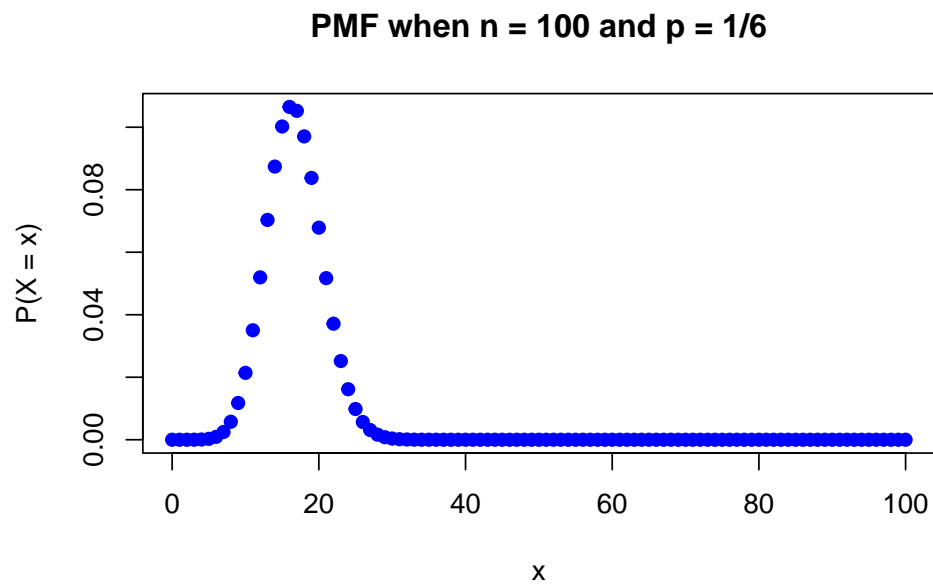


Figure 4.3: PMF of Binomial distribution with $n = 100$ and $p = \frac{1}{6}$.

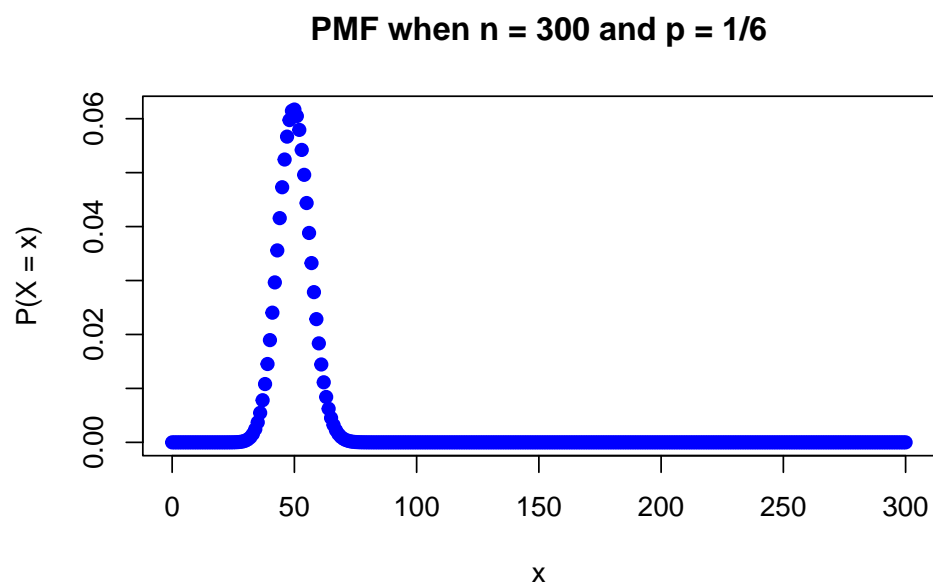


Figure 4.4: PMF of Binomial distribution with $n = 300$ and $p = \frac{1}{6}$.

4.5 Sampling Distribution of a Sample Proportion and the Normal Approximation

When studying categorical data, we are often interested not just in individual outcomes, but in the proportion of successes observed in a sample. Understanding how this proportion behaves across repeated samples is crucial for making inferences about a population. In this section, we explore the sampling distribution of a sample proportion and how it can be approximated by a normal distribution under certain conditions.

Draw a *Simple Random Sample (SRS)* of size n from a large population that contains proportion p of “successes”. Let \hat{p} be the **sample proportion** of successes:

$$\hat{p} = \frac{\text{number of successes in the sample}}{n}$$

Then:

- The **mean** of the sampling distribution of \hat{p} is p .
- The **standard deviation** of the sampling distribution is $\sqrt{\frac{p(1-p)}{n}}$.

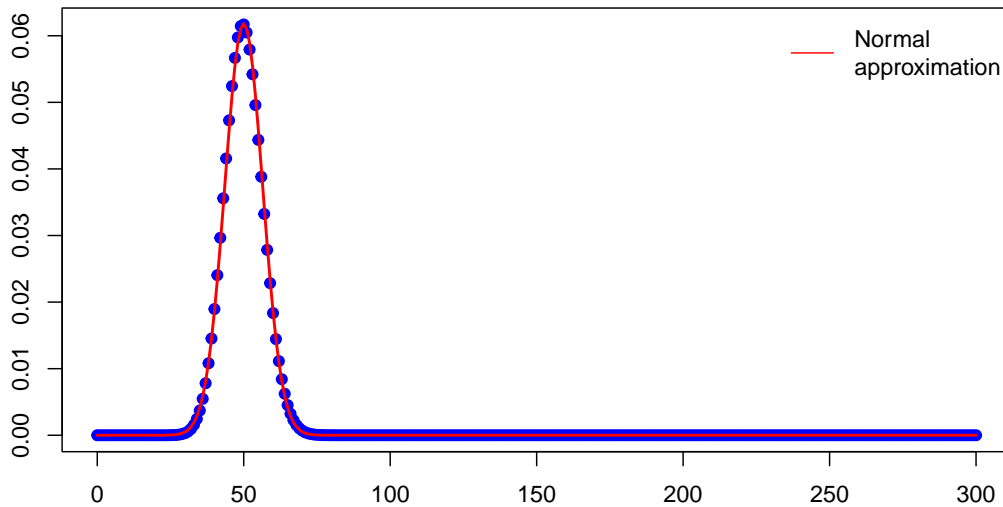


Figure 4.5: Binomial distribution with $n = 300$, $p = \frac{1}{6}$ and its Normal approximation.

According to the Central Limit Theorem (CLT), the sampling distribution of a sample proportion becomes approximately normal as the sample size increases.

That is:

$$\hat{p} \sim \mathcal{N}\left(p, \sqrt{\frac{p(1-p)}{n}}\right)$$

This approximation is most accurate when both $np \geq 10$ and $n(1 - p) \geq 10$. These are called the **success-failure conditions**.

Key Point: When the success-failure conditions are met, the normal approximation to the sampling distribution of \hat{p} can be used for probability calculations.

Conditions for Using the Normal Approximation

Suppose $X \sim \text{Binomial}(n, p)$. Then:

$$\mu = np, \quad \sigma^2 = np(1 - p)$$

Binomial probabilities can be approximated by the normal distribution:

$$X \approx \mathcal{N}(np, np(1 - p))$$

This approximation is *useful for large n* and valid under the following conditions:

Standard Conditions

The binomial setting holds (i.e., independent trials, fixed n , same probability p) and

$$np \geq 10 \quad \text{and} \quad np(1 - p) \geq 10$$

Alternatively, a more conservative criterion for using the normal approximation is:

$$n > 9 \cdot \left(\frac{\max(p, 1 - p)}{\min(p, 1 - p)} \right)$$

These ensure that the binomial distribution is sufficiently symmetric and smooth to approximate with the normal distribution.

We derive the sampling distribution of \hat{p} using properties of the Bernoulli distribution.

Bernoulli Distribution (Binomial with $n = 1$)

$$X_i = \begin{cases} 1 & \text{if the } i\text{-th roll is a six} \\ 0 & \text{otherwise} \end{cases}$$

$$\mu = \mathbb{E}(X_i) = p, \quad \sigma^2 = \text{Var}(X_i) = p(1 - p)$$

Let \hat{p} be our estimate of p . Note that $\hat{p} = \frac{1}{n} \sum_{i=1}^n X_i = \bar{X}$. Let $\hat{p} = \frac{\# \text{ successes } (X)}{\text{sample size } (n)}$. Recall that for $X \sim \text{Binomial}(n, p)$:

$$X \dot{\sim} \mathcal{N}(np, np(1 - p))$$

Let $\hat{p} = \frac{X}{n}$

Mean of \hat{p} :

$$\mathbb{E}(\hat{p}) = \mathbb{E}\left(\frac{X}{n}\right) = \frac{1}{n} \cdot \mathbb{E}(X) = \frac{1}{n} \cdot np = p$$

Variance of \hat{p} :

$$\text{Var}(\hat{p}) = \text{Var}\left(\frac{X}{n}\right) = \frac{1}{n^2} \cdot \text{Var}(X) = \frac{1}{n^2} \cdot np(1-p) = \frac{p(1-p)}{n}$$

By the Central Limit Theorem (CLT), for sufficiently large n :

$$\hat{p} \sim \mathcal{N}\left(p, \frac{p(1-p)}{n}\right)$$

Standardization of \hat{p} :

$$Z = \frac{\hat{p} - p}{\sqrt{\frac{p(1-p)}{n}}}$$

If n is large, then by the Central Limit Theorem:

$$\bar{X} \approx \mathcal{N}\left(\mu, \frac{\sigma}{\sqrt{n}}\right) \Rightarrow \hat{p} \sim \mathcal{N}\left(p, \sqrt{\frac{p(1-p)}{n}}\right)$$

Example 4.1.

[Normal Approximation for Proportions] In the last election, a state representative received 52% of the votes cast. One year after the election, the representative organized a survey that asked a random sample of 300 people whether they would vote for him in the next election. If we assume that his popularity has not changed, what is the probability that more than half the sample would vote for him?

Solution 1 (using Normal Approximation)

We want to determine the probability that the sample proportion is greater than 50%. In other words, we want to find $P(\hat{p} > 0.50)$.

We want to determine the probability that the sample proportion is greater than 50%. In other words, we want to find $P(\hat{p} > 0.50)$.

Thus, we calculate

$$\begin{aligned} P(\hat{p} > 0.50) &= P\left(\frac{\hat{p} - p}{\sqrt{p(1-p)/n}} > \frac{0.50 - 0.52}{0.0288}\right) \\ &= P(Z > -0.69) = 1 - P(Z < -0.69) \quad (\text{Z is symmetric}) \\ &= P(Z > -0.69) = 1 - P(Z > 0.69) \\ &= 1 - 0.2451 = 0.7549. \end{aligned}$$

If we assume that the level of support remains at 52%, the probability that more than half the sample of 300 people would vote for the representative is 0.7549.

R code (Normal Approximation):

```
1 - pnorm(0.50, mean = 0.52, sd = 0.0288)
## [1] 0.7562982
```

Recall that, `pnorm` will give you the area to the left of 0.50, for a Normal distribution with mean 0.52 and standard deviation 0.0288.

Solution 2 (using Binomial)

We want to determine the probability that the sample proportion is greater than 50%. In other words, we want to find $P(\hat{p} > 0.50)$. We know that $n = 300$ and $p = 0.52$.

Thus, we calculate

$$\begin{aligned} P(\hat{p} > 0.50) &= P\left(\frac{\sum_{i=1}^n x_i}{n} > 0.50\right) \\ &= P\left(\sum_{i=1}^{300} x_i > 150\right) \\ &= 1 - P\left(\sum_{i=1}^{300} x_i \leq 150\right) \end{aligned}$$

(it can be shown that $Y = \sum_{i=1}^{300} x_i$ has a Binomial distribution with

$$\begin{aligned} n &= 300 \text{ and } p = 0.52) \\ &= 1 - F_Y(150) \end{aligned}$$

R code (using Binomial distribution):

```
1- pbinom(150, size = 300, prob = 0.52);
## [1] 0.7375949
```

Recall that, `pbinom` will give you the CDF at 150, for a Binomial distribution with $n = 300$ and $p = 0.52$.

Solution 3 (using continuity correction)

We have that $n = 300$ and $p = 0.52$. Thus, we calculate

$$\begin{aligned} P(\hat{p} > 0.50) &= P\left(\frac{\sum_{i=1}^n x_i}{n} > 0.50\right) \\ &= P\left(\sum_{i=1}^{300} x_i > 150\right) \\ &= 1 - P\left(\sum_{i=1}^{300} x_i \leq 150\right) \end{aligned}$$

$$\begin{aligned}
& \text{(it can be shown that } Y = \sum_{i=1}^{300} x_i \text{ has a Binomial distribution with} \\
& n = 300 \text{ and } p = 0.52). \\
& \approx 1 - P\left(\sum_{i=1}^{300} x_i \leq 150.5\right) \quad (\text{continuity correction}) \\
& = 1 - P\left(\frac{\sum_{i=1}^{300} x_i}{n} \leq \frac{150.5}{300}\right) \\
& = 1 - P(\hat{p} \leq 0.5017) \\
& = 1 - P(Z \leq -0.6354) \quad (\text{Why?})
\end{aligned}$$

R code (Normal approximation with continuity correction):

```
1 - pnorm(0.5017, mean = 0.52, sd = 0.0288)
## [1] 0.7374216
```

Recall that, `pnorm` will give you the area to the left of 0.5017, for a Normal distribution with mean 0.52 and standard deviation 0.0288.

4.6 Normal Approximation to Binomial

Let $X = \sum_{i=1}^n Y_i$ where Y_1, Y_2, \dots, Y_n are iid Bernoulli random variables. Note that $X = n\hat{p}$.

1. $n\hat{p}$ is approximately Normally distributed provided that $np \geq 10$ and $n(1-p) \geq 10$.
2. Another criterion is that the Normal approximation is adequate if

$$n > 9 \left(\frac{\text{larger of } p \text{ and } q}{\text{smaller of } p \text{ and } q} \right)$$

3. The expected value: $E(\hat{p}) = np$.
4. The variance: $V(\hat{p}) = np(1-p) = npq$.

4.7 Continuity Correction

The normal distribution is continuous, while the binomial distribution is discrete. When we approximate a binomial probability using the normal distribution, this mismatch can lead to inaccuracy—especially near the boundaries of discrete values. A continuity correction improves the approximation by adjusting for this difference. In this section, we explore how and why this correction is applied.

Continuity Correction Table

Binomial Probability	Continuity Correction	Normal Approximation
$P(X = x)$	$P(x - 0.5 \leq X \leq x + 0.5)$	$P\left(\frac{x - 0.5 - \mu}{\sigma} \leq Z \leq \frac{x + 0.5 - \mu}{\sigma}\right)$
$P(X \leq x)$	$P(X \leq x + 0.5)$	$P\left(Z \leq \frac{x + 0.5 - \mu}{\sigma}\right)$
$P(X < x)$	$P(X \leq x - 0.5)$	$P\left(Z \leq \frac{x - 0.5 - \mu}{\sigma}\right)$
$P(X \geq x)$	$P(X \geq x - 0.5)$	$P\left(Z \geq \frac{x - 0.5 - \mu}{\sigma}\right)$
$P(X > x)$	$P(X \geq x + 0.5)$	$P\left(Z \geq \frac{x + 0.5 - \mu}{\sigma}\right)$
$P(a \leq X \leq b)$	$P(a - 0.5 \leq X \leq b + 0.5)$	$P\left(\frac{a - 0.5 - \mu}{\sigma} \leq Z \leq \frac{b + 0.5 - \mu}{\sigma}\right)$

Suppose that Y has a Binomial distribution with $n = 20$ and $p = 0.4$. We will find the exact probabilities that $Y \leq y$ and compare these to the corresponding values found by using two Normal approximations. One of them, when X is Normally distributed with $\mu_X = np$ and $\sigma_X = \sqrt{np(1-p)}$. The other one, W , a shifted version of X .

For example,

$$P(Y \leq 8) = 0.5955987$$

As previously stated, we can think of Y as having approximately the same distribution as X .

$$P(Y \leq 8) \approx P(X \leq 8) = P\left[\frac{X - np}{\sqrt{np(1-p)}} \leq \frac{8 - 8}{\sqrt{20(0.4)(0.6)}}\right] = P(Z \leq 0) = 0.5$$

$$P(Y \leq 8) \approx P(W \leq 8.5) = P\left[\frac{W - np}{\sqrt{np(1-p)}} \leq \frac{8.5 - 8}{\sqrt{20(0.4)(0.6)}}\right] = P(Z \leq 0.2282) = 0.5902615$$

Example 4.2.

Fifty-one percent of adults in the U. S. whose New Year's resolution was to exercise more achieved their resolution. You randomly select 65 adults in the U. S. whose resolution was to exercise more and ask each if he or she achieved that resolution. What is the probability that exactly forty of them respond yes?

We are given that $p = 0.51$, $n = 65$, and we want to find $P(X = 40)$ where $X \sim \text{Binomial}(n = 65, p = 0.51)$.

Use Normal Approximation We use normal approximation to the binomial. First, compute the mean and standard deviation:

$$\begin{aligned}\mu &= np = 65 \times 0.51 = 33.15 \\ \sigma^2 &= np(1 - p) = 65 \times 0.51 \times 0.49 = 16.485 \\ \sigma &= \sqrt{16.485} \approx 4.06\end{aligned}$$

We apply continuity correction:

$$\begin{aligned}P(X = 40) &= P(39.5 \leq X \leq 40.5) \\ &= P\left(\frac{39.5 - 33.15}{4.06} \leq Z \leq \frac{40.5 - 33.15}{4.06}\right) = P(1.56 \leq Z \leq 1.81)\end{aligned}$$

From the standard normal table:

$$= P(Z \leq 1.81) - P(Z \leq 1.56) = 0.0594 - 0.0352 = 0.0242$$

So the approximate probability is:

$$P(X = 40) \approx 0.0242$$

Chapter 5

Law of Large Numbers

5.1 Convergence in Probability

Definition 5.1 (Convergence in Probability).

The sequence of random variables $X_1, X_2, X_3, \dots, X_n, \dots$ is said to **converge in probability** to the constant c , if for every $\epsilon > 0$,

$$\lim_{n \rightarrow \infty} P(|X_n - c| \leq \epsilon) = 1$$

or equivalently,

$$\lim_{n \rightarrow \infty} P(|X_n - c| > \epsilon) = 0$$

Notation: $X_n \xrightarrow{P} c$

This concept plays a key role in the Law of Large Numbers, where the sample mean of independent and identically distributed random variables converges in probability to the population mean as the sample size grows.

Definition 5.2 (Chebyshev's Inequality).

Let X be a random variable with finite mean μ and variance σ^2 . Then, for any $k > 0$,

$$P(|X - \mu| \geq k) \leq \frac{\sigma^2}{k^2}$$

Using complements:

$$P(|X - \mu| < k) \geq 1 - \frac{\sigma^2}{k^2}$$

5.2 Weak Law of Large Numbers (WLLN)

Definition 5.3 (Weak Law of Large Numbers (WLLN)).

Let X_1, X_2, \dots be a sequence of independent and identically distributed random variables, each having finite mean $E(X_i) = \mu$ and variance $\text{Var}(X_i) = \sigma^2$. Then, for any $\epsilon > 0$,

$$P\left(\left|\frac{X_1 + X_2 + \dots + X_n}{n} - \mu\right| \geq \epsilon\right) \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

Notation: $\bar{X}_n \xrightarrow{P} \mu$

Proof of the Weak Law of Large Numbers (WLLN)

We aim to show that for every $\epsilon > 0$,

$$\lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| > \epsilon) = 0$$

where \bar{X}_n is the sample mean of n independent and identically distributed (i.i.d.) random variables with

$$E(X_i) = \mu, \quad \text{and} \quad \text{Var}(X_i) = \sigma^2.$$

Let

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i.$$

By the Central Limit Theorem (CLT), we know that

$$\bar{X}_n \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right).$$

Now, applying **Chebyshev's Inequality**, which states that for any random variable X with mean μ and variance σ^2 ,

$$P(|X - \mu| > k) \leq \frac{\sigma^2}{k^2} \quad \text{for } k > 0,$$

to \bar{X}_n , we set $k = \epsilon$, and obtain:

$$P(|\bar{X}_n - \mu| > \epsilon) \leq \frac{\text{Var}(\bar{X}_n)}{\epsilon^2} = \frac{\sigma^2/n}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2}.$$

Taking the limit as $n \rightarrow \infty$, we have:

$$\lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| > \epsilon) \leq \lim_{n \rightarrow \infty} \frac{\sigma^2}{n\epsilon^2} = 0.$$

Since probabilities are always non-negative, we conclude:

$$\lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| > \epsilon) = 0.$$

By the definition of convergence in probability,

$$\bar{X}_n \xrightarrow{P} \mu.$$

□

Example 5.1.

[Poisson Convergence via WLLN]

Let X_i , for $i = 1, 2, 3, \dots$, be independent Poisson random variables with rate parameter $\lambda = 3$. Prove that:

$$\bar{X}_n \xrightarrow{P} 3$$

Properties of Poisson Distribution:

$$E(X_i) = \lambda, \quad \text{Var}(X_i) = \lambda$$

In this case, $\lambda = 3$, so:

$$E(X_i) = \text{Var}(X_i) = 3$$

Proof:

We know:

$$E\left(\frac{X_1 + X_2 + \dots + X_n}{n}\right) = 3, \quad \text{and} \quad \text{Var}\left(\frac{X_1 + X_2 + \dots + X_n}{n}\right) = \frac{3}{n}$$

Applying Chebyshev's Inequality:

$$P\left(\left|\frac{X_1 + X_2 + \dots + X_n}{n} - 3\right| \geq \epsilon\right) \leq \frac{3}{n\epsilon^2}$$

Taking the limit as $n \rightarrow \infty$:

$$P\left(\left|\frac{X_1 + X_2 + \dots + X_n}{n} - 3\right| \geq \epsilon\right) \rightarrow 0$$

Conclusion:

$$\bar{X}_n \xrightarrow{P} 3$$

R Simulation Code (Single Sample Path):

```
n = 10
trial = seq(1, n, by = 1)
sample = rbinom(n, 1, 1/2)

plot(trial, cumsum(sample)/trial, type = "l", ylim = c(0,1), col = "blue")
points(trial, cumsum(sample)/trial, col = "red")
abline(h = 0.5, lty = 2, col = "black")
```

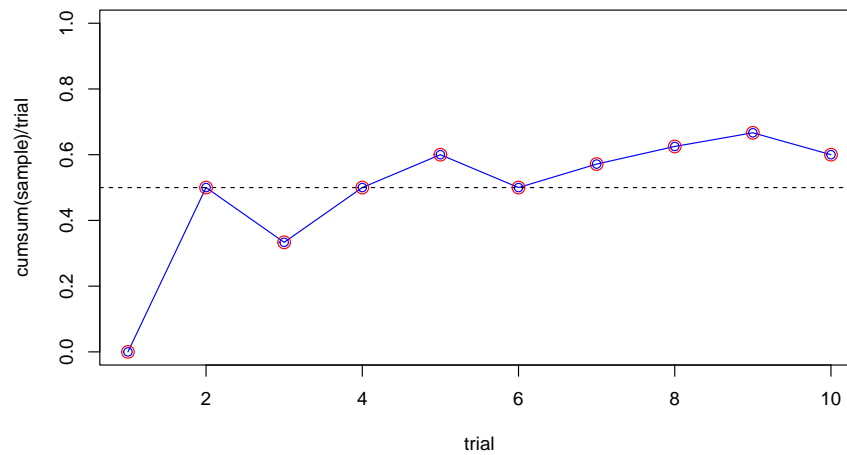



Figure 5.1: Simulation of running sample mean of Bernoulli($p = 0.5$) trials over time.

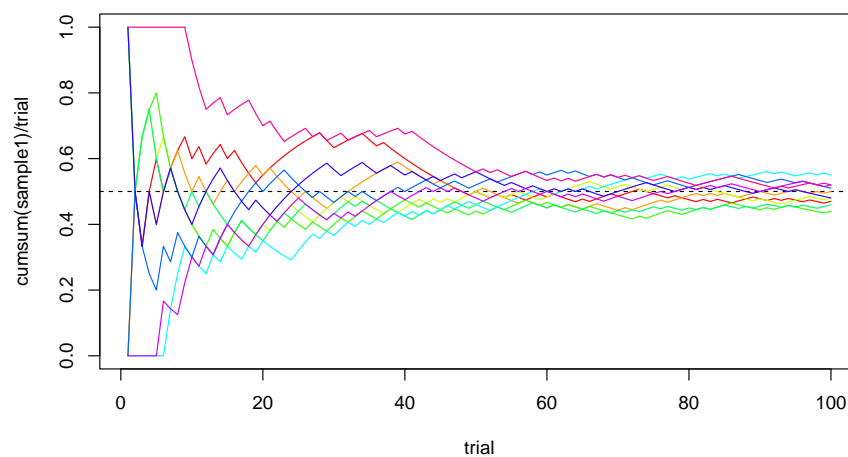


Figure 5.2: Simulation of 10 running sample means of Bernoulli($p = 0.5$) trials converging over 100 trials.

R Simulation Code (Multiple Sample Paths):

```
n = 100
trial = seq(1, 100, by = 1)

sample1 = rbinom(n, 1, 1/2)
sample2 = rbinom(n, 1, 1/2)
sample3 = rbinom(n, 1, 1/2)
sample4 = rbinom(n, 1, 1/2)
sample5 = rbinom(n, 1, 1/2)
sample6 = rbinom(n, 1, 1/2)
```

```
sample7 = rbinom(n, 1, 1/2)
sample8 = rbinom(n, 1, 1/2)

colors = rainbow(8)

plot(trial, cumsum(sample1)/trial, type = "l", col = colors[1], ylim = c(0,1))
lines(trial, cumsum(sample2)/trial, col = colors[2])
lines(trial, cumsum(sample3)/trial, col = colors[3])
lines(trial, cumsum(sample4)/trial, col = colors[4])
lines(trial, cumsum(sample5)/trial, col = colors[5])
lines(trial, cumsum(sample6)/trial, col = colors[6])
lines(trial, cumsum(sample7)/trial, col = colors[7])
lines(trial, cumsum(sample8)/trial, col = colors[8])
abline(h = 0.5, lty = 2, col = "black")
```

Empirical Probability Insight

The Law of Large Numbers gives us empirical probabilities. Consider tossing a fair coin. Define the random variable X as:

$$X = \begin{cases} 1 & \text{heads up} \\ 0 & \text{tails up} \end{cases}$$

Then as we sample more and more values of X , the sample mean \bar{X}_n converges in probability to $P(\text{heads up})$, that is:

$$\bar{X}_n \xrightarrow{P} P(\text{heads up})$$

Chapter 6

One Sample Confidence Intervals on a Mean When the Population Variance is Known

6.1 Introduction

Statistical inference is concerned primarily with understanding the quality of parameter estimates. For example, a classic inferential question is, “How sure are we that the estimated mean, \bar{x} , is near the true population mean, μ ?” While the equations and details change depending on the setting, the foundations for inference are the same throughout all of statistics. We introduce these common themes by discussing inference about the population mean, μ , and set the stage for other parameters and scenarios. Some advanced considerations are discussed. Understanding this chapter will make the rest of this book, and indeed the rest of statistics, seem much more familiar.

Definition 6.1 (Key Terms).

Population: A group of interest (typically large).

Sample: A subset of a population.

Parameter (of population): A numerical characteristic of a population. These are usually *unknown* in real-life settings.

μ : population mean

σ^2 : population variance

σ : population standard deviation

Note: Different from a parameter of a distribution.

Statistic (of sample): A numerical characteristic of a sample, which is calculated and known (i.e., a function of the data).

\bar{x} : sample mean

s^2 : sample variance

s : sample standard deviation

Statistical Inference: Use statistics (known) to make conclusions on parameters (un-

known) and quantify the degree of certainty of statements made.

The sample mean, $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$, is a number we use to estimate the population mean, μ . This is called a **point estimate**.

But, we know it's not equal to μ . Then, we'd rather estimate the population mean using an **interval estimate** that gives a *range of real numbers* that we hope contains the population mean, μ .

Example 6.1.

- \bar{x} is a point estimate of μ
- s^2 is a point estimate of σ^2
- s is a point estimate of σ

(All calculated with data from a sample)

Due to the nature of randomness and calculating based on a subset, statistics are not guaranteed to be exactly equal to parameters.

Therefore, we create intervals around statistics which we believe capture the parameter.

Definition 6.2 (Confidence Interval).

A confidence interval is a plausible range of values that captures a parameter with a quantified degree of confidence.

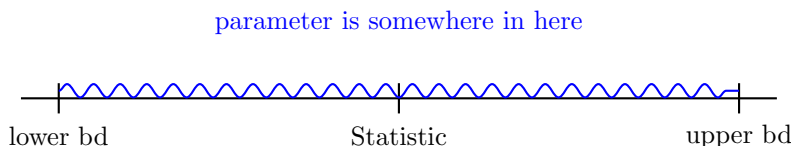


Figure 6.1: Parameter location within the interval.

Suppose we are interested in the average mark for STA258 for the current semester. We

are 100% confident that the average mark is between 0 and 100; however, this is not useful information as we already know that the average mark must lie between 0 and 100. Using the marks of previous years, we can construct a 95% interval for the average mark. If it is determined that the average mark lies within 70% and 80%, this is much more meaningful as we can state with a high degree of certainty that the average mark is going to lie within a substantially narrow range.

In this course, all confidence intervals have the same basic skeleton:

$$\text{estimator} \pm \underbrace{(\text{value from reference distribution}) \times (\text{standard error of estimate})}_{\text{margin of error}}$$

The value from the reference distribution in the skeleton above will be either a value from the standard normal distribution or the Student t -distribution. The margin of error (MOE) can be considered as the distance around our estimator in which the true value of the parameter of interest will be found, with a specified level of confidence.

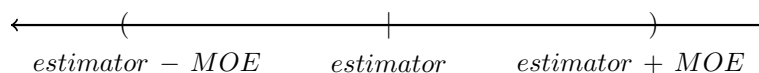


Figure 6.2: Visualization of a confidence interval on the real number line. The margin of error is abbreviated as MOE . The estimator is the centre of the interval. The confidence interval consists of all values between the estimator $-MOE$ and the estimator $+MOE$.

6.2 Interpretation

We use very specific language when we interpret a confidence interval.

Suppose we construct a $C\%$ confidence interval for some parameter such that C is between 0 and 100. In repeated sampling, we are $C\%$ confident that approximately $C\%$ of the intervals will capture the true value of the parameter.

By this we mean that if we constructed several $C\%$ confidence intervals using different samples (with or without replacing the units), then we should expect approximately $C\%$ of these intervals to capture the parameter of interest. For example suppose we construct 1000 95% confidence intervals for the population mean μ . We would expect approximately 95% of these 1000 intervals (i.e. $95\% \times 1000 = 950$) to actually capture μ .

Note 6.1.

A more intuitive but equivalent interpretation is to state that we are $C\%$ confident that our target parameter is inside the interval constructed.

It is incorrect to state that there is a $C\%$ probability that the interval we constructed contains the parameter of interest. We assume that the value of a parameter is fixed. Therefore when we construct a confidence interval, the interval either contains the parameter or it does not.

6.3 Confidence Interval for μ (Known Variance)

When we know the population standard deviation σ , we can construct a confidence interval for μ in the following manner.

Confidence Interval 6.1 (Confidence Interval on μ when σ is Known)

A $(100 - \alpha)\%$ confidence interval on μ when σ is known is

$$\bar{x} \pm z_{\alpha/2} \left(\frac{\sigma}{\sqrt{n}} \right)$$

The $z_{\alpha/2}$ value is obtained from standard normal tables. The standard error is $\frac{\sigma}{\sqrt{n}}$ and the margin of error is $z_{\alpha/2} \left(\frac{\sigma}{\sqrt{n}} \right)$.

Let X_1, X_2, \dots, X_n be iid $N(\mu, \sigma^2)$, where μ is unknown and σ is known. We know that:

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

and

$$P(-1.96 < Z < 1.96) = 0.95$$

Therefore:

$$P\left(-1.96 < \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} < 1.96\right) = 0.95 \Rightarrow P\left(\bar{X} - 1.96 \frac{\sigma}{\sqrt{n}} < \mu < \bar{X} + 1.96 \frac{\sigma}{\sqrt{n}}\right) = 0.95$$

Interpretation of Confidence Interval:

- This is a random interval $\bar{X} \pm 1.96 \frac{\sigma}{\sqrt{n}}$
- The interval is random since \bar{X} is random due to sampling.
- The population mean μ is a fixed, but unknown, number.
- The probability μ is inside the random interval is 0.95 (success rate of the method).
- 95% of all samples give an interval that captures μ , and 5% do not.

Once we observe our sample:

- This is **not** a random interval $\bar{X} \pm 1.96 \frac{\sigma}{\sqrt{n}}$
- The probability μ is inside this interval is either 1 or 0

Confidence Interval Isn't Always Right:

Not all CIs contain the true value of the parameter. This can be illustrated by plotting many intervals simultaneously and observing.

R Output:

```
## Step 1. Generate random samples;
set.seed(2017)
m = 50;          # m = number of samples;
n = 25;          # n = number of obs in sample;
mu.i = 0;        # mu.i = mean of obs;
sigma.i = 5;     # sigma.i = std. dev. of obs;

mu.total = n * mu.i;          # mean of Total;
sigma.total = sqrt(n) * sigma.i; # std. dev. of Total;
```

```
## Step 2. Construct CIs;
xbar = rnorm(m, mu.total, sigma.total) / n;
SE = sigma.i / sqrt(n);

alpha = 0.10;
z.star = qnorm(1 - alpha / 2);
```

```
## Step 3. Graph CIs;
matplot(rbind(xbar - z.star * SE, xbar + z.star * SE),
        rbind(1:m, 1:m),
        type = "l", lty = 1,
        xlab = " ", lab = " ");
abline(v = 0, lty = 2);
```

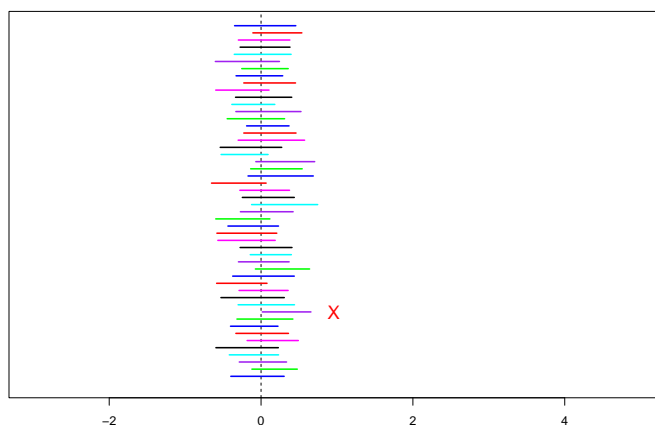


Figure 6.3: Simulated 95% confidence intervals for the population mean. Red “X” marks indicate intervals that do not contain the true mean ($\mu = 0$).

Confidence Interval for the Mean of a Normal Population

Draw an SRS (Simple Random Sample) of size n from a Normal population having unknown mean μ and **known** standard deviation σ . A level C confidence interval for μ is:

$$\bar{x} \pm z_* \cdot \frac{\sigma}{\sqrt{n}}$$

The critical value z_* is illustrated in a Figure below and depends on C .

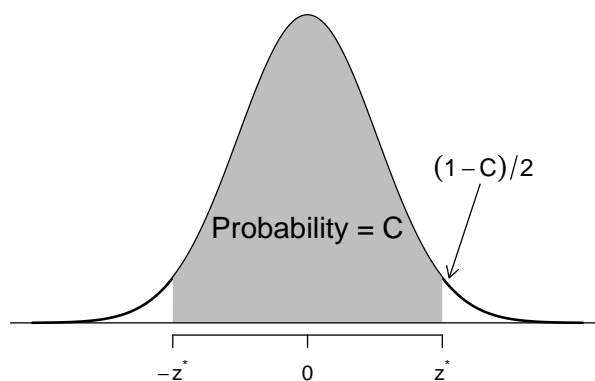


Figure 6.4: The central area under the standard normal curve with confidence level C .

Large Sample CI for μ (Normal data)

When we have a large sample from a Normal distribution, the confidence interval for the population mean μ can be approximated by the formula:

$$\bar{x} \pm z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

This formula is valid under the following assumptions:

- n large
- random sample from a Normal distribution
- independent observations

Some definitions:

- $1 - \alpha$ is the confidence coefficient
- $100(1 - \alpha)\%$ is the confidence level

One Sample CI on the Population Mean μ

To construct a confidence interval for the population mean, we rely on several important assumptions:

- When population standard deviation σ is **known**
- Formula: $\bar{x} \pm z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$
- Margin of error comes from standard normal and standard error

How to find $z_{\alpha/2}$?

Example: Find $z_{\alpha/2}$ for a 95% CI on μ :

$$1 - \alpha = 0.95, \quad \alpha = 0.05, \quad \alpha/2 = 0.025$$

$$z_{\alpha/2} = 1.96 \quad (\text{from table or R: } \text{qnorm}(0.975))$$

Table of Common z -values

Confidence coefficient	Confidence level	z
0.90	90%	1.645
0.95	95%	1.96
0.99	99%	2.576

Example 6.2.

Playbill magazine reported that the mean annual household income of its readers is \$119,155. Assume this estimate is based on a sample of 80 households, and that the population standard deviation is known to be $\sigma = 30,000$.

- $\bar{x} = 119,155$
- $n = 80$
- $\sigma = 30,000$

Tasks:

- Develop a 90% confidence interval estimate of the population mean.
- Develop a 95% confidence interval estimate of the population mean.
- Develop a 99% confidence interval estimate of the population mean.

90% CI Calculation

$$\begin{aligned}\bar{x} \pm z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} &= 119,155 \pm 1.645 \cdot \frac{30,000}{\sqrt{80}} \\ &= 119,155 \pm 5,500.73 \\ &= (113,654.27, 124,655.73)\end{aligned}$$

95% CI Calculation

$$\begin{aligned}\bar{x} \pm z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} &= 119,155 \pm 1.96 \cdot \frac{30,000}{\sqrt{80}} \\ &= 119,155 \pm 6,574.04 \\ &= (112,580.96, 125,729.04)\end{aligned}$$

99% CI Calculation

$$\begin{aligned}\bar{x} \pm z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} &= 119,155 \pm 2.576 \cdot \frac{30,000}{\sqrt{80}} \\ &= 119,155 \pm 8,620.04 \\ &= (110,534.96, 127,775.04)\end{aligned}$$

Interpretation

We are 99% confident the mean household income of magazine readers is between \$110,534.96 and \$127,775.04.

Example 6.3.

Scenario:

The number of cars sold annually by used car salespeople is known to be **normally distributed**, with a population standard deviation of $\sigma = 15$. A random sample of $n = 15$

salespeople was taken, and the number of cars each sold is recorded below. Construct a **95% confidence interval** for the population mean number of cars sold, and provide an interpretation.

Raw data:

79	43	58	66	101
63	79	33	58	71
60	101	74	55	88

The sample mean is:

$$\bar{x} = \frac{79 + 43 + \cdots + 55 + 88}{15} = 68.6$$

R function:

```
simple.z.test = function(x, sigma, conf.level = 0.95) {
  n = length(x);
  xbar = mean(x);
  alpha = 1 - conf.level;
  zstar = qnorm(1 - alpha/2);
  SE = sigma / sqrt(n);
  xbar + c(-zstar * SE, zstar * SE);
}
```

R output:

```
# Step 1. Entering data;
cars = c(79, 43, 58, 66, 101, 63, 79,
         33, 58, 71, 60, 101, 74, 55, 88)

# Step 2. Finding CI;
simple.z.test(cars, 15)

## [1] 61.00909 76.19091
```

Interpretation: We estimate that the mean number of cars sold annually by all used car salespeople lies between 61 and 76, approximately. This type of estimate is correct 95% of the time.

Cases Where Valid

- Large samples where population is **normal**.
- Large samples where population is **not normal** (By CLT).
- Small samples where population is **normal**.

Note: A sample is considered large if $n \geq 30$.

Example 6.4.

Suppose a student measuring the boiling temperature of a certain liquid observes the readings (in degrees Celsius) 102.5, 101.7, 103.1, 100.9, 100.5, and 102.2 on 6 different samples of the liquid. He calculates the sample mean to be 101.82. If he knows that the distribution of boiling points is Normal, with standard deviation 1.2 degrees, what is the confidence interval for the population mean at a 95% confidence level?

A **confidence interval** uses sample data to estimate an unknown population parameter with an indication of how accurate the estimate is and of how confident we are that the result is correct.

The **interval** often has the form
estimate \pm margin of error

The **confidence level** is the success rate of the method that produces the interval. A level C **confidence interval for the mean** μ of a Normal population with **known** standard deviation σ , based on an SRS of size n , is given by

$$\bar{x} \pm z^* \frac{\sigma}{\sqrt{n}}$$

The **critical value** z^* is chosen so that the standard Normal curve has area C between $-z^*$ and z^* .

Other things being equal, the **margin of error** of a confidence interval gets smaller as

- the confidence level C decreases,
- the population standard deviation σ decreases, and
- the sample size n increases.

6.4 APPENDIX

Interval estimators are commonly called **confidence intervals**. The upper and lower endpoints of a confidence interval are called the **upper** and **lower confidence limits**, respectively. The probability that a (random) confidence interval will enclose θ (a fixed quantity) is called the **confidence coefficient**.

Suppose that $\hat{\theta}_L$ and $\hat{\theta}_U$ are the (random) lower and upper confidence limits, respectively, for a parameter θ . Then, if

$$P(\hat{\theta}_L \leq \theta \leq \hat{\theta}_U) = 1 - \alpha,$$

the probability $(1 - \alpha)$ is the **confidence coefficient**.

Pivotal quantities

One very useful method for finding confidence intervals is called the **pivotal method**. This method depends on finding a pivotal quantity that possesses two characteristics:

- It is a function of the sample measurements and the unknown parameter θ , where θ is the **only** unknown quantity.
- Its probability distribution does not depend on the parameter θ .

Chapter 7

One-Sample Confidence Intervals on a Mean When the Population Variance is Unknown

7.1 CIs for μ

Definition 7.1 (Large-Sample Confidence Interval for μ).

Let μ be the population mean. When the population standard deviation σ is known and the sample size is large, a confidence interval for μ is given by:

$$\bar{Y} \pm z_{\alpha/2} \left(\frac{\sigma}{\sqrt{n}} \right)$$

This interval is valid under the following conditions:

- *The sample is random.*
 - *The observations are independent and identically distributed (i.i.d).*
 - *The sample size n is large enough for the Central Limit Theorem (CLT) to apply.*
-

Definition 7.2 (Small-Sample Confidence Interval for μ).

Let μ be the population mean. When the population standard deviation is unknown and the sample size is small, a confidence interval for μ is given by:

$$\bar{Y} \pm t_{\alpha/2} \left(\frac{S}{\sqrt{n}} \right), \quad \nu = n - 1$$

This interval is valid under the following conditions:

- The observations are independent and identically distributed (*i.i.d.*).
- The sample is random.
- The population **must** follow a Normal distribution (*CLT does not apply*).

Independence Assumption

The data values should be independent. There's really no way to check independence of the data by looking at the sample, but we should think about whether the assumption is reasonable.

Randomization Condition

The data arise from a random sample or suitably randomized experiment. Randomly sampled data — especially data from a Simple Random Sample — are ideal.

Normal Population Assumption

- For very small samples ($n < 15$ or so), the data should follow a Normal model pretty closely. If you do find outliers or strong skewness, don't use this method.
- For moderate samples (n between 15 and 40 or so), the *t*-method will work well as long as the data is unimodal and reasonably symmetric. Make a histogram, boxplot, or Q-Q plot to check.
- When the sample size is larger than 40 or 50, the *t*-method is safe to use unless the data are extremely skewed. Make a histogram, boxplot, or Q-Q plot to check.

Standard Error

When the standard deviation of a statistic is estimated from data, the result is called the *standard error* of the statistic. The standard error of the sample mean \bar{x} is

$$\frac{s}{\sqrt{n}}.$$

The *t* Distributions

- The density curves of the *t* distributions are similar in shape to the Standard Normal curve. They are symmetric about 0, single-peaked, and bell-shaped.
- The spread of the *t* distributions is a bit greater than that of the Standard Normal distribution. The *t* distributions have more probability in the tails and less in the center than the Standard Normal. This is because substituting the estimate s for the fixed parameter σ introduces more variation into the statistic.
- As the degrees of freedom increase, the *t* density curve approaches the $N(0, 1)$ curve more closely. This happens because s estimates σ more accurately as the

sample size increases. So using s in place of σ causes little extra variation when the sample is large.

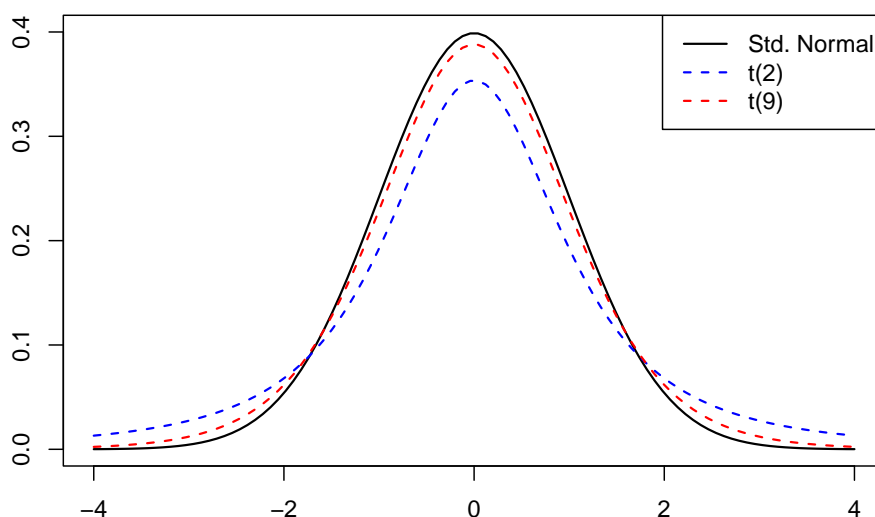


Figure 7.1: Comparison of the standard normal distribution and t-distributions with 2 and 9 degrees of freedom.

Example 7.1.

[Ancient Air]

The composition of the Earth's atmosphere may have changed over time. To study the nature of the atmosphere long ago, scientists examined the gas in air bubbles trapped in ancient amber. Amber is fossilized tree resin that preserved the atmospheric gases at the time it was formed.

Measurements on amber specimens from the late Cretaceous era (75 to 95 million years ago) give the following percent values of nitrogen:

63.4, 65.0, 64.4, 63.3, 54.8, 64.5, 60.8, 49.1, 51.0

Assume these observations are a simple random sample (SRS) from the population of all ancient air bubbles. Construct a **90% confidence interval** to estimate the mean percent of nitrogen in ancient air. (Today's atmosphere contains about 78.1% nitrogen.)

Solution:

Let μ represent the true mean percent of nitrogen in ancient air. We compute a 90% confidence interval for μ using the sample data.

Given:

$$\bar{x} = 59.5888, \quad s = 6.2552, \quad n = 9, \quad t^* = 1.860 \quad (\text{df} = 8)$$

$$59.5888 \pm 1.860 \left(\frac{6.2552}{\sqrt{9}} \right) = 59.5888 \pm 3.8782$$

55.7106 to 63.4670

R code:

```
# Step 1: Entering the data
nitrogen <- c(63.4, 65.0, 64.4, 63.3, 54.8, 64.5, 60.8, 49.1, 51.0)

# Step 2: Constructing the 90% confidence interval
t.test(nitrogen, conf.level = 0.90)
```

R output:

```
One Sample t-test

data:  nitrogen
t = 28.578, df = 8, p-value = 2.43e-09
alternative hypothesis: true mean is not equal to 0
90 percent confidence interval:
 55.71155 63.46622
sample estimates:
mean of x
 59.58889
```

Example 7.2.

[Digital Camera Storage]

Most owners of digital cameras store their pictures on the camera. Some will eventually download these to a computer or print them using their own printers or a commercial printer. A film-processing company wanted to know how many pictures were stored on cameras. A random sample of 10 digital camera owners produced the following data:

25, 6, 22, 26, 31, 18, 13, 20, 14, 2

Estimate with **95% confidence** the mean number of pictures stored on digital cameras.

Solution:

We are given raw data with $n = 10$ and no information about the population standard deviation, so we construct a confidence interval for the population mean using the t-distribution.

Step 1: Compute sample statistics

- Sample mean: $\bar{x} = \frac{177}{10} = 17.7$

- Sample variance (method 1 – direct):

$$s^2 = \frac{\sum (x_i - \bar{x})^2}{n - 1} = \frac{742}{9} = 82.4556$$

- Sample standard deviation:

$$s = \sqrt{82.4556} = 9.081$$

Step 2: Find the critical value

For a 95% confidence interval with $n = 10$, degrees of freedom = 9. From the t-distribution table:

$$t_{(9,0.025)} = 2.262$$

Step 3: Construct the confidence interval

$$\bar{x} \pm t^* \cdot \frac{s}{\sqrt{n}} = 17.7 \pm 2.262 \cdot \frac{9.081}{\sqrt{10}} = 17.7 \pm 6.495$$

11.205 to 24.195

Interpretation:

We are 95% confident that the mean number of images stored on digital cameras is between 11.205 and 24.195.

R code:

```
# Step 1: Entering data
dataset <- c(25, 6, 22, 26, 31, 18, 13, 20, 14, 2)

# Step 2: Finding 95% confidence interval
t.test(dataset, conf.level = 0.95)
```

R output:

One Sample t-test

```

data:  dataset
t = 6.164, df = 9, p-value = 0.0001659
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 11.2042 24.1958
sample estimates:
mean of x
 17.7

```

Example 7.3.

[Electric Insulators]

A manufacturing company produces electric insulators. If the insulators break when in use, a short circuit is likely. To test the strength of the insulators, destructive testing is performed to determine how much force (in pounds) is required to break them.

The following dataset consists of force values (in pounds) recorded for a random sample of 30 insulators:

```

1870, 1728, 1656, 1610, 1634, 1784, 1522, 1696, 1592, 1662, 1866, 1764,
1734, 1662, 1734, 1774, 1550, 1756, 1762, 1866, 1820, 1744, 1788, 1688,
1810, 1752, 1680, 1810, 1652, 1736

```

Construct a **95% confidence interval** for the population mean force required to break the insulators.

Solution:

We want a confidence interval for the population mean μ , where μ = mean force required to break electric insulators. The population standard deviation is unknown, so we use a *one-sample* t-interval.

R code:

```

# Step 1. Entering data;
dataset <- c(1870, 1728, 1656, 1610, 1634, 1784, 1522, 1696, 1592, 1662,
            1866, 1764, 1734, 1662, 1734, 1774, 1550, 1756, 1762, 1866,
            1820, 1744, 1788, 1688, 1810, 1752, 1680, 1810, 1652, 1736)

# Step 2. Finding CI;
t.test(dataset, conf.level = 0.95)

```

R output:

One Sample t-test

```
data: dataset
t = 105.41, df = 29, p-value < 2.2e-16
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 1689.961 1756.839
sample estimates:
mean of x
 1723.4
```

Interpretation:

We are 95% confident that the average force required to break an electric insulator is between **1689.961 pounds** and **1756.839 pounds**.

Example 7.4.

[Assembly Time Estimation]

The operations manager of a production plant would like to estimate the mean amount of time a worker takes to assemble a new electronic component. After observing 120 workers assembling similar devices, she noticed that their average time was 16.2 minutes (with a standard deviation of 3.6 minutes).

Construct a **92% confidence interval** for the mean assembly time. State all necessary assumptions.

Example 7.5.

[Tax Collected from Audited Returns]

In 2010, 142,823,000 tax returns were filed in the United States. The Internal Revenue Service (IRS) examined 1.107%, or 1,581,000, of them to determine if they were correctly done. To evaluate auditor performance, a random sample of these returns was drawn and the additional tax was recorded.

Estimate with 95% confidence the mean additional income tax collected from the 1,581,000 files audited.

Solution:

We use a one-sample confidence interval for the population mean additional tax collected.

Step 1: Import the data from taxes.txt

```
# url of taxes;
url <- "https://mcs.utm.utoronto.ca/~nosedal/data/taxes.txt"
taxes_data <- read.table(url, header = TRUE)

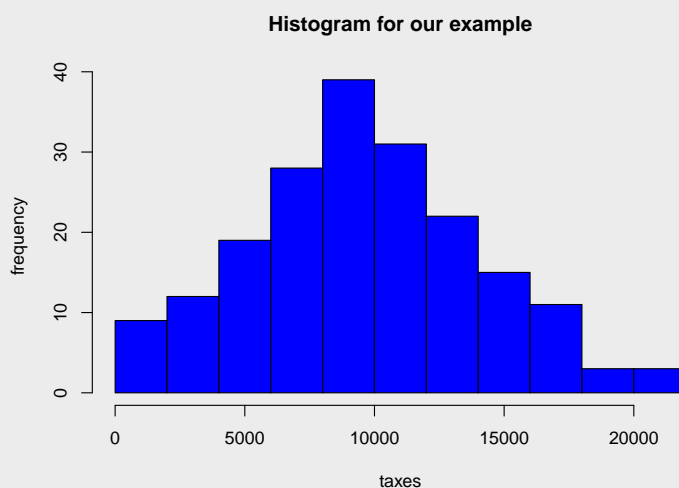
# inspect structure
names(taxes_data)
head(taxes_data)

# isolate the tax values
taxes <- taxes_data$Taxes
```

Step 2: Plot the data

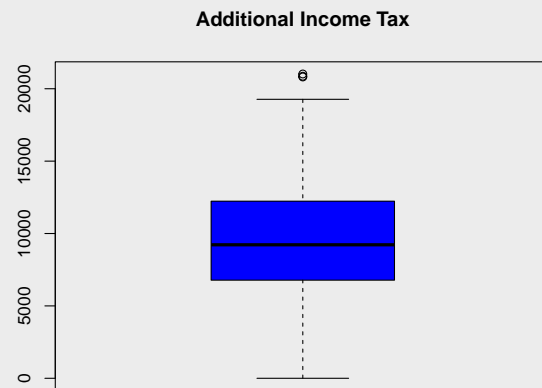
Histogram:

```
hist(taxes,
     main = "Histogram for our example",
     xlab = "taxes", ylab = "frequency",
     col = "blue")
```



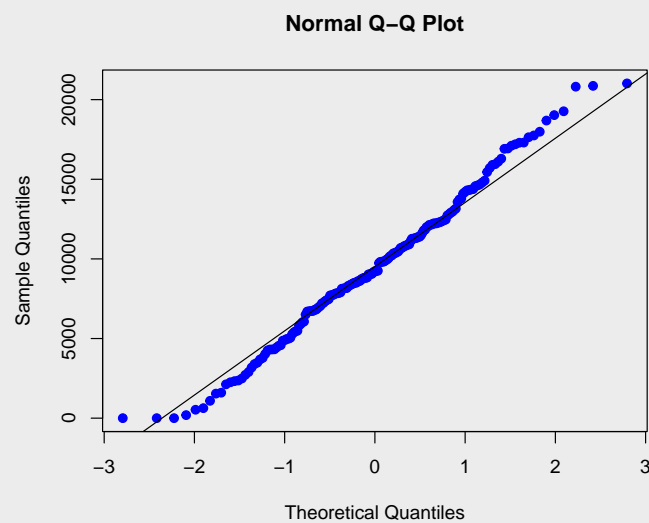
Boxplot:

```
boxplot(taxes,
       main = "Additional Income Tax",
       col = "blue")
```



Q-Q Plot:

```
qqnorm(taxes, col = "blue", pch = 19)  
qqline(taxes)
```



Step 3: Construct 95% CI

```
t.test(taxes, conf.level = 0.95)
```

Interpretation: Based on the t-test, we are 95% confident that the average additional tax collected lies within the interval calculated from the sample.

Assumptions:

- The sample is a random sample from the population of interest.
- Observations are independent.
- The population is approximately Normal, or the sample size is large enough (justified by the histogram, boxplot, and Q-Q plot).

```
##
## One Sample t-test
##
## data: taxes
## t = 29.345, df = 191, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
## 8886.932 10167.721
## sample estimates:
## mean of x
## 9527.326
```

Interpretation:

We estimate that the mean additional tax collected lies between \$8,887 and \$10,168 (with 95% confidence).

A few final comments

When we introduced the Student t -distribution, we pointed out that the t -statistic is Student t -distributed if the population from which we've sampled is Normal. However, statisticians have shown that the mathematical process that derived the Student t -distribution is **robust**, which means that if the population is non-Normal, the results of the confidence interval estimate are still valid provided that the population is **not extremely non-Normal**. Our histogram, boxplot, and Q-Q plot suggest that our variable of interest is not extremely non-Normal, and in fact, may be Normal.

Chapter 8

One Sample Confidence Intervals On a Proportion

Perviously, we have introduced two types of confidence interval based on known and unknown variance. Moreover, confidence intervals are also applied to an unknown population proportion. For example, suppose we are interested the proportion of total number of left-handed students among all students who are currently studying at University of Toronto Mississauga. The question is: how do we know such the parameter which estimates the proportion of left-handed students at UTM? While, it is impossible to proceed it directly by counting both the total number of students and all left-handed students at UTM, due to the complexity and the total workload of that task. Then, we have to work with confidence intervals.

Firstly, we take a random sample of students at UTM, then we calculate how many students are left-handed by dividing total number of left-handed students in that sample with total number of students in it, and denote the proportion as \hat{p} . Next we begin our confidence interval calculation to get a range of number with a certain level of confidence.

Now let's begin with the proper definition of confidence interval on proportion.

Definition 8.1 (One Sample Confidence Intervals On a Proportion).

We select a random sample of size n from a population with **unknown** proportion p of success. An approximate confidence interval for p is:

$$p = \hat{p} \pm z_{\frac{\alpha}{2}} \cdot \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}, \text{ where } \hat{p} = \frac{\text{number of observations satisfying the criteria}}{n}.$$

In addition, n is the sample size.

To apply this confidence interval, there are 3 conditions that we need to guarantee:

- 1. Random sample;
- 2. Independent and identically distributed Bernoulli trials;
- 3. We have a large chosen sample size ($n\hat{p} \geq 10$ and $n(1 - \hat{p}) \geq 10$).

A good way to understand confidence interval is visualization. Now, suppose we have a valid estimation \hat{p} . After the entire procedure of confidence interval, our population proportion (p) should be as the following number line shows:



Remember that your final answer of the range of p must be between 0 and 1, since we are working with proportion.

Summary about One Sample Confidence Intervals

We have introduced one sample confidence interval under three different cases: given population variance, unknown population variance and unknown population proportion. All the material of one sample confidence interval comes from chapter 6, 7, 8, which seems like you to remember a lot. However, the reason why we give this summary is to help you to remember the basic skeleton of one sample confidence interval. Let's revisit the three distinct types of confidence interval:

- Known variance: $\hat{x} \pm z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$ (Chapter 7).
- Unknown variance: $\bar{x} \pm t_{\alpha/2} \cdot \frac{s}{\sqrt{n}}$
- Proportion: $\hat{p} \pm z_{\alpha/2} \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$

The question is: what is the similarity between the three distinct types of confidence interval? You may have already noticed that the confidence intervals above are all follow such a skeleton that \bar{x} plus or minus its margin of error (different between each type of C.I.).

If we keep questioning ourselves that how the margin of error comes from, you will catch the pattern. The margin of error contains reference distribution and the standard deviation of \bar{x} under its reference distribution. Let's analyze each type of confidence interval to prove my statement is true:

The first type (given population variance) confidence interval is quite easy to recognize. Recall chapter 3: The Central Limit Theorem, we state that $\bar{x} \sim N(\mu, \frac{\sigma^2}{n})$, which is how reference distribution comes from with given population variance. To get the standard deviation of \bar{x} , we simply take the square root of the variance, then $s_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$. Finally, we multiply reference distribution at the point $\frac{\alpha}{2}$ with the standard deviation of \bar{x} under normal distribution to get the margin of error.

The second type (unknown population variance) confidence interval is similar to the first type, but the reference distribution is t-distribution instead of normal distribution. In chapter 7, we introduced the calculation of sample variance (s^2) to estimate population variance (σ^2), and s^2 is an unbiased estimator of σ^2 (the proof of this statement is in STA260, in

this course we can assume it freely). In chapter 2, we defined that $T = \frac{\bar{x} - \mu}{(\frac{s}{\sqrt{n}})} \sim t_{n-1}$, then the term $\frac{s}{\sqrt{n}}$ (verify this by yourself as an extra exercise) is the standard deviation of \bar{x} under t-distribution with $n - 1$ degrees of freedom. Finally, we multiply multiply reference distribution at the point $\frac{\alpha}{2}$ with the standard deviation of \bar{x} under t-distribution to get the margin of error.

The third type (estimate population proportion) confidence interval is slightly harder to identify. Recall chapter 4 that we can approximate binomial distribution by normal distribution. Suppose that a random variable $X \sim \text{Binomial}(n, p)$, then the random variable $X \sim N(np, np(1-p))$. From chapter 4, we know that $\hat{p} \sim N(\mu_{\hat{p}} = p, \sigma_{\hat{p}}^2 = \frac{p(1-p)}{n})$. Trivially, the standard deviation of \hat{p} is $\sqrt{\frac{p(1-p)}{n}}$, since we don't know the value p and use \hat{p} to estimate that. Then, standard deviation of \hat{p} is $\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$. Finally, by multiplying the reference distribution and standard deviation, we get the margin of error of the confidence interval.

Conclusion About One Sample Confidence Intervals

If you follow the skeleton below, one sample confidence interval will become easier:

- 1. Identify what type of one sample confidence interval to use from given information;
- 2. Construct your confidence interval that fits the circumstance which you are facing, it either going to be $\bar{x} \pm M.E.(\bar{x})$ or $\hat{p} \pm M.E.(\hat{p})$;
- 3. Check the validity of your final answer. For example, the range of p must between 0 and 1.
- 4. Clearly state your final conclusion: we have a certain percentage of confidence to guarantee that the value of the chosen sample is between its lower bound and upper bound.

Chapter 9

Sample Size Selection using Confidence Intervals

In this section we will examine techniques to calculate the minimum sample size required to obtain a confidence interval to be within a specified margin of error. Recall the one-sample confidence intervals we have constructed for a population mean μ are

$$\bar{x} \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \quad (\text{When } \sigma \text{ is known})$$

$$\bar{x} \pm t_{\alpha/2, n-1} \frac{s}{\sqrt{n}} \quad (\text{When } \sigma \text{ is not known})$$

and the one-sample confidence interval for a proportion is

$$\hat{p} \pm z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}$$

9.0.1 Empirical Rule

For any sample from a population that is close to Normally distributed:

- about 68% of all observations will lie in the interval $\mu \pm \sigma$
- about 95% of all observations will lie in the interval $\mu \pm 2\sigma$
- about 99.7% of all observations will lie in the interval $\mu \pm 3\sigma$

This suggests that for a sample drawn from a population that is approximately to Normally distributed, we can approximate the standard deviation using

$$\hat{\sigma} \approx \frac{\text{Sample Range}}{4}.$$

9.1 Calculating Sample Size for a Confidence Interval on a Mean

We will examine how to calculate the minimum sample size n for a confidence interval on a mean for a margin of error E at confidence level $1 - \alpha$.

When σ is Known

For a desired margin of error E and confidence level $1 - \alpha$:

$$E = z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$$

We can rearrange E to calculate the sample size using

$$n = \left(\frac{z_{\alpha/2} \sigma}{E} \right)^2$$

where n is always *rounded up* to the next integer.

Example 9.1.

A manufacturer of pharmaceutical products analyzes a specimen from each batch of a product to verify the concentration of the active ingredient. The chemical analysis is not perfectly precise. Repeated measurements on the same specimen give slightly different results. Suppose we know that the results of repeated measurements follow a Normal distribution with mean μ equal to the true concentration and standard deviation $\sigma = 0.0068$ grams per liter. (That the mean of the population of all measurements is the true concentration says that the measurements process has no bias. The standard deviation describes the precision of the measurement.) The laboratory analyzes each specimen n times and reports the mean result.

Management asks the laboratory to produce results accurate to within ± 0.005 with 95% confidence. How many measurements must be averaged to comply with this request?

$$n = \left(\frac{z_{0.025} \sigma}{E} \right)^2 = \left(\frac{1.96 \times 0.0068}{0.005} \right)^2 \approx 7.1$$

Since the sample size should be a whole number, we round our result up to $n = 8$ measurements.

In Example 9.1, we note that 7 measurements will give a slightly larger margin of error than desired, and 8 measurements a slightly smaller margin of error, the lab must take 8 measurements on each specimen to meet management's demand. Always round up to the next higher whole number when finding n .

Example 9.2.

Planning value $\sigma = 22.50$, desired margin $E = 2$.

1. 90% confidence, $z_{0.05} = 1.65$:

$$n = \left(\frac{1.65 \times 22.50}{2} \right)^2 \approx 344.6 \implies n = 345.$$

2. 95% confidence, $z_{0.025} = 1.96$:

$$n = \left(\frac{1.96 \times 22.50}{2} \right)^2 \approx 486.2 \implies n = 487.$$

3. 99% confidence, $z_{0.005} = 2.58$:

$$n = \left(\frac{2.58 \times 22.50}{2} \right)^2 \approx 842.5 \implies n = 843.$$

9.2 Calculating Sample Size for a Confidence Interval on a Proportion

We will examine how to calculate the minimum sample size n for a confidence interval on a proportion for a margin of error E at confidence level $1 - \alpha$. For sample of size n with unknown population proportion p :

$$\hat{p} \pm z^* \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}.$$

where the margin of error is

$$E = z^* \sqrt{\frac{p^*(1 - p^*)}{n}}$$

we can rearrange E to calculate the sample size using

$$n = \left(\frac{z^*}{E} \right)^2 p^*(1 - p^*),$$

where p^* can be a *planning value*, which is value obtained from prior information such as a pilot study. If we do not have any prior information on p^* , we can use $p^* = 0.5$ which is the conservative value that maximizes the product $p^*(1 - p^*)$.

Example 9.3.

Aisha Shariff and Yvette Ye are the candidates for mayor in a large city. You are planning a sample survey to determine what percent of the voters plan to vote for Shariff. This is a population proportion p . You will contact an SRS of registered voters in the city. You want to estimate p with 95% confidence and a margin of error no greater than 3%, or 0.03. How large a sample do you need?

For a 95% CI on p : $z_{0.025} = 1.96$. Margin of error = 0.03. Since no information on a good estimate of p , use $p^* = 0.5$.

$$1.96 \sqrt{\frac{(0.5)(1 - 0.5)}{n}} \leq 0.03 \implies n = \left(\frac{1.96}{0.03} \right)^2 (0.5)(0.5) \approx 1067.1.$$

Round up:

$$n = 1068.$$

Example 9.4.

The percentage of people not covered by health care insurance in 2007 in the USA was 15.6%. A congressional committee has been charged with conducting a sample survey to obtain more current information.

1. What sample size would you recommend if the committee's goal is to estimate the current proportion of individuals without health care insurance with a margin of error of 0.03? Use a 95% confidence level.
2. Repeat part (a) using a 99% confidence level.

$$(a) \ n = \left(\frac{z^*}{E} \right)^2 p^*(1 - p^*), \quad z^* = 1.96, \ E = 0.03, \ p^* = 0.156.$$

$$n = \left(\frac{1.96}{0.03} \right)^2 (0.156)(1 - 0.156) \approx 563.$$

$$(b) \ n = \left(\frac{2.58}{0.03} \right)^2 (0.156)(1 - 0.156) \approx 974.$$

Example 9.5.

A consumer advocacy group would like to find the proportion of consumers who bought the newest generation of iPhone and were happy with their purchase. How large a sample should they take to estimate p with 2% margin of error and 90% confidence?

Parameters:

$$E = 0.02, \quad (\text{margin of error})$$

$$\text{Confidence level} = 0.90 \implies \alpha = 0.10, \ \alpha/2 = 0.05,$$

$$z^* = z_{0.05} = 1.645,$$

$$p^* = 0.5, \quad p^*(1 - p^*) = 0.5 \times 0.5 = 0.25.$$

Sample-Size Formula:

$$n = \left(\frac{z^*}{E} \right)^2 p^*(1 - p^*).$$

Substituting $z^* = 1.645$, $E = 0.02$, and $p^*(1 - p^*) = 0.25$:

$$\begin{aligned} n &= \left(\frac{1.645}{0.02} \right)^2 \times 0.25 = (82.25)^2 \times 0.25 = 6,764.0625 \times 0.25 \\ &= 1,691.015625. \end{aligned}$$

Since n must be a whole number and we always round up to ensure the margin of error is at most 2%, we take

$$n = 1,692.$$

Chapter 10

Two Sample Confidence Interval

We have discussed three distinct types of one sample confidence interval. Now, let's keep moving forward to see how confidence interval works for two sample. The aim of one sample confidence interval is giving a range of numbers to estimate population mean or proportion with a certain percentage of confidence. For two samples, the aim is comparing with sample has a relatively larger or smaller population mean or proportion with a certain percentage of confidence.

10.1 Two Sample Confidence Interval on a Difference of Mean

Suppose we are interested in the final mark of MAT135 from the same semester but with different campuses at the University of Toronto (let's use UTSG and UTM as the two independent population groups). We want to know which campus has a relatively higher average score, the question is: how do we determine that? It is going to be complicated if we proceed with the study directly by determining the sum of everyone's final marks and calculating the average for the two campuses. Similarly, as one sample confidence interval, we can select two groups of random sample from the two campuses (one group per each campus), and then calculate each sample mean. Finally, we apply a confidence interval to approximate which population has a higher mean (or average).

Two Sample Confidence Interval for Two Independent Groups of Population

We are going to introduce several definitions because two sample confidence interval has distinct cases. You need to be able to identify which exact case you are facing from given information. If you know how to solve one sample confidence interval, then two sample confidence interval is going to be easy, because all the techniques from one sample confidence interval are still usable.

Case 1: Two sample confidence interval with given population variance for both groups.

Definition 10.1 (Two sample confidence interval with given population variances). ———
Suppose we are given the population variance for both two independent groups of population. The confidence interval of $\mu_1 - \mu_2$ (difference of mean between population group 1 and 2) is

given by the following:

$$(\bar{x}_1 - \bar{x}_2) \pm z_{\alpha/2} \cdot \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}.$$

For σ_1^2 , which is population variance of population group 1; n_1 is the sample size chosen from population group 1. Similarly for σ_2^2 , which is population variance of population group 2; n_2 is the sample size chosen from population group 2.

Additionally, case 1 is a bit unrealistic with other cases because the population variance (σ^2) from both groups are rare to know.

Case 2: Two sample confidence interval with equal unknown population variance

Ideally, we have all the information about population variance from two chosen samples. However, that case does not usually happen. We may face the case with unknown variance.

Definition 10.2.

Suppose that the chosen two independent samples have same unknown population variance. Then the two sample confidence interval for $\mu_1 - \mu_2$ is given by the following:

$$(\bar{x}_1 - \bar{x}_2) \pm t_{n_1+n_2-2;\alpha/2} \cdot s_p \cdot \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}.$$

In this case, n_1 and n_2 are sample size from the two chosen samples respectively; s_p is aggregated variance of both samples combined which accommodates samples of different sizes. Additionally, s_p is called pooled standard deviation which is calculated by the following equation:

$$s_p^2 = \frac{(n_1 - 1) \cdot s_1^2 + (n_2 - 1) \cdot s_2^2}{n_1 + n_2 - 2},$$

where s_1^2 and s_2^2 are sample variance of the two chosen samples respectively.

Then we take the square root $s_p = \sqrt{s_p^2}$ to get pooled standard deviation.

Alternatively, we can write the equation for two sample confidence interval with equal unknown variance as:

$$(\bar{x}_1 - \bar{x}_2) \pm t_{n_1+n_2-2;\alpha/2} \cdot \sqrt{s_p^2 \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}, \text{ which is same as the one above.}$$

Pooled Variance and Standard Deviation

In statistics, pooled variance (also known as combined variance, composite variance, or overall variance) is a method to calculate such a value in order to estimate variance between several distinct populations. The mean of each population may or may not be the same, but

the variance of these populations are same. Pooled standard deviation does similar thing, we use that value to estimate standard deviation instead of variance.

Case 3: Two sample confidence interval with unequal unknown population variance

At this point, you may wonder that what if the population variance is both unequal and unknown? Does two sample confidence interval still doable in this case? The answer is: Yes. We can still proceed with two sample confidence interval.

Definition 10.3.

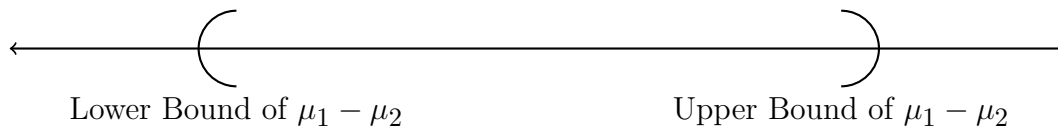
Suppose that our chosen two independent samples with unequal and unknown population variance, then the confidence interval for $\mu_1 - \mu_2$ is given by:

$$(\bar{x}_1 - \bar{x}_2) \pm t_{df; \alpha/2} \cdot \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}, \text{ where: } df = \min(n_1 - 1, n_2 - 1).$$

Moreover, s_1^2 and s_2^2 are sample variance of the two chosen groups; and n_1, n_2 are the sample size of the two chosen groups respectively.

Visualization of Two Sample Confidence Interval

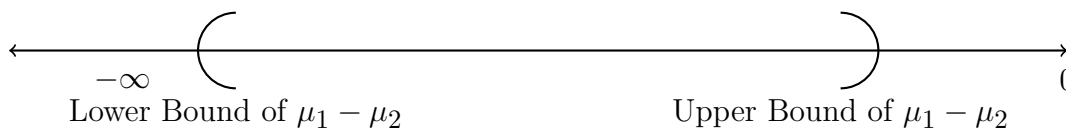
Only with the equation seems hard to understand, the following number line helps you to visualize what we try to indicate:



Visualization of two-sample confidence interval (Case 1, 2, 3)

Earlier in this chapter we said that two sample confidence interval aims to compare the mean between two populations. The number line above shows the result of difference of means between the two populations. Now, the question is, how do we know which population has a relatively larger mean? While, we can summarize it from that number line, with different cases:

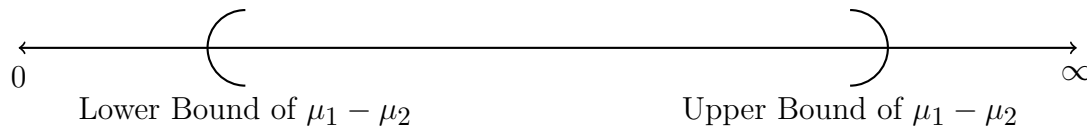
1. $\mu_1 < \mu_2$:



Visualization of the case when $\mu_1 < \mu_2$

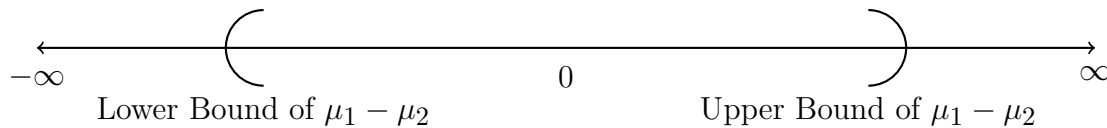
Now, we know that the difference between $\mu_1 < \mu_2$ lies on the negative side on the number line, such that: $\mu_1 - \mu_2 < 0$. Hence, by solving the inequality above we get: $\mu_1 < \mu_2$ trivially.

2. $\mu_1 > \mu_2$:

Visualization of the case when $\mu_1 > \mu_2$

Similarly as the case above, we know that $\mu_1 - \mu_2 > 0$, by observing the number line. Thus, we have: $\mu_1 > \mu_2$.

3. $\mu_1 = \mu_2$:

Visualization of the case when $\mu_1 = \mu_2$

However, 0 is an element in the range of the difference between $\mu_1 - \mu_2$, such that there is a chance when the two means could be same. Hence, we conclude that $\mu_1 = \mu_2$ in this case. While, if you prefer to use $\mu_2 - \mu_1$, this strategy is going to work as well. Just simply following the same steps, you will get the same conclusion.

Conditions of Two Sample Confidence Interval

Same as all previous confidence intervals, we still need several conditions that guarantee the validity two sample confidence interval:

- 1. The two chosen sample is required to be independent and random;
- 2. If both sample size are small (both $n_1 < 30$ and $n_2 < 30$), then both sample should be from normal population;
- 3. If one of the sample has a small size (either $n_1 < 30$ or $n_2 < 30$), then the smaller sample must be from a normal population;

Note that if both $n_1 \geq 30$ and $n_2 \geq 30$, then normality assumption is not required by the Central Limit Theorem.

Example (Comparing Two Population Means Managerial Success Indexes for Two Groups)

Example 10.1.

Behavioural researchers have developed an index designed to measure managerial success. The index (measured on a 100- point scale) is based on the manager's length of time in the organization and their level within the term; the higher the index, the more successful the manager. Suppose a researcher wants to compare the average index for the two groups of managers at a large manufacturing plant. Managers in group 1 engage in high volume of interactions with people outside the managers' work unit (such interaction include phone and face-to-face meetings with customers and suppliers, outside meetings, and public relation work). Managers in group 2 rarely interact with people outside their work unit. Independent

random samples of 12 and 15 managers are selected from groups 1 and 2, respectively, and success index of each is recorded.

Comparing Two Population Means Managerial Success Indexes for Two Group (With Equal Variances Assumed) Note: The response variable is “Managerial Success Indexes”.

Managerial success indexes is a continuous quantitative variable, measured on 100-point scale.

The explanatory variable is “Type of group”.

Type of group (Group 1: Interaction with outsiders, Group 2: Fewer interactions) is a nominal categorical variable.

Let’s use R-code to demonstrate this example. The following lines of code helps you to get started.

```
# Importing data file into R;

success=read.csv(file="success.csv",header=TRUE);

# Getting names of variables;

names(success);

# Seeing first few observations;

head(success);

# Attaching data file; attach(success);
```

Now, you will get the following table by running the code above from R-studio.

```
## [1] "Success_Index" "Group"
## Success_Index Group
## 1 65 1
## 2 66 1
## 3 58 1
## 4 70 1
## 5 78 1
## 6 53 1
```

Then, we use R-studio to obtain some descriptive statistics.

```
## .group min    Q1 median    Q3 max    mean    sd  n
## 1      1   53 62.25   65.5 69.25   78 65.33333 6.610368 12
## 2      2   34 42.50   50.0 54.50   68 49.46667 9.334014 15
## missing
## 1      0
## 2      0
```

Note that: Group 1 = “interaction with outsiders” and Group 2 = “fewer interactions”. Then, we can proceed with two sample confidence interval.

```
# 95\% CI for the difference between means;
# equal variances is assumed;

t.test(Success_Index~Group,
var.equal=TRUE, conf.level=0.95)$conf.int;
```

Finally, the output is:

```
## [1] 9.288254 22.445079
## attr("conf.level")
## [1] 0.95
```

Therefore, We are 95% confident that the mean success index is between 9.28 and 22.44 points higher for group 1 than group 2.

10.2 Two Sample Confidence Interval on Paired Data

It seems like two sample confidence interval only works on two independent samples, however what about two dependent samples? Suppose we are interested the growth of height from several distinct elementary students. We measure their height recently, then we will do it another time with five years later. The question is: how are we going to proceed with two confidence interval? While, the answer is yes. We are able to do so by constructing two sample confidence interval, but with a different strategy. Now, let’s introduce two sample confidence interval with paired data:

Sample Units	Measurement 1 (M_1)	Measurement 2 (M_2)	Difference ($M_2 - M_1$ or $M_1 - M_2$)
1	x_{11}	x_{12}	$x_{d1} = x_{12} - x_{11}$
2	x_{21}	x_{22}	$x_{d2} = x_{22} - x_{21}$
3	x_{31}	x_{32}	$x_{d2} = x_{32} - x_{31}$
.....			
n	x_{n1}	x_{n2}	$x_{dn} = x_{n2} - x_{n1}$

A table of paired data

The table shows how to get a paired data. The first column on the left is the sample size, the second column records the first time of measurement of objects, the third column records

the second time of measurement of the same objects, the last column on the right is the difference between the second and the first measurement ($M_2 - M_1$). Then we can use the fourth column to get the mean value, sample variance and sample standard deviation of the difference. Now, let's begin with the proper definition:

Definition 10.4 (Two Sample Confidence Interval on Paired Data). —————

Suppose we have two samples that are dependent with each other, the confidence interval on paired data's mean (μ_d) is given by:

$$\bar{x}_d \pm t_{n-1, \alpha/2} \cdot \frac{s_d}{\sqrt{n}}.$$

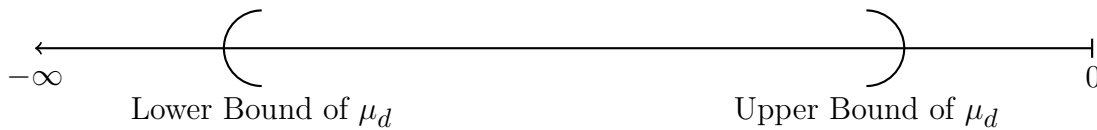
In this case, the reference distribution is t -distribution with $n - 1$ degrees of freedom (sample size minus 1), \bar{x}_d represents the sample mean of difference between the two measurements on the paired data, s_d is the sample standard deviation of difference between the two measurements.

Note that: two sample confidence interval on paired data is to calculate a range of number on **the mean of difference between the two measurement**. Then, we can continue our analysis about the data.

Visualization of Two Sample Confidence Interval on Paired Data

Next, we need to state our final conclusion from the result of two sample confidence interval on paired data. Again, let's construct a number line for each case.

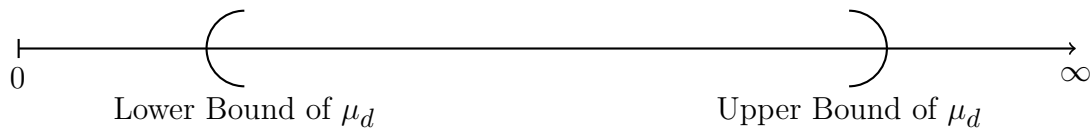
1. $\bar{M}_1 < \bar{M}_2$:



Visualization of the case when $\bar{M}_1 < \bar{M}_2$

From the number line above, we know that the result of μ_d lies only in the negative side of the number line, also we use $M_1 - M_2$ to get the difference data then calculate the average of difference data. Now, we have: $\bar{M}_1 - \bar{M}_2 = \mu_d < 0$. Hence, we conclude that $\bar{M}_1 < \bar{M}_2$.

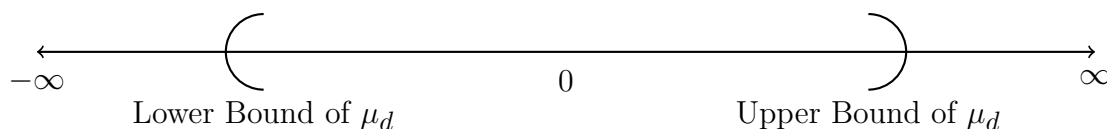
2. $\bar{M}_1 > \bar{M}_2$:



Visualization of the case when $\bar{M}_1 > \bar{M}_2$

From the number line above, we know that the result of μ_d lies only in the positive side of the number line, also we use $M_1 - M_2$ to get the difference data then calculate the average of difference data. Now, we have: $\bar{M}_1 - \bar{M}_2 = \mu_d > 0$. Hence, we conclude that $\bar{M}_1 > \bar{M}_2$.

3. $\bar{M}_1 = \bar{M}_2$:

Visualization of the case when $\bar{M}_1 = \bar{M}_2$

While, 0 is included in the range of μ_d , then there is a chance that $\bar{M}_1 - \bar{M}_2 = \mu_d = 0$. Hence, we conclude that $\bar{M}_1 = \bar{M}_2$.

Conditions of Two Sample Confidence Interval on Paired Data

We need the following conditions to make sure the validity of two sample confidence interval on paired data:

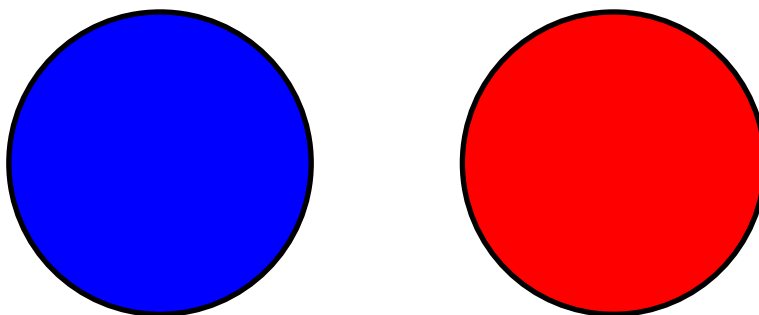
- 1. Units are independent (measurements are dependent on each unit)
- 2. Units must be random sample
- 3. If we have a small sample ($n < 30$), then the population of difference should be normal (no restrictions on large samples).

Also, note that two sample confidence interval on paired data can only be applied with two dependent groups of data. For independent groups of data, you need to refer chapter 10.1.

10.3 Two Sample Confidence Interval on Proportions

Furthermore, two sample confidence intervals can approximate the proportion as well. Suppose we are interested in the proportion of left-handed students in UTSG and UTM, and we are asked to find the campus that has a relatively larger proportion of left-handed students. To begin with this task, it is impossible to complete it directly by calculation, due to its complexity and high workload. We can use select two independent groups (one group from each campus), then apply two sample confidence interval to approximate which campus has a larger proportion.

It may still be difficult to understand, now let's begin with figures:



Visualization of two population of all students from UTSG (left) and UTM (right)

This figure represents the population of all students from two campuses. To begin with our task (find the proportion of left-handed students), we can select a group of random sample from each campus:



Visualization of two selected random sample from UTSG (left) and UTM (right)

As you can see, we have chosen our random sample from each campus with sample size n_1 and n_2 , respectively. Now we need estimators to construct our confidence interval: \hat{p}_1 and \hat{p}_2 . Those are the proportion of left-handed students from each random sample respectively. Since we have all the information we need, now we can apply our confidence interval from the two random sample.

Definition 10.5 (Two Sample Confidence Interval on Proportions). —————

Draw an SRS of size n_1 from a population having proportion p_1 of successes and draw an independent SRS of size n_2 from another population having proportion p_2 of successes. When n_1 and n_2 are large, an approximate level C confidence interval for $p_1 - p_2$ is given by:

$$(\hat{p}_1 - \hat{p}_2) \pm z_{\alpha/2} \cdot \sqrt{\frac{\hat{p}_1(1 - \hat{p}_1)}{n_1} + \frac{\hat{p}_2(1 - \hat{p}_2)}{n_2}}.$$

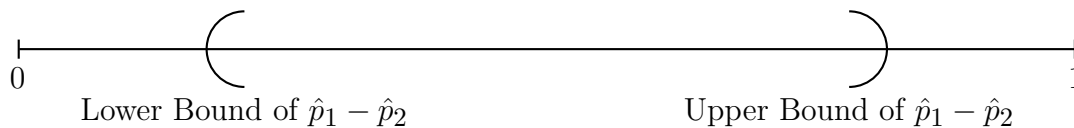
Now, n_1 and n_2 are sample size of selected random sample from each population; \hat{p}_1 and \hat{p}_2 are the proportion of success of each selected random sample respectively.

Note that, $\hat{p}_1 = \frac{\text{number of successes in random sample 1}}{n_1}$ and $\hat{p}_2 = \frac{\text{number of successes in random sample 2}}{n_2}$.

Visualization of $p_1 - p_2$

Similarly as confidence interval on independent and dependent data, we are going to provide number lines, in order to help you to visualize the result easily.

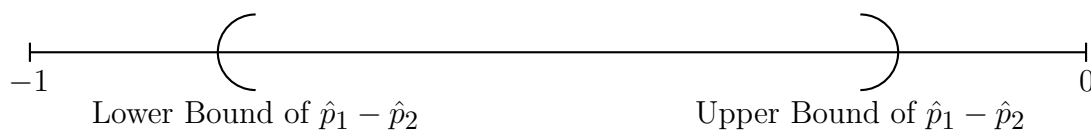
1. $p_1 > p_2$:



Visualization of the case when $p_1 > p_2$

From the number line, the result of $\hat{p}_1 - \hat{p}_2$ lies only on the positive side, such that $\hat{p}_1 - \hat{p}_2 > 0$. Hence, $\hat{p}_1 > \hat{p}_2$. Note that proportion is a number between 0 and 1, such that the difference of two proportions only between -1 and 1 .

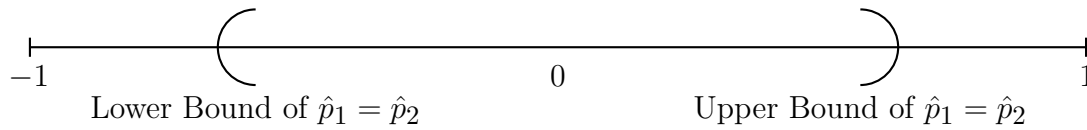
2. $\hat{p}_1 < \hat{p}_2$



Visualization of the case when $p_1 < p_2$

Now, the result of $\hat{p}_1 - \hat{p}_2$ lies only on the positive side, such that $\hat{p}_1 - \hat{p}_2 < 0$. Hence, $\hat{p}_1 < \hat{p}_2$.

3. $\hat{p}_1 = \hat{p}_2$



Visualization of the case when $\hat{p}_1 = \hat{p}_2$

In this case, 0 lies in the range of $\hat{p}_1 - \hat{p}_2$, such that there is a chance when $\hat{p}_1 - \hat{p}_2 = 0$. Hence, we conclude that: $\hat{p}_1 = \hat{p}_2$.

Conditions of Two Sample Confidence Interval on Proportion

- 1. Randomization Condition: The data in each group should be drawn independently and at random from a population or generated by a completely randomized designed experiment.
- 2. The 10% Condition: If the data are sampled without replacement, the sample should not exceed 10% of the population. If samples are bigger than 10% of the target population, random draws are no longer approximately independent.
- 3. Independent Groups Assumption: The two groups we are comparing must be independent from each other.
- 4. Sample size requirement: both selected sample size must greater than 70.

10.4 Two Sample Confidence Interval on Variances

Confidence interval is a strong technique in inferential statistics, we have discussed its application on population mean, proportion and dependent data. Now, let's move on to variance.

One simple method involves just looking at two sample variances. Logically, if two population variances are equal, then the two sample variances should be very similar. When the two sample variances are reasonably close, you can be reasonably confident that the homogeneity assumption is satisfied and proceed with, for example, Student t-interval. However, when one sample variance is three or four times larger than the other, then there is reason for a concern. The common statistical procedure for comparing population variances σ_1^2 and

σ_2^2 makes an inference about the ratio of $\frac{\sigma_1^2}{\sigma_2^2}$.

To make an inference about the ratio of $\frac{\sigma_1^2}{\sigma_2^2}$ we collect sample data and use the ratio of the sample variances $\frac{s_1^2}{s_2^2}$.

At this point, let's derive the confidence interval. We know that: $\frac{s_1^2/\sigma_1^2}{s_2^2/\sigma_2^2} \sim F_{n_1-1, n_2-1}$.

Then, we can construct our confidence interval as:

$$P[F_{n_1-1, n_2-1; 1-\alpha/2} < \frac{s_1^2/\sigma_1^2}{s_2^2/\sigma_2^2} < F_{n_1-1, n_2-1; \alpha/2}] = 1 - \alpha.$$

Now, the reference distribution of this confidence interval is F-distribution with $n_1 - 1$ and $n_2 - 1$ degrees of freedom, leaving areas of $1 - \alpha/2$ and $\alpha/2$, respectively, to the right. Rearranging gives us:

$$P\left[\frac{s_1^2}{s_2^2} \cdot \frac{1}{F_{n_1-1, n_2-1; \alpha/2}} < \frac{\sigma_1^2}{\sigma_2^2} < \frac{s_1^2}{s_2^2} \cdot \frac{1}{F_{n_1-1, n_2-1; 1-\alpha/2}}\right] = 1 - \alpha.$$

Using the fact that $F_{n_1-1, n_2-1; 1-\alpha/2} = \frac{1}{F_{n_2-1, n_1-1; \alpha/2}}$, we have:

$$P\left[\frac{s_1^2}{s_2^2} \cdot \frac{1}{F_{n_1-1, n_2-1; \alpha/2}} < \frac{\sigma_1^2}{\sigma_2^2} < \frac{s_1^2}{s_2^2} \cdot F_{n_2-1, n_1-1; \alpha/2}\right] = 1 - \alpha.$$

Chapter 11

Introduction to Hypothesis Testing

11.1 Test of Hypothesis for One Mean

Definition 11.1 (Hypothesis Tests).

An inferential procedure to determine whether there is sufficient evidence to suggest a condition for a population parameter using statistics from a sample.

Attach a probability to the conclusion of a hypothesis test.

Steps

1. Decide on a level of significance (α)
2. State the null hypothesis (H_0) and the alternative hypothesis (H_a) (H_1)
3. Calculate the appropriate test statistic.
4. Use the test statistic and a reference distribution to calculate a p-value.
(Also refer back to H_a)
5. Compare p-value to α to make a conclusion.

Note:

The definition of a p-value can be confusing. We will define it later.

Step 1: Decide on a Level of Significance (α)

-Threshold for decision making.

-Depends on tolerance for consequences of errors, sample size, nature of the study, and variability.

-Common values: 0.10, 0.01, 0.05 (very common default)

Step 2: State the Null Hypothesis (H_0) and the Alternative Hypothesis (H_a)

Θ : parameter of interest

Θ_0 : numerical value of the parameter of interest hypothesized under the null hypothesis.

$$\begin{array}{llll} H_0 : \Theta = \Theta_0 & (\Theta \leq \Theta_0) & H_a : \Theta > \Theta_0 & \text{one-sided (one-tailed)} \\ H_0 : \Theta = \Theta_0 & (\Theta \geq \Theta_0) & H_a : \Theta < \Theta_0 & \text{one-sided (one-tailed)} \\ H_0 : \Theta = \Theta_0 & & H_a : \Theta \neq \Theta_0 & \text{two-sided (two-tailed)} \end{array}$$

Null (H_0): Represents the current belief ([status quo](#)) or the safe belief.

Alternative (H_a): Represents the research hypothesis (or what you are asked to test)

Step 3: Calculate an appropriate test statistic

Depends on the hypothesis test conducted and the information available.

Definition 11.2 (Test Statistic Skeleton). —————

$$\text{test statistic} = \frac{(a \text{ statistic}) - (\text{hypothesized value of parameters under } H_0)}{\text{standard error of statistic}}$$

The test statistic follows a reference distribution (Z , t , F , χ^2).

Step 4: Calculate the p-value

Use the test statistic, reference distribution, and refer back to H_a .

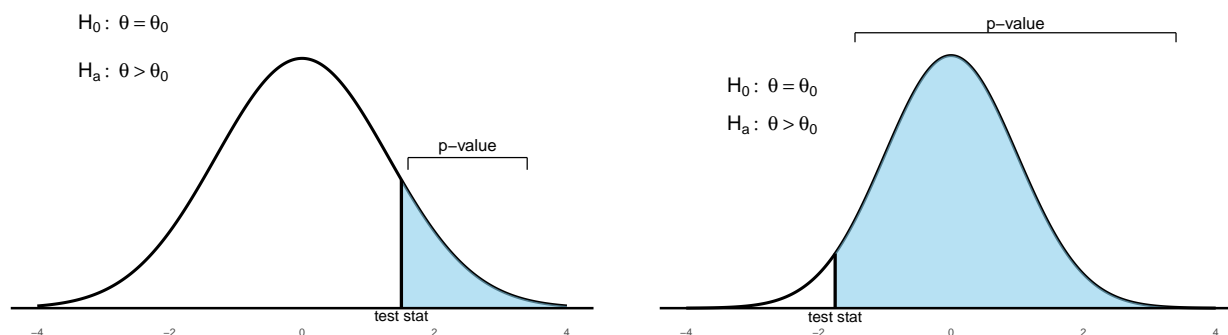


Figure 11.1: Right-tailed test: p -value is the area to the right of the test statistic.

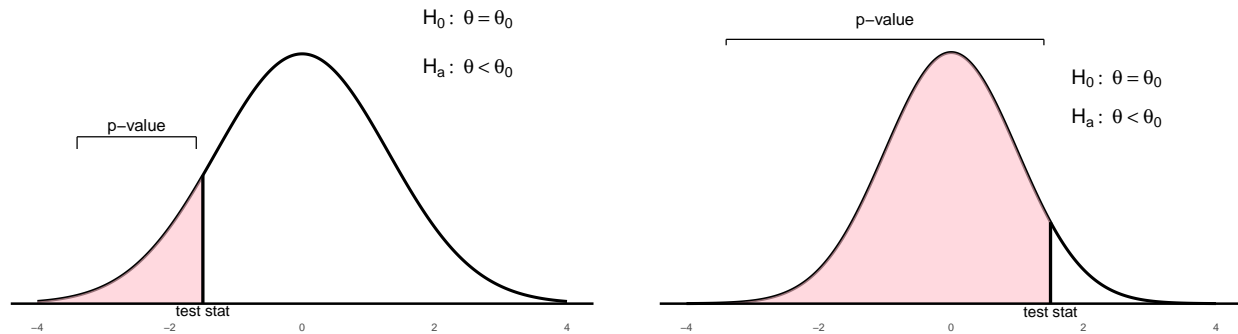


Figure 11.2: Left-tailed test: p -value is the area to the left of the test statistic.

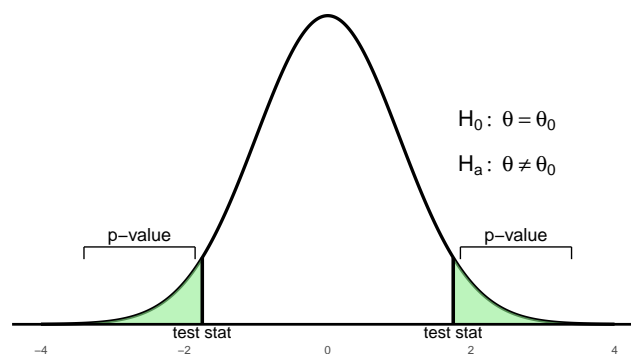


Figure 11.3: Two-tailed test: p -value is the total area in both tails beyond \pm test statistic.

Step 5: Compare p -value to level of significance α and make a conclusion

- If $p\text{-value} < \alpha$:
Sufficient evidence against H_0 . The hypothesis test rejects H_0 in favor of H_a .
- If $p\text{-value} > \alpha$:
Insufficient evidence against H_0 . Do not reject H_0 (fail to reject H_0).

Note: It is not good practice to give conclusions in the context of stating we *accept* H_0 or *accept* H_a .

Example 11.1.

[Sweetening Colas] Diet colas use artificial sweeteners to avoid sugar. These sweeteners gradually lose their sweetness over time. Manufacturers therefore test new colas for loss of sweetness before marketing them. Trained tasters sip the cola along with drinks of standard sweetness and score the cola on a “sweetness score” of 1 to 10. The cola is then stored for a month at high temperature to imitate the effect of four months’ storage at room temperature. Each taster scores the cola again after storage. This is a matched pairs experiment. Our data are the differences (score before storage minus score after storage) in the tasters’ scores. The bigger these differences, the bigger the loss of sweetness.

Suppose we know that for any cola, the sweetness loss scores vary from taster to taster according to a Normal distribution with standard deviation $\sigma = 1$. The mean μ for all tasters measures loss of sweetness.

The following are the sweetness losses for a new cola as measured by 10 trained tasters:

2.0, 0.4, 0.7, 2.0, -0.4, 2.2, -1.3, 1.2, 1.1, 2.3

Are these data good evidence that the cola lost sweetness in storage?

Solution

μ = mean sweetness loss for the population of **all** tasters.

Step 1: State hypotheses.

$$H_0 : \mu = 0$$

$$H_a : \mu > 0$$

Step 2: Test statistic: $z_{\star} = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} = \frac{1.02 - 0}{1/\sqrt{10}} = 3.23$

Step 3: P-value. $P(Z > z_{\star}) = P(Z > 3.23) = 0.0006$

Step 4: Conclusion. We would rarely observe a mean as large as 1.02 if H_0 were true. The small p-value provides strong evidence against H_0 , supporting $H_a : \mu > 0$. That is, the mean sweetness loss is likely positive.

R code (Simulation)

```
# n = sample size;
n<-10;
mu.zero<-0;
sigma<-1;
sigma.xbar<-sigma/sqrt(n);

# x bar = sample mean with 10 obs;
x.bar<-rnorm(1,mean=mu.zero,sd=sigma.xbar);
x.bar;

## [1] 0.3265859

# z.star = test statistic;
z.star<-(x.bar-mu.zero)/sigma.xbar;
z.star;

## [1] 1.032755
```

R code (10,000 Simulations)

```

n <- 10;
mu.zero <- 0;
sigma <- 1;
sigma.xbar <- sigma / sqrt(n);
# x bar = sample mean with 10 obs;
# m = number of simulations;
m <- 10000;
x.bar <- rnorm(m, mean = mu.zero, sd = sigma.xbar);

# z.star = test statistic;
z.star <- (x.bar - mu.zero) / sigma.xbar;
hist(z.star, xlab = "differences", col = "blue");

```

Histogram from simulation (see Section 7 for R code format)

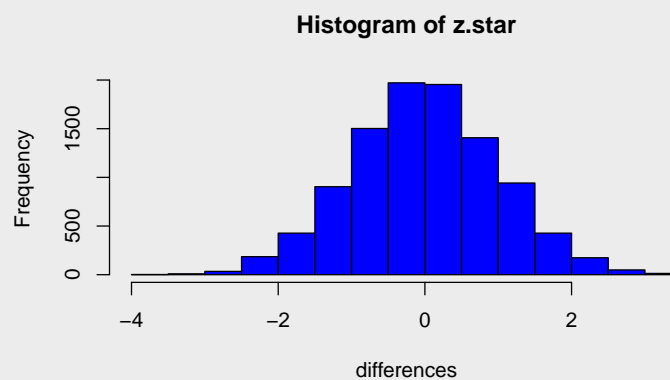


Figure 11.4: Histogram of z_* values from 10,000 simulations under H_0 .

R code (Empirical p-value)

```

## P-value

p_value <- length(z.star[z.star > 3.23]) / m;

p_value

## [1] 8e-04

```

One-Sample Hypothesis Test for Population Mean (μ) (known σ)**When σ is known:**

- $H_0: \mu = \mu_0$ (or $\mu \leq \mu_0$) $H_a: \mu > \mu_0$
- $H_0: \mu = \mu_0$ (or $\mu \geq \mu_0$) $H_a: \mu < \mu_0$
- $H_0: \mu = \mu_0$ $H_a: \mu \neq \mu_0$

Test statistic: $z^* = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}$ **Reference distribution:** Standard normal (Z)**Example 11.2.**

[UTM Deer] Deer are a common sight on the UTM campus. Suppose an ecologist is interested in the average mass of adult white-tailed does (female deer) around the Mississauga campus to determine whether they are healthy for the upcoming winter. The ecologist captures a sample of 36 adult females around the UTM and measures the average mass of this sample to be 42.53 kg.

From previous studies conducted in the area, the average mass of healthy does was reported to be 45 kg. Conduct a hypothesis test at the 5% significance level to determine whether the mass of does around UTM has decreased. Assume the standard deviation is known to be 5.25 kg.

1. **Level of significance.** $\alpha = 0.05$
2. **State the null and alternative hypotheses.**

$$H_0: \mu = 45 \quad H_a: \mu < 45$$

3. **Calculate appropriate test statistic.**

Given:

$$n = 36, \quad \bar{x} = 42.53, \quad \sigma = 5.25$$

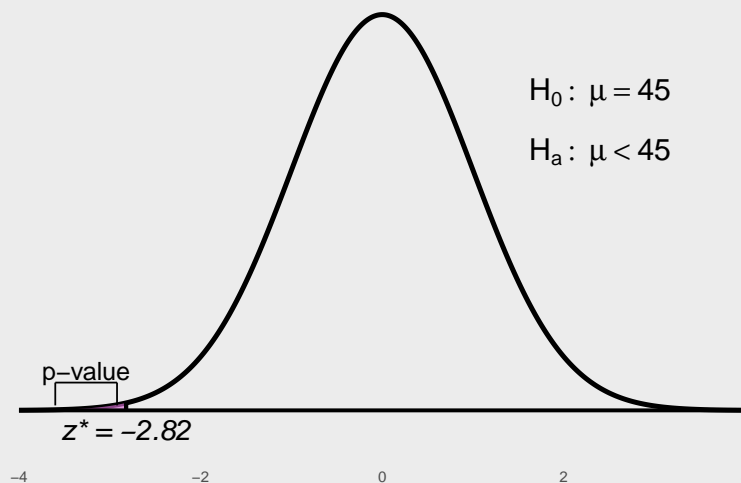
Since σ is known, the test statistic is:

$$z^* = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} = \frac{42.53 - 45}{5.25/\sqrt{36}} = -2.82$$

Reference distribution: standard normal

4. **Calculate p-value**

$$\text{p-value} = P(Z < -2.82) \approx 0.0024$$

Figure 11.5: Left-tailed p-value for the test statistic $z^* = -2.82$

5. Compare p-value with level of significance α and make a conclusion:

$$0.0024 < 0.05 \Rightarrow \text{p-value} < \alpha$$

There is sufficient evidence at the 5% level of significance to reject the null that does this winter weigh the same as in the past and to conclude the alternative that does this winter weigh less than 45 kg.

R code:

```
# Find test stat
z_test_stat = (42.53 - 45) / (5.25 / sqrt(36))
z_test_stat
[1] -2.822857

# Find the p-value
# Since the alternative is Ha : mu < 45
p-value = pnorm(z_test_stat)
[1] 0.00237989
```

Note: The `pnorm()` function in R, by default, returns the cumulative probability (area) to the left of the given value.

R code: Using BSDA package

```
# Using the BSDA library. install BSDA if it is not already installed.
# install.packages("BSDA")
> library(BSDA)
> # Conduct the z-test with the zsum.test function
> zsum.test(mean.x = 42.53, sigma.x = 5.24, n.x = 36, mu = 45, alternative = "less")

One-sample z-Test

data: Summarized x
z = -2.8282, p-value = 0.00234
alternative hypothesis: true mean is less than 45
95 percent confidence interval:
 NA 43.96651
sample estimates:
mean of x
 42.53
```

Interpretation:

There is sufficient evidence at the 5% level of significance to reject the null hypothesis. We conclude that the average mass of does this winter is significantly less than 45 kg.

Example 11.3.

[Executives' Blood Pressures]

The National Center for Health Statistics reports that the systolic blood pressure for males 35 to 44 years of age has mean 128 and standard deviation 15.

The medical director of a large company looks at the medical records of 72 executives in this age group and finds that the mean systolic blood pressure in this sample is $\bar{x} = 126.07$. Is this evidence that the company's executives have a different mean blood pressure from the general population?

Suppose we know that executives' blood pressures follow a Normal distribution with standard deviation $\sigma = 15$.

Solution: Let μ be the mean systolic blood pressure of the executive population.

1. **State hypotheses:**

$$H_0 : \mu = 128$$

$$H_a : \mu \neq 128$$

2. **Test statistic:**

$$z_* = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} = \frac{126.07 - 128}{15/\sqrt{72}} = -1.09$$

3. **P-value:**

$$2P(Z > |z_*|) = 2P(Z > 1.09) = 2(1 - 0.8621) = 0.2758$$

4. Conclusion:

More than 27% of the time, a simple random sample of size 72 from the general male population would have a mean blood pressure at least as far from 128 as that of the executive sample. The observed $\bar{x} = 126.07$ is therefore not good evidence that executives differ from other men.

Tests for a Population Mean

There are four steps in carrying out a significance test:

1. State the hypotheses.
2. Calculate the test statistic.
3. Find the P-value.
4. State your conclusion in the context of your specific setting.

Once you have stated your hypotheses and identified the proper test, you or your computer can do Steps 2 and 3 by following a recipe.

Z Test for a Population Mean (μ)

Here is the recipe for the test we have used in our examples.

Draw a simple random sample of size n from a Normal population that has unknown mean μ and known standard deviation σ . To test the null hypothesis that μ has a specified value, $H_0 : \mu = \mu_0$, calculate the **one-sample z statistic**:

$$z_* = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$$

In terms of a variable Z having the standard Normal distribution, the P-value for a test of H_0 against:

- $H_a : \mu > \mu_0$ is $P(Z > z_*)$
- $H_a : \mu < \mu_0$ is $P(Z < z_*)$
- $H_a : \mu \neq \mu_0$ is $2P(Z > |z_*|)$

Example 11.4.

Consider the following hypothesis test:

$$H_0 : \mu = 20$$

$$H_a : \mu < 20$$

A sample of 50 provided a sample mean of 19.4. The population standard deviation is 2.

- (a) Compute the value of the test statistic.
- (b) What is the p-value?
- (c) Using $\alpha = 0.05$, what is your conclusion?

Solution:

- (a) **Test statistic:**

$$z_* = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} = \frac{19.4 - 20}{2/\sqrt{50}} = -2.1213$$

- (b) **P-value:**

$$P(Z < z_*) = P(Z < -2.1213) = 0.0169$$

- (c) **Conclusion:**

Since the P-value = 0.0169 < $\alpha = 0.05$, we reject $H_0 : \mu = 20$. We conclude that $\mu < 20$.

Example 11.5.

Consider the following hypothesis test:

$$H_0 : \mu = 25$$

$$H_a : \mu > 25$$

A sample of 40 provided a sample mean of 26.4. The population standard deviation is 6.

- (a) Compute the value of the test statistic.
- (b) What is the p-value?
- (c) Using $\alpha = 0.01$, what is your conclusion?

Solution:

- (a) **Test statistic:**

$$z_* = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} = \frac{26.4 - 25}{6/\sqrt{40}} = 1.4757$$

- (b) **P-value:**

$$P(Z > z_*) = P(Z > 1.4757) = 0.0700$$

(c) Conclusion:

Since P-value = 0.0700 > $\alpha = 0.01$, we **cannot reject** $H_0 : \mu = 25$.

We conclude that we don't have enough evidence to claim that $\mu > 25$.

Example 11.6.

Consider the following hypothesis test:

$$H_0 : \mu = 15$$

$$H_a : \mu \neq 15$$

A sample of 50 provided a sample mean of 14.15. The population standard deviation is 3.

- (a) Compute the value of the test statistic.
- (b) What is the p-value?
- (c) Using $\alpha = 0.05$, what is your conclusion?

Solution:**(a) Test statistic:**

$$z_* = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} = \frac{14.15 - 15}{3/\sqrt{50}} = -2.0034$$

(b) P-value:

$$2P(Z > |z_*|) = 2P(Z > |-2.0034|) = 2P(Z > 2.0034) = 0.0451$$

(c) Conclusion:

Since P-value = 0.0451 < $\alpha = 0.05$, we reject $H_0 : \mu = 15$.

We conclude that $\mu \neq 15$.

Confidence Interval Interpretation:

The 95% confidence interval for μ is:

$$\bar{x} \pm z_* \left(\frac{\sigma}{\sqrt{n}} \right)$$

$$14.15 \pm 1.96 \left(\frac{3}{\sqrt{50}} \right) = (13.3184, 14.9815)$$

Since the hypothesized value $\mu_0 = 15$ falls **outside** this interval, we again reject $H_0 : \mu = 15$.

Note 11.1.

A level α two-sided significance test rejects a hypothesis $H_0 : \mu = \mu_0$ exactly when the value μ_0 falls outside a level $1 - \alpha$ confidence interval for μ .

One-Sample Hypothesis Test for Population Mean (μ) (unknown σ)**When σ is NOT known:**

- $H_0 : \mu = \mu_0$ (or $\mu \geq \mu_0$) $H_a : \mu < \mu_0$
- $H_0 : \mu = \mu_0$ (or $\mu \leq \mu_0$) $H_a : \mu > \mu_0$
- $H_0 : \mu = \mu_0$ $H_a : \mu \neq \mu_0$

Test statistic: $t^* = \frac{\bar{X} - \mu_0}{s/\sqrt{n}}$

Reference distribution: t distribution with $n - 1$ degrees of freedom

Example 11.7.

[Hypothesis Test: Laughter and Heart Rate, Unknown σ]

Researchers studied the physiological effects of laughter. They measured heart rates (in beats per minute) of $n = 25$ subjects (ages 18–34) while they laughed. They obtained:

$$\bar{x} = 73.5, \quad s = 6, \quad \alpha = 0.05$$

It is well known that the resting heart rate is 71 bpm. Is there evidence that the mean heart rate during laughter exceeds 71 bpm?

Step 1: State the hypotheses.

$$H_0 : \mu = 71$$

$$H_a : \mu > 71$$

Step 2: Check assumptions.

- The sample is an independent random sample of individuals aged 18–34.
- The population of heart rates during laughter is normally distributed.

Step 3: Compute the test statistic.

Since σ is unknown, we use the t statistic:

$$t^* = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} = \frac{73.5 - 71}{6/\sqrt{25}} = 2.083$$

Reference distribution: t distribution with $n - 1 = 25 - 1 = 24$ degrees of freedom.

Step 4: Determine the p-value.

Using the t distribution with 24 df:

$$0.01 < \text{p-value} < 0.025$$

Step 5: Make a conclusion.

Since $p\text{-value} < \alpha = 0.05$, we reject H_0 .

There is sufficient evidence at the 5% level of significance to reject the null that the mean is 71 bpm in favor of the alternative that the mean is greater than 71 bpm for people who are laughing.

Example 11.8.

A researcher is asked to test the hypothesis that the average price of a 2-star (CAA rating) motel room has decreased since last year. Last year, a study showed that the prices were Normally distributed with a mean of \$89.50.

A random sample of twelve 2-star motels produced the following room prices:

\$85.00, 92.50, 87.50, 89.90, 90.00, 82.50, 87.50, 90.00, 85.00, 89.00, 91.50, 87.50

At the 5% level of significance, can we conclude that the mean price has decreased?

Solution:

Let μ be the true average price of a 2-star motel room.

1. State hypotheses.

$$H_0 : \mu = 89.5$$

$$H_a : \mu < 89.5$$

2. Compute test statistic.

$$t^* = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} = \frac{88.1583 - 89.5}{2.9203/\sqrt{12}} = -1.5915$$

3. Find the P-value.

With $df = 11$, the P-value (from the t -distribution table) is between 0.05 and 0.10.

4. Conclusion.

Since $P\text{-value} > 0.05$, we **fail to reject** H_0 .

There is not sufficient evidence to conclude that the average price of 2-star motels has decreased this year.

R code (One Sample t-test)

```
# Step 1. Entering data;
prices=c(85.00, 92.50, 87.50, 89.90, 90.00, 82.50,
        87.50, 90.00, 85.00, 89.00, 91.50, 87.50);

# Step 2. Hypothesis test;
t.test(prices, alternative="less", mu=89.5);
```

R output

```
##
## One Sample t-test
##
## data: prices
## t = -1.5915, df = 11, p-value = 0.0699
## alternative hypothesis: true mean is less than 89.5
## 95 percent confidence interval:
## -Inf 89.67229
## sample estimates:
## mean of x
## 88.15833
```

The one-sample t test

Draw an SRS of size n from a large population having unknown mean μ .
 To test the hypothesis $H_0 : \mu = \mu_0$, compute the *one-sample t statistic*

$$t^* = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$$

In terms of a variable T having the t_{n-1} distribution, the P-value for a test of H_0 against

$$\begin{aligned} H_a : \mu > \mu_0 & \text{ is } P(T \geq t^*) \\ H_a : \mu < \mu_0 & \text{ is } P(T \leq t^*) \\ H_a : \mu \neq \mu_0 & \text{ is } 2P(T \geq |t^*|) \end{aligned}$$

These P-values are exact if the population distribution is Normal and are approximately correct for large n in other cases.

Example 11.9.

We are conducting a two-sided one-sample t -test for the hypotheses:

$$\begin{aligned} H_0 : \mu &= 64 \\ H_a : \mu &\neq 64 \end{aligned}$$

based on a sample of $n = 15$ observations, with test statistic $t^* = 2.12$.

a) Degrees of freedom:

$$df = n - 1 = 15 - 1 = 14$$

b) Critical values and P-value bounds:

From the t -distribution table for $df = 14$:

- $t = 1.761$ corresponds to a two-tailed probability of 0.10
- $t = 2.145$ corresponds to a two-tailed probability of 0.05

Since $t^* = 2.12$ falls between these values, the two-sided P-value satisfies:

$$0.05 < \text{P-value} < 0.10$$

c) Significance:

- At the 10% level: **Yes**, since $\text{P-value} < 0.10$
- At the 5% level: **No**, since $\text{P-value} > 0.05$

d) Exact two-sided P-value using R:

```
# Compute exact two-sided P-value for t* = 2.12 with df = 14
2 * (1 - pt(2.12, df = 14))

## [1] 0.05235683
```

Thus, the exact two-sided P-value is approximately **0.0524**, confirming the bracketing result.

11.2 Test of Hypothesis for One Proportion

One-Sample Hypothesis Test for Population Proportion (p)

When sample size is large enough ($np, n(1-p) \geq 10$):

- $H_0: p = p_0$ (or $p \geq p_0$) $H_a: p < p_0$
- $H_0: p = p_0$ (or $p \leq p_0$) $H_a: p > p_0$
- $H_0: p = p_0$ $H_a: p \neq p_0$

Test statistic: $z^* = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$

Reference distribution: Standard normal (\mathcal{Z})

Example 11.10.

[100-Cup Challenge] A YouTuber goes to her nearest Tim Hortons and buys 100 empty cups.

After rolling up the rims, she ends up with 12 winning cups out of the 100 she bought, all of them were food prizes.

If the probability of winning a food prize is supposed to be $\frac{1}{6}$, does she have evidence to claim that the probability of winning a food prize is less than $\frac{1}{6}$?

Definition 11.3.

The **sample space** S of a random phenomenon is the set of all possible outcomes.

An **event** is an outcome or a set of outcomes of a random phenomenon. That is, an event is a subset of the sample space.

A **probability model** is a mathematical description of a random phenomenon consisting of two parts: a sample space S and a way of assigning probabilities to events.

Rolling a fair die (random phenomenon). There are 6 possible outcomes when we roll a die. The sample space for rolling a die and counting the pips is

$$S = \{1, 2, 3, 4, 5, 6\}$$

“Roll a 6” is an event that contains one of these 6 outcomes.

Definition 11.4.

A random variable X has a **discrete uniform distribution** if each of the n values in its range, say, x_1, x_2, \dots, x_n , has equal probability. Then,

$$f(x_i) = \frac{1}{n}$$

R code:

```
# Define a die with values 1 through 6
die <- c(1, 2, 3, 4, 5, 6)

# Roll the die once
sample(die, 1, replace = TRUE)
## [1] 2

# Roll the die six times
sample(die, 6, replace = TRUE)
## [1] 1 3 2 6 3 1
```

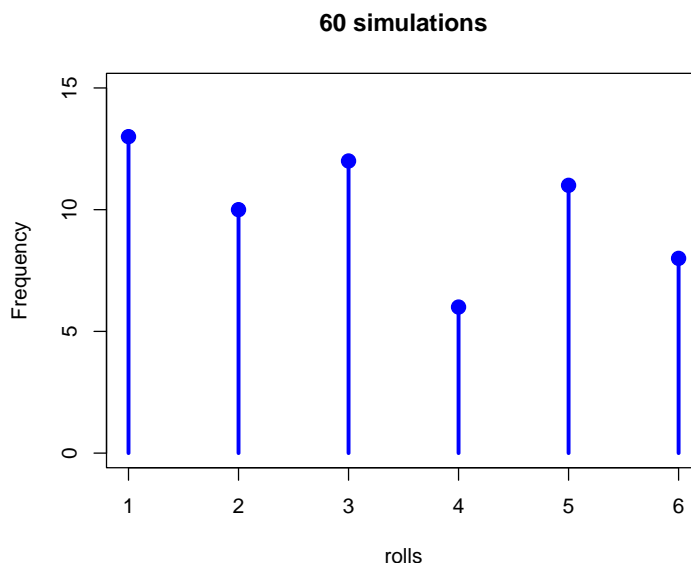


Figure 11.6: Plot of frequencies from 60 simulations of a fair six-sided die.

Definition 11.5.

A **random variable** is a variable whose value is a numerical outcome of a random phenomenon.

The **probability distribution** of a random variable X tells us what values X can take and how to assign probabilities to those values.

Note 11.2.

The Binomial setting

- There are a fixed number n of observations.
 - The n observations are all **independent**. That is, knowing the result of one observation tells you nothing about the other observations.
 - Each observation falls into one of just two categories, which for convenience we call “success” and “failure”.
 - The probability of a success, call it p , is the same for each observation.
-

A random variable Y is said to have a **binomial distribution** based on n trials with success probability p if and only if

$$p(y) = \frac{n!}{y!(n-y)!} p^y (1-p)^{n-y}, \quad y = 0, 1, 2, \dots, n \quad \text{and} \quad 0 \leq p \leq 1.$$

Example 11.11.

Think of rolling a die n times as an example of the binomial setting. Each roll gives either a six or a number different from six. Knowing the outcome of one roll doesn't tell us anything about other rolls, so the n rolls are independent.

If we call six a success, then p is the probability of a six and remains the same as long as we roll the same die. The number of sixes we count is a random variable X . The distribution of X is called a **binomial distribution**.

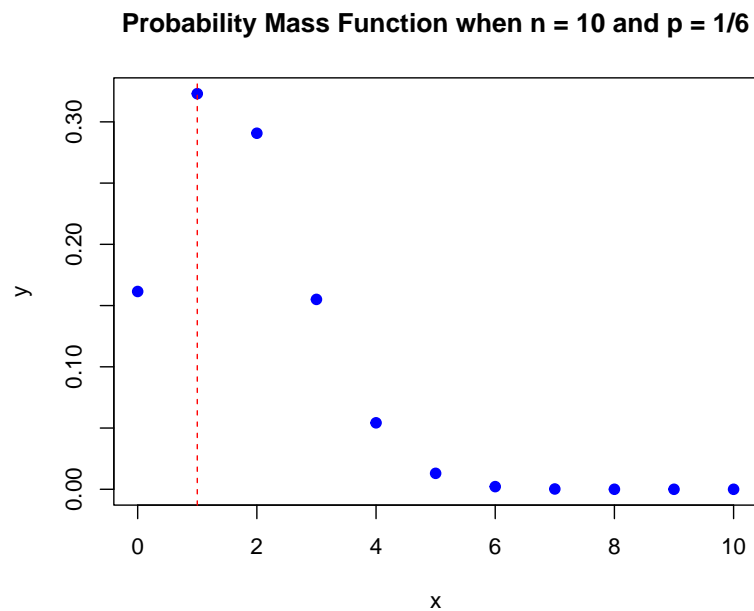
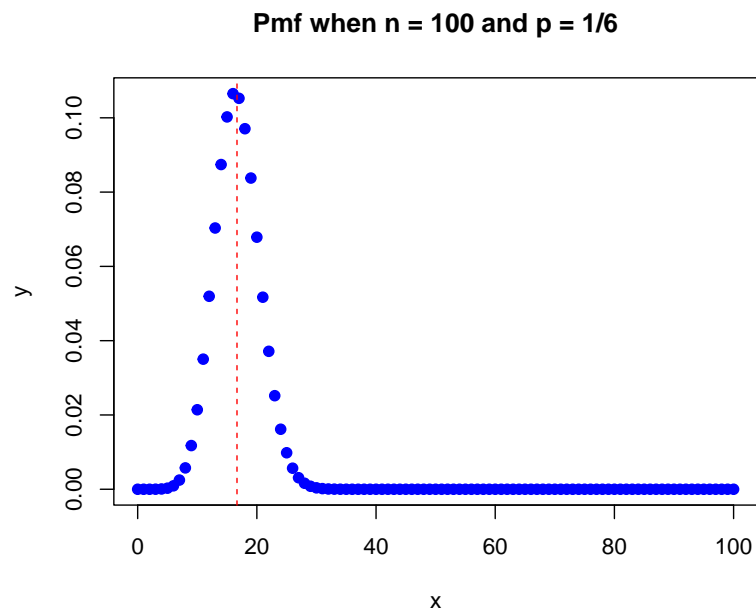
R code (Binomial Simulations and PMF)

```
## Simulation: Binomial with n = 10 and p = 1/6.
rbinom(1, size = 10, prob = 1/6);
## [1] 3

rbinom(1, size = 10, prob = 1/6);
## [1] 1

rbinom(1, size = 10, prob = 1/6);
## [1] 0

## Pmf: Binomial with n = 10 and p = 1/6.
x <- seq(0, 10, by = 1);
y <- dbinom(x, 10, 1/6);
plot(x, y, type = "p", col = "blue", pch = 19);
```

Figure 11.7: PMF when $n = 10$ and $p = 1/6$ Figure 11.8: PMF when $n = 100$ and $p = 1/6$

R code (PMF values for selected x values)

```
dbinom(c(15, 16, 17, 18), size = 100, prob = 1/6);
## [1] 0.10023663 0.10650142 0.10524847 0.09706247
```

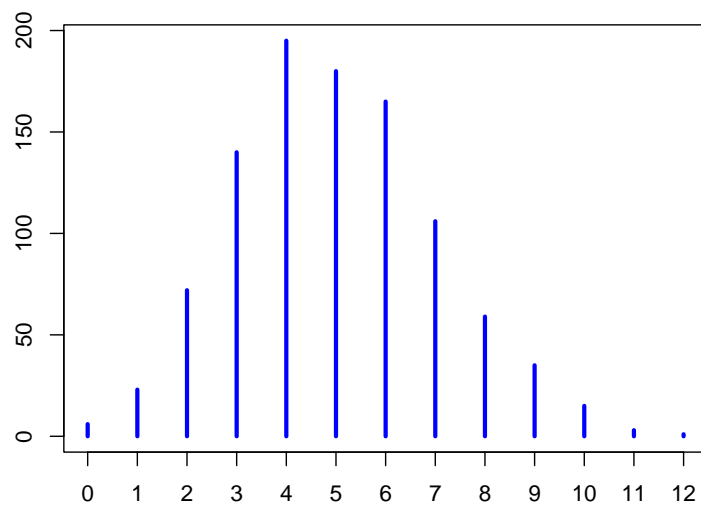


Figure 11.9: Simulation: 2000 YouTuber, $n = 100$, and $p = 1/6$

R code (A few values from our simulation)

```
## vec.prop  
## 6 7 8 9 10 11 12  
## 7 3 8 24 46 72 106  
## [1] 266  
## [1] 0.133
```

It turns out that our P-value for this simulation is:
0.133

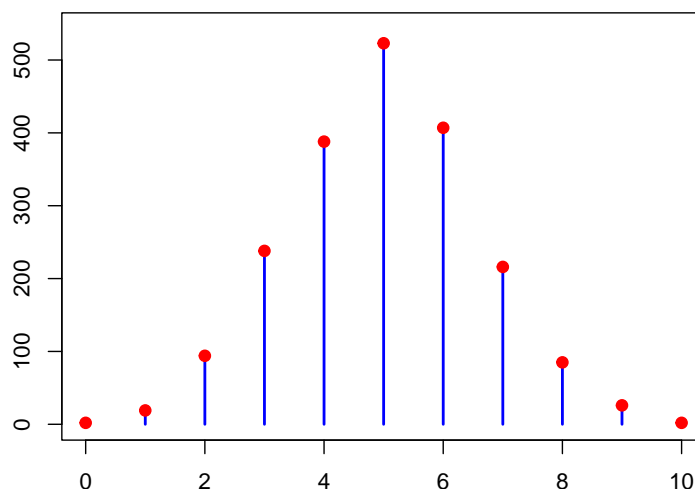


Figure 11.10: Simulation vs Theoretical pmf

Sampling Distribution of a Sample Proportion

Draw an SRS of size n from a large population that contains proportion p of “successes”. Let \hat{p} be the **sample proportion** of successes,

$$\hat{p} = \frac{\text{number of successes in the sample}}{n}$$

Then:

- The **mean** of the sampling distribution of \hat{p} is p .
- The **standard deviation** of the sampling distribution is

$$\sqrt{\frac{p(1-p)}{n}}.$$

- As the sample size increases, the sampling distribution of \hat{p} becomes **approximately Normal**. That is, for large n , \hat{p} has approximately the

$$N\left(p, \sqrt{\frac{p(1-p)}{n}}\right)$$

distribution.

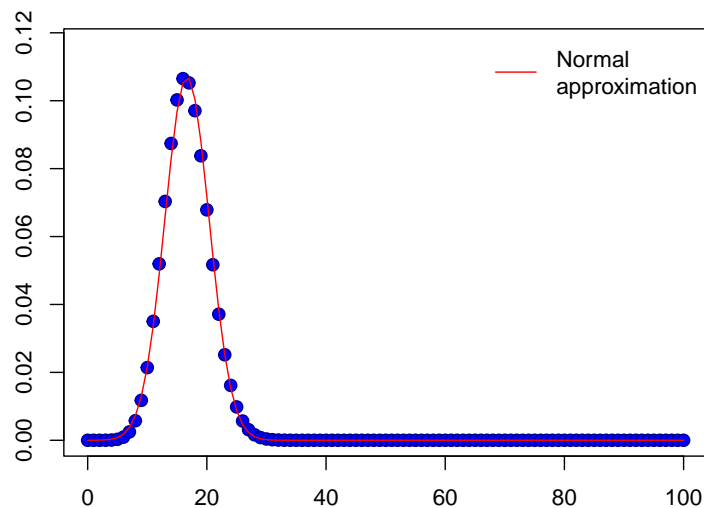


Figure 11.11: Binomial with Normal Approximation

Hypotheses Tests for a Proportion

To test the hypothesis $H_0 : p = p_0$, compute the z_* statistic:

$$z_* = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1 - p_0)}{n}}}$$

In terms of a variable Z having the standard Normal distribution, the approximate P-value for a test of H_0 against:

$$\begin{aligned} H_a : p > p_0 & \text{ is } P(Z > z_*) \\ H_a : p < p_0 & \text{ is } P(Z < z_*) \\ H_a : p \neq p_0 & \text{ is } 2P(Z > |z_*|) \end{aligned}$$

Introduction to Hypothesis Testing (Significance Test)

Consider the following problem: In 1980s, it was generally believed that congenital abnormalities affect 5% of the nation's children. Some people believe that the increase in the number of chemicals in the environment in recent years has led to an increase in the incidence of abnormalities. A recent study examined 384 children and found that 46 of them showed signs of abnormality. Is this strong evidence that the risk has increased?

- The above statement serves as a hypothesis, moreover it is a Research Hypothesis.

A hypothesis is:

- a statement about a population.
- a prediction that a parameter describing some characteristics of a variable (e.g., true proportion, p) takes a particular numerical value or falls in a certain range of values.

For conducting a Significance Test:

- Researchers (you) use data to summarize the evidence about a hypothesis.
- With data, you can compare the point estimates of parameters to the values predicted by the hypothesis.

Important Ideas about Hypothesis Testing

- All the hypothesis tests boil down to the same question: “Is an observed difference or pattern too large to be attributed to chance?”
- We measure “how large” by putting our sample results in the context of a sampling distribution model (e.g., Normal model, t distribution).

To plan a statistical hypothesis test, specify the model you will use to test the null hypothesis and the parameter of interest.

- All models require assumptions, so you will need to state them and check any corresponding conditions.
- For example, if the conditions are satisfied, we can model the sampling distribution of the proportion with a Normal model. Otherwise, we cannot proceed with the test (we need to stop and reconsider).

Steps in conducting Hypothesis Testing

1. State the null and the alternative hypothesis.
2. Check the necessary assumptions.
3. Identify the test-statistic. Find the value of the test-statistic.
4. Find the p-value of the test-statistic.
5. State (if any) a conclusion.

Example 11.12.

Example of Hypothesis Testing for a Proportion

In 1980s, it was generally believed that congenital abnormalities affect 5% of the nation’s children. Some people believe that the increase in the number of chemicals in the environment in recent years has led to an increase in the incidence of abnormalities. A recent study

examined 384 children and found that 46 of them showed signs of abnormality. Is this strong evidence that the risk has increased?

Step 1. Set up the null and alternative hypothesis:

- The null hypothesis is the current belief: $H_0 : p = p_0$

In our example it would have a form: $H_0 : p = 0.05$

- The Alternative hypothesis is what the researcher(s) [you] want to prove: $H_a : p > p_0$

In our example it would have a form: $H_a : p > 0.05$

This means a one-sided test.

- The goal here is to provide evidence against H_0 (e.g., suggest H_a).

You want to conclude H_a .

Try a Proof by Contradiction: Assume H_0 is true ... and hope your data contradicts it.

Step 2. Check the Necessary Assumptions:

- **Independence Assumption:** There is no reason to think that one child having genetic abnormalities would affect the probability that other children have them.
- **Randomization Condition:** This sample may not be random, but genetic abnormalities are plausibly independent. The sample is probably representative of all children, with regards to genetic abnormalities.
- **10% Condition:** The sample of 384 children is less than 10% of all children.
- **Success/Failure Condition:** $np = (384)(0.05) = 19.2$ and $n(1 - p) = (384)(0.95) = 364.8$ are both greater than 10, so the sample is large enough.

Step 3. Identify the test-statistics. Find the value of the test-statistic:

Since the conditions are met, assume H_0 is true:

The sampling distribution of \hat{p} becomes **approximately Normal**. That is, for large n , \hat{p} has approximately the

$$N\left(p_0, \sqrt{\frac{p_0(1-p_0)}{n}}\right)$$

distribution.

$$z_* = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} = \frac{0.1198 - 0.05}{\sqrt{\frac{(0.05)(0.95)}{384}}} \approx 6.28$$

Recall that

$$\hat{p} = \frac{46}{384} = 0.1198.$$

The value of z^* is approximately 6.28, meaning that the observed proportion of children with genetic abnormalities is over 6 standard deviations above the hypothesized proportion ($p_0 = 0.05$).

Step 4. Find the p-value of the test-statistic.

P-value = $P(Z > 6.28) \approx 0.000$ (better to report $p\text{-value} < 0.0001$)

Note: We find the area above $Z = 6.28$ since $H_a : p > 0.05$.

Meaning of this p-value:

If 5% of children have genetic abnormalities, the chance of observing 46 children with genetic abnormalities in a random sample of 384 children is almost 0.

Step 5. Give (if any) a conclusion.

p-value is less than 0.0001, which is less than $\alpha = 0.05$; We reject $H_0 : p = 0.05$, and conclude $H_a : p > 0.05$. Our result is statistically significant at $\alpha = 0.05$.

There is very strong evidence that more than 5% of children have genetic abnormalities.

R code (1-sample proportion test)

```
prop.test(x=46, n = 384 ,p=0.05,alternative="greater", correct=FALSE);

##
## 1-sample proportions test without continuity correction
##
## data:  46 out of 384, null probability 0.05
## X-squared = 39.377, df = 1, p-value = 1.747e-10
## alternative hypothesis: true p is greater than 0.05
## 95 percent confidence interval:
##  0.09516097 1.00000000
## sample estimates:
##           p
## 0.1197917
```

Note 11.3. ————— About the *P*-value of the Test-statistics

- *P*-value is a conditional probability.
- It is not the probability that H_0 (null hypothesis: current belief) is true.
- It is: $P(\text{observed statistic value [or even more extreme]} \mid H_0)$. Given H_0 (the null hypothesis), because H_0 gives the parameter values that we need to find required probability.

- *P-value serves as a measure of the strength of the evidence against the null hypothesis (but it should not serve as a hard and fast rule for decision).*
- *If $p\text{-value} = 0.03$ (for example) all we can say is that there is 3% chance of observing the statistic value we actually observed (or one even more inconsistent with the null value).*
- *P-value is the chance (the proportion) of getting a, for instance, \hat{p} as far as or further from H_0 than the value observed.*
- *P-value is the probability of getting at least something (e.g., sample proportion \hat{p}) more extreme (e.g., unusual, unlikely, or rare) than what we have already found (our observed value of \hat{p}) that provide even stronger evidence against H_0 .*
- *The more extreme the z-score (large in absolute values) are the ones that denote farther departure of the observed value (e.g., our \hat{p}) from the parameter value (p_0) in H_0 .*
- *In the one-sided test, e.g., $H_a : p > p_0$, p-value is one-tailed probability. This is the probability that sample proportion \hat{p} falls at least as far from p_0 in one direction as the observed value of \hat{p} .*
- *In the two-sided test, e.g., $H_a : p \neq p_0$, p-value is two-tailed probability. This is the probability that sample proportion \hat{p} falls at least as far from p_0 in either direction as the observed value of \hat{p} .*

The probability, computed assuming that H_0 is true, that the test statistic would take a value as extreme or more extreme than that actually observed is called the **P-value** of the test. The smaller the P-value, the stronger the evidence against H_0 provided by the data. Small P-values are evidence against H_0 , because they say that the observed result is unlikely to occur when H_0 is true. Large P-values fail to give evidence against H_0 .

The P-value Scale

- If $P\text{-value} < 0.001$, we have very strong evidence against H_0 .
- If $0.001 \leq P\text{-value} < 0.01$, we have strong evidence against H_0 .
- If $0.01 \leq P\text{-value} < 0.05$, we have evidence against H_0 .
- If $0.05 \leq P\text{-value} < 0.075$, we have some evidence against H_0 .
- If $0.075 \leq P\text{-value} < 0.10$, we have slight evidence against H_0 .

Use p-value Method to Make a Decision (Reject or Fail to Reject H_0)

But how small is small p-value?

We would need to choose an α -level (significance-level): a number such that if:

- $P\text{-value} \leq \alpha\text{-level}$, we reject H_0 ; We can conclude H_a (we have evidence to support our claim). Often we phrase as a statistically significant result at that specified α -level.

- P -value $> \alpha$ -level, we fail to reject H_0 ; We cannot conclude H_a (we have not enough evidence to support our claim; thus, H_0 is plausible - We do not accept H_0). Often we phrase as the result is not statistically significant at that specified α -level.
- The default α -level (significance-level) is typically $\alpha = 0.05$ (but it can be different based on the context of the study - it is usually not higher than 0.10).

The p -value in the previous example was extremely small (less than 0.0001). That is a strong evidence to suggest that more than 5% of children have genetic abnormalities. However, it does not say that the percentage of sampled children with genetic abnormalities was “a lot more than 5%”. That is, the p -value by itself says nothing about how much greater the percentage might be. The confidence interval provides that information.

To assess the difference in practical terms, we should also construct a confidence interval:

$$0.1198 \pm (1.96 \times 0.0166)$$

$$0.1198 \pm 0.0324$$

$$(0.0874, 0.1522)$$

Interpretation: We are 95% Confident that the true percentage of children with genetic abnormalities is between 8.74% and 15.22%.

95% CI for p : (9.1%, 15.6%) – We are 95% confident that the true percentage of all children that have genetic abnormalities is between approximately 9.1% and 15.6%. Since both values of this CI are more than the hypothesized value of $p = 0.05$ (5%), we can further infer that this true percentage is more than 5%.

Do environmental chemicals cause congenital abnormalities?

We do not know that environmental chemicals cause genetic abnormalities. We merely have evidence that suggests that a greater percentage of children are diagnosed with genetic abnormalities now, compared to the 1980s.

Note 11.4.

More About P -values

- *Big p -values just mean that what we have observed is not surprising. It means that the results are in line with our assumption that the null hypothesis models the world, so we have no reason to reject it.*
 - *A big p -value does not prove that the null hypothesis is true.*
 - *When we see a big p -value, all we can say is: we cannot reject H_0 (we fail to reject H_0) – we cannot conclude H_a (We have no evidence to support H_a).*
-

Some Additional Examples

Example 11.13.

Consider the following hypothesis test:

$$H_0 : p = 0.75$$

$$H_a : p < 0.75$$

A sample of 300 items was selected. Compute the p-value and state your conclusion for each of the following sample results. Use $\alpha = 0.05$.

a. $\hat{p} = 0.68$

b. $\hat{p} = 0.72$

c. $\hat{p} = 0.70$

d. $\hat{p} = 0.77$

Solution a.

$$z_* = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)/n}} = \frac{0.68 - 0.75}{\sqrt{0.75(1 - 0.75)/300}} = -2.80$$

Using Normal table, P-value = $P(Z < z_*) = P(Z < -2.80) = 0.0026$

P-value $< \alpha = 0.05$, reject H_0 .

Solution b.

$$z_* = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)/n}} = \frac{0.72 - 0.75}{\sqrt{0.75(1 - 0.75)/300}} = -1.20$$

Using Normal table, P-value = $P(Z < z_*) = P(Z < -1.20) = 0.1151$

P-value $> \alpha = 0.05$, do not reject H_0 .

Solution c.

$$z_* = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)/n}} = \frac{0.70 - 0.75}{\sqrt{0.75(1 - 0.75)/300}} = -2.00$$

Using Normal table, P-value = $P(Z < z_*) = P(Z < -2.00) = 0.0228$

P-value $< \alpha = 0.05$, reject H_0 .

Example 11.14.

Consider the following hypothesis test:

$$H_0 : p = 0.20$$

$$H_a : p \neq 0.20$$

A sample of 400 provided a sample proportion $\hat{p} = 0.175$.

- Compute the value of the test statistic.
- What is the p-value?
- At the $\alpha = 0.05$, what is your conclusion?
- What is the rejection rule using the critical value? What is your conclusion?

Solution

a.

$$z_* = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)/n}} = \frac{0.175 - 0.20}{\sqrt{(0.20)(0.80)/400}} = -1.25$$

b. Using Normal table, P-value =

$$2P(Z > |z_*|) = 2P(Z > |-1.25|) = 2P(Z > 1.25) = 2(0.1056) = 0.2112$$

c. P-value $> \alpha = 0.05$, we CAN'T reject H_0 .

Example 11.15.

A study found that, in 2005, 12.5% of U.S. workers belonged to unions. Suppose a sample of 400 U.S. workers is collected in 2006 to determine whether union efforts to organize have increased union membership.

- Formulate the hypotheses that can be used to determine whether union membership increased in 2006.
- If the sample results show that 52 of the workers belonged to unions, what is the p-value for your hypothesis test?
- At $\alpha = 0.05$, what is your conclusion?

Solution

a.

$$H_0 : p = 0.125$$

$$H_a : p > 0.125$$

b.

$$\hat{p} = \frac{52}{400} = 0.13$$

$$z_* = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)/n}} = \frac{0.13 - 0.125}{\sqrt{(0.125)(0.875)/400}} = 0.30$$

Using Normal table, P-value =

$$P(Z > z_*) = P(Z > 0.30) = 1 - 0.6179 = 0.3821$$

c. P-value > 0.05, do not reject H_0 . We cannot conclude that there has been an increase in union membership.

R code

```
prop.test(52, 400, p=0.125, alternative="greater", correct=FALSE);

##
## 1-sample proportions test without continuity correction
##
## data: 52 out of 400, null probability 0.125
## X-squared = 0.091429, df = 1, p-value = 0.3812
## alternative hypothesis: true p is greater than 0.125
## 95 percent confidence interval:
## 0.1048085 1.0000000
## sample estimates:
##      p
## 0.13
```

11.3 Test of Hypothesis for One Variance

In many practical situations, we are interested in testing whether the variability in a population (i.e., its variance) has changed. This is especially important in quality control, finance, and experimental science. When we have data from a single normal population and want to test a claim about the population variance, we use the chi-squared (χ^2) test for one variance. This method assumes that the underlying population is normally distributed and the sample observations are independent.

Hypothesis Tests for One Variance

- Data from a single normal population; independent observations

- Variance unknown
- Large or small sample

Hypothesis Test

$$H_0 : \sigma^2 = \sigma_0^2$$

$$H_a : \sigma^2 \neq \sigma_0^2 \quad (\text{or } \sigma^2 > \sigma_0^2 \text{ or } \sigma^2 < \sigma_0^2)$$

Assume H_0 is true, then:

$$\text{Test statistic: } \chi_*^2 = \frac{(n-1)s^2}{\sigma_0^2} \sim \chi_{n-1}^2$$

Decision rules:

$$H_a : \sigma^2 \neq \sigma_0^2.$$

Reject H_0 if $\chi_*^2 > \chi_{n-1;\alpha/2}^2$ or if $\chi_*^2 < \chi_{n-1;1-\alpha/2}^2$.

$$H_a : \sigma^2 > \sigma_0^2.$$

Reject H_0 if $\chi_*^2 > \chi_{n-1;\alpha}^2$ or if $P[\chi_{n-1}^2 > \chi_*^2]$ is too small.

$$H_a : \sigma^2 < \sigma_0^2.$$

Reject H_0 if $\chi_*^2 < \chi_{n-1;1-\alpha}^2$ or if $P[\chi_{n-1}^2 < \chi_*^2]$ is too small.

Note. This is **NOT** robust to departures from Normality.

Example 11.16.

A company produces metal pipes of a standard length, and claims that the standard deviation of the length is at most 1.2 cm. One of its clients decides to test this claim by taking a sample of 25 pipes and checking their lengths. They found that the standard deviation of the sample is 1.5 cm. Does this undermine the company's claim? Use $\alpha = 0.05$.

Note: Assume length is Normally distributed.

Solution

$$H_0 : \sigma^2 \leq 1.2^2$$

$$H_a : \sigma^2 > 1.2^2$$

$$\chi_*^2 = \frac{(n-1)s^2}{\sigma^2} = \frac{(25-1) \cdot 1.5^2}{1.2^2} = 37.5$$

$$\text{P-value} = P[\chi_{24}^2 > 37.5] \approx 0.0389$$

R Code

```
1 - pchisq(37.5, df = 24);
## [1] 0.0389818
```

Conclusion

We reject $H_0 : \sigma^2 \leq 1.2^2$. We have evidence to indicate that the variance of the length of metal pipes is more than 1.2^2 .

One-Sample Hypothesis Test for Population Variance (σ^2)

Assumptions: Y_1, Y_2, \dots, Y_n constitute a random sample from a Normal distribution with $E(Y_i) = \mu$ and $V(Y_i) = \sigma^2$.

Hypotheses:

$$H_0 : \sigma^2 = \sigma_0^2$$

$$H_a : \begin{cases} \sigma^2 > \sigma_0^2 & \text{(upper-tailed alternative)} \\ \sigma^2 < \sigma_0^2 & \text{(lower-tailed alternative)} \\ \sigma^2 \neq \sigma_0^2 & \text{(two-tailed alternative)} \end{cases}$$

Test statistic: $\chi^2 = \frac{(n-1)S^2}{\sigma_0^2}$

Rejection Region: $\begin{cases} \chi^2 > \chi_{\alpha}^2 & \text{upper-tailed RR} \\ \chi^2 < \chi_{1-\alpha}^2 & \text{lower-tailed RR} \\ \chi^2 > \chi_{\alpha/2}^2 \text{ or } \chi^2 < \chi_{1-\alpha/2}^2 & \text{two-tailed RR} \end{cases}$

Example 11.17.

[Car Battery Lifetime Variance Test] A manufacturer of car batteries claims that the life of his batteries is approximately Normally distributed with a standard deviation equal to 0.9 year. If a random sample of 10 of these batteries has a standard deviation of 1.2 years, do you think that $\sigma > 0.9$ year? Use a 0.05 level of significance.

Step 1. State hypotheses.

$$H_0 : \sigma^2 = 0.81$$

$$H_a : \sigma^2 > 0.81$$

Step 2. Compute test statistic.

$S^2 = 1.44$, $n = 10$, and

$$\chi^2 = \frac{(9)(1.44)}{0.81} = 16$$

Step 3. Find Rejection Region.

From the chi-squared table, the null hypothesis is rejected when $\chi^2 > 16.919$, where $\nu = 9$ degrees of freedom.

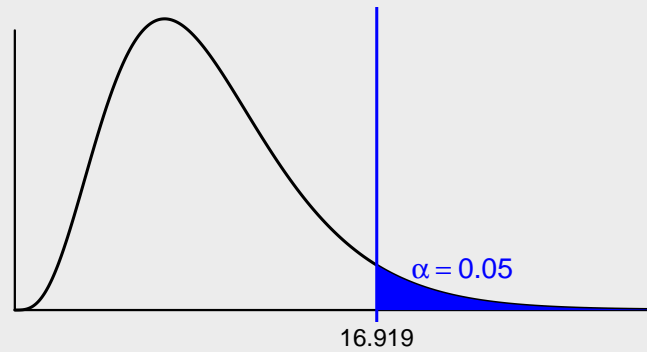


Figure 11.12: Right-tailed chi-squared distribution with critical value at 16.919.

Step 4. Conclusion.

The χ^2 statistic is not significant at the 0.05 level. We conclude that there is insufficient evidence to claim that $\sigma > 0.9$ year.

Chapter 12

Statistical Power

Definition 12.1 (Power of a Test).

*The probability that a fixed level α significance test will reject H_0 when a particular alternative value of the parameter is true is called the **power** of the test against that alternative.*

The statistical power of a test is its ability to detect an effect if it exists in reality. It is the probability of correctly rejecting H_0 when H_0 is false in reality.

$$\text{Power} = P(\text{reject } H_0 \mid H_0 \text{ false})$$

$$0 < \text{power} < 1$$

Power close to 1 (high power):
Test is good at detecting effects.

Power close to 0 (low power):
Test is not reliable (i.e., we expect the test will not reject H_0 when H_0 is false).

Power is affected by:

- **The effect**
(larger differences between reality and the null are easier to detect)
- **Sample size**
(larger samples increase power)
- **Significance level (α)**
(as α increases, easier to reject H_0)
- **Variability in data**
(lower variability, higher power)

Type I and II Errors

It is possible to make an incorrect conclusion on a hypothesis test.

Type I: Incorrectly reject H_0 when H_0 is true in reality.

Type II: Incorrectly fail to reject H_0 when H_0 is false in reality.

Reality vs Conclusion Table:

Conclusion	Reality	
	H_0 True	H_0 False
	Reject H_0	Type I (α)
	Fail to reject H_0	No error ✓
		No error ✓
		Type II (β)

Note: Type I errors are generally considered worse.

Let β be the probability of a Type II error. Then:

$$\text{Power} = 1 - \beta = 1 - P(\text{Type II})$$

Index

Overview, [1](#)

Statistics

Definition, [2](#)

Introduction, [1](#)