

# MA22004 - Statistics and Probability II

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# **Course Documents**



# Welcome

Welcome to MA22004 at the University of Dundee.

This course covers the basics of statistical inference. The first part of this document contains information of a practical nature regarding the mechanics of the course. The second part of this document contains the content.

These are some trying times.

Please try to stay healthy.

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These notes are available at [dundeemath.github.io/MA22004/](https://dundeemath.github.io/MA22004/) and also as a PDF (visit the page and click on the PDF icon to download).





# Course Guide

## Organisation

This module runs for 11 teaching weeks and is worth 20 SCQF credits (equivalently, 10 ECTS points). All organisation and teaching will be carried out by:



Dr Eric Hall  
ehall001@dundee.ac.uk  
Mathematics Division  
Room TBA, Fulton Building  
01382 TBA

This course uses Blackboard Ultra (look for course MA22004\_SEM0000\_2021) for communicating all announcements/deadlines and also for running online meetings. This course also uses Gradescope for submission of some of the continuous assessment items and Perusall for collaborative engagement with reading materials.

If you have a problem regarding the course, then you should make an appointment to see Dr Hall. You may also bring matters of concern about the course to the attention of the Mathematics Division Staff/Student Committee, which meets once each semester. A volunteer from Level 2 Mathematics will act as class representative to sit on the Staff/Student Committee (see Ultra for contact details).

## Timetable



Due to COVID19, these plans may be subject to change.

The delivery of this module consists of a blend of synchronous and asynchronous content delivered both in-person and online. On an average week, there will be seven planned teaching and learning activities.

Activity	Timetabled	Group	Hours	Delivery
Reading	asynchronous	individually & in groups	6	online
Investigation	asynchronous	individually	1	online
Seminar	synchronous	whole class	1	online
Computer Lab	asynchronous	individually	6	online
Workshop Preparation	asynchronous	individually or in groups	2	online
Workshop	synchronous	in groups	1	face-to-face
Office Hours	synchronous	in groups	1	online

The anticipated student effort is 200 hours over the length of the module. You are expected to be “present” for all synchronous timetabled activities except for the online office hours, which are optional. You may engage with the

asynchronous material at your own pace, keeping in mind to meet any deadlines for engagement and/or attainment that will be posted to Ultra and discussed.

## Pre-requisites

To take this course, you must have passed module MA12003 or equivalent.

## Syllabus

**Sampling Distributions** Mean and standard deviation of samples, sampling from a single population, sampling from two populations, shape of sampling distributions. Normal distribution,  $\chi^2$ -square distribution, F-distribution.

**Hypothesis tests** Null and Alternate hypotheses, inferences, confidence intervals, estimating means, proportions and standard deviations.

**Linear Regression** Least squares, assessing usefulness of a model, using a model.

**Industrial Quality Control** Control Charts, acceptance sampling.

**R software package** Appropriate use of computational software to carry out statistical and probabilistic calculations.

## Recommended Books

In addition to the course notes, here are some textbooks you may wish to consult.

- *Probability and Statistics for Engineering and the Sciences*, [Devore, 2016, §6-10, 12, 14, 16]
- *Probability and Statistics*, [DeGroot and Schervish, 2001, §7-10]
- *Mathematical statistics and data analysis*, [Rice, 2006, §6-12]
- *All of Statistics*, [Wasserman, 2004, Concise general reference]



You do not need to purchase these books.

## Assessment

The module will be *continuously* assessed using coursework and examinations. Deadlines, as well as test dates, will be posted on Ultra and announcements made in the class hours. The module assessment weighting is as follows.

Assessment	Weight
Assignments	20%
Midterm Exam 1	20%
Midterm Exam 2	20%
Final Exam	40%

## Coursework

Assessed coursework includes:

- six hand-in laboratory reports and
- weekly engagement with the reading material using Perusall.

There will also be alternative means of demonstrating your mastery of course material through:

- one (group) lab presentation and
- short seminar quizzes (announced in advance).

## Examinations

The **Midterm Exams** will be computer-assessed and will be one (1) hour in scope. These will likely be in weeks 4 and 8.

The **Final Exam** will be a two (2) hour hand-written exam that will be submitted using Gradescope. This process will be thoroughly discussed and trialled with a dummy exam in advance of the real submission. The Final Exam will be in week 11 (i.e., during the last week of the term).

To pass this module, you must:

- obtain an overall grade of at least D3 in the overall assessment **and**
- obtain a grade of at least M1 for the exam **and**
- obtain a grade of at least M1 for the coursework.

For those who fail the module, there may be an opportunity to take a two-hour resit examination paper at the next available exam diet.



Resit marks are based on the resit exam only.

Unless you have mitigating circumstances, if you fail to achieve a module grade of CF or above at first attempt, then you may not be permitted to resit the exam. Also, unless you have mitigating circumstances, any pass after a resit will be capped at a grade of D3 regardless of the weighted average mark obtained.

## Your Commitment

You should attend all synchronous timetabled sessions except on medical grounds or with the special permission of Dr Hall. If you are unable to attend the degree examination or complete elements of the coursework on time, then you should inform Dr Hall and submit a medical certificate. Medical certificates should be submitted to your School Office as soon as possible after the absence.



You must also submit a Mitigating Circumstances form to explain which aspects of assessment have been affected by your absence.

A Medical Certificate will only be taken into account if accompanied by a completed Mitigating Circumstances form that refers to the medical certificate.

## Approved Calculators

The Casio FX83 and the Casio FX85 are the only calculators approved for use in assessments in the School of Engineering, Physics and Mathematics.

## Study Support

If you are having difficulty with the course, you are encouraged to seek help at an early stage by making an appointment with Dr Hall. You may also obtain additional help from the Maths Base (see Ultra for details).

## Disability

The University of Dundee is committed to making reasonable, effective and appropriate accommodations to meet the needs of students with disabilities and to create an inclusive and barrier-free campus. If you require accommodation for a documented disability, then you are advised to register with Disability Services. Please communicate

any needs you may have directly with Dr Hall and as soon as possible to ensure timely management of any accommodations.

## **Academic Honesty**

Honesty in scholarship and research is integral to the integrity of the academic enterprise of any higher education institution. Therefore, all students at the University of Dundee must practice academic honesty. Academic dishonesty includes cheating, fabrication, plagiarism, and facilitating dishonesty. Cases of academic dishonesty will be subject to appropriate sanctions and ignorance of such standards is not sufficient evidence of lack of intent. Please see the *Code of Practice on Academic Misconduct by Students* for more information about what constitutes academic dishonesty.

## **End of Module Questionnaire**

You will have the opportunity to complete a confidential questionnaire regarding the content and presentation of the module periodically. These questionnaires form an important element in the University's Academic Standards procedures. Thank you in advance for your cooperation.

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# **Course Notes**



# Preliminaries

## Notation

Uppercase roman letters, e.g.,  $X$ , will typically denote random variables (rvs); lower case letters, e.g.,  $x$ , will denote a particular value (observation) of a rv. Rvs have probability distributions. Distributions are typically characterized by *parameters* which are fixed real numbers. Parameters describe population characteristics that are often unknown and must be estimated from data. Statistical inference is a tool that will help us to do this.



Statistical models comprise both rvs and parameters. Be careful not to confuse them!

## Abbreviations

Abbreviation	Expanded
pdf	probability density function
cdf	cumulative distribution function
rv	random variable
iid	independent and identically distributed
obs	observations
CI	confidence interval
df	degrees of freedom





# Chapter 1

## Sampling distributions

A **statistic** is a quantity that can be calculated from sample data. Prior to obtaining data, a statistic is an unknown quantity and is therefore a rv. We refer to the probability distribution for a statistic as a **sampling distribution** to emphasize how the distribution will vary across all possible sample data.

### 1.1 Normal distribution

Normal distributions play an important role in probability and statistics as they describes many natural phenomenon. For instance, the Central Limit Theorem tells us that sums of rvs are approximately normal in distribution.

**Definition 1.1.** A continuous rv  $X$  has a **normal distribution** with parameters  $\mu$  and  $\sigma^2$ , where  $-\infty < \mu < \infty$  and  $\sigma > 0$ , if  $X$  has pdf

$$f(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/(2\sigma^2)}, \quad -\infty < x < \infty.$$

We write  $X \sim N(\mu, \sigma^2)$ .

For  $X \sim N(\mu, \sigma^2)$ , it can be shown that  $E(X) = \mu$  and  $\text{Var}(X) = \sigma^2$ , that is,  $\mu$  is the *mean* and  $\sigma^2$  is the *variance* of  $X$ . The pdf takes the form of a bell-shaped curve that is symmetric about  $\mu$ . The value  $\sigma$  (*standard deviation*) is the distance from  $\mu$  to the inflection points of the curve. Thus, the position (location) and spread of the distribution depends on  $\mu$  and  $\sigma$ .

**Definition 1.2.** We say that  $X$  has a **standard normal distribution** if  $\mu = 0$  and  $\sigma = 1$  and we will usually denote standard Normal rvs by  $Z$  (why? tradition!).

#### 1.1.1 Some useful facts about Normals

Here are some useful facts about how to manipulate Normal rvs.

1. If  $X \sim N(\mu, \sigma^2)$ , then  $Z = (X - \mu)/\sigma \sim N(0, 1)$ .
2. If  $Z \sim N(0, 1)$ , then  $X = \mu + \sigma Z \sim N(\mu, \sigma^2)$ .
3. If  $X_i \sim N(\mu_i, \sigma_i^2)$  for  $i = 1, \dots, n$  are independent rvs, then

$$\sum_{i=1}^n X_i \sim N\left(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2\right).$$

In particular, we note that for differences of independent rvs  $X_1 \sim N(\mu_1, \sigma_1^2)$  and  $X_2 \sim N(\mu_2, \sigma_2^2)$  then the variances also add:

$$X_1 - X_2 \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2).$$

Probabilities  $P(a \leq X \leq b)$  are found by converting the problem in  $X \sim N(\mu, \sigma^2)$  to the *standard normal* distribution

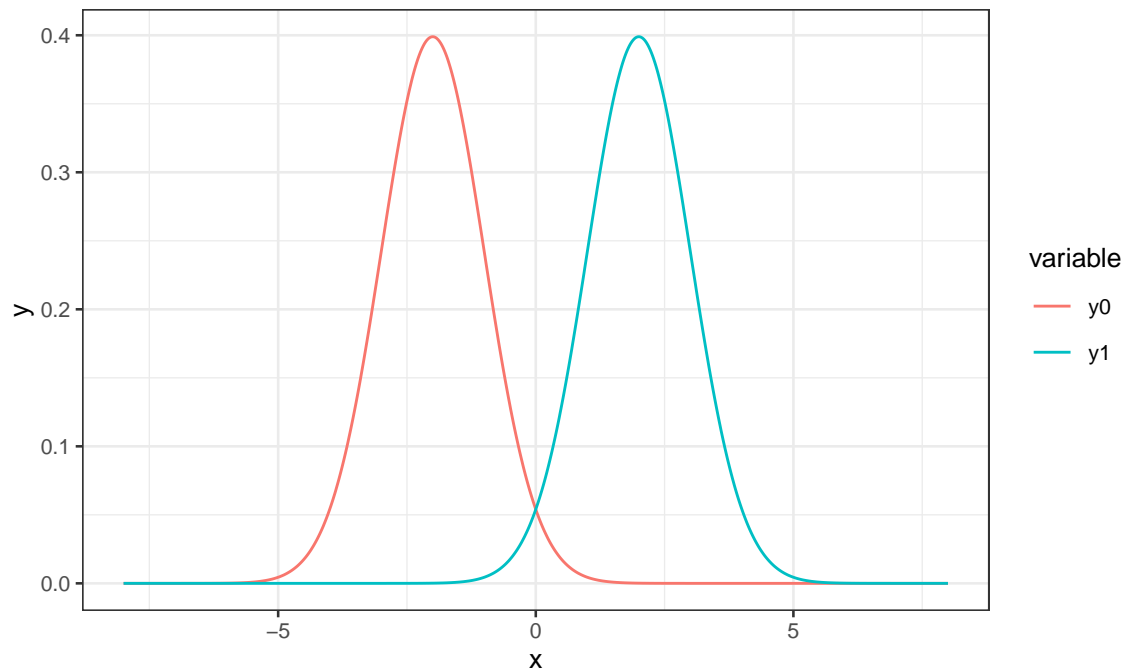


Figure 1.1: The pdfs of two normal rvs with different means and the same standard deviations.

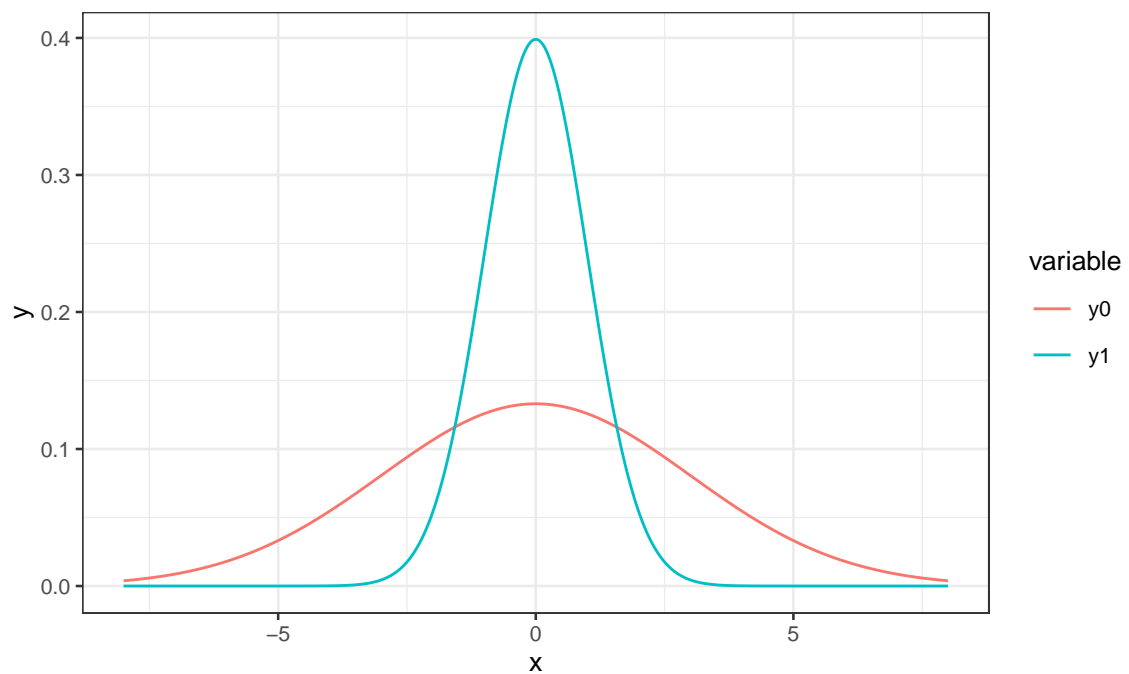


Figure 1.2: The pdfs of two normal rvs with the same means and different standard deviations.

$Z \sim N(0, 1)$  whose probability values  $\Phi(z) = P(Z \leq z)$  can then be looked up in a table. From (1.) above,

$$\begin{aligned} P(a < X < b) &= P\left(\frac{a - \mu}{\sigma} < Z < \frac{b - \mu}{\sigma}\right) \\ &= \Phi\left(\frac{b - \mu}{\sigma}\right) - \Phi\left(\frac{a - \mu}{\sigma}\right). \end{aligned}$$

This process is often referred to as *standardizing* (the normal rv).

**Example 1.1.** Let  $X \sim N(5, 9)$  and find  $P(X \geq 5.5)$ .

$$\begin{aligned} P(X \geq 5.5) &= P\left(Z \geq \frac{5.5 - 5}{3}\right) \\ &= P(Z \geq 0.1667) \\ &= 1 - P(Z \leq 0.1667) \\ &= 1 - \Phi(0.1667) \\ &= 1 - 0.5662 \\ &= 0.4338, \end{aligned}$$

where we look up the value of  $\Phi(z) = P(Z \leq z)$  in a table of standard normal curve areas.

Alternatively, we can use the `r` code:

```
pnorm(5.5, mean = 5, sd = 3, lower.tail = FALSE)
```

```
[1] 0.4338162
```

**TODO:** plot of area under normal curve (right tail) ◇

**Example 1.2.** Let  $X \sim N(5, 9)$  and find  $P(4 \leq X \leq 5.25)$ .

$$\begin{aligned} P(4 \leq X \leq 5.25) &= P\left(\frac{4 - 5}{3} \leq Z \leq \frac{5.25 - 5}{3}\right) \\ &= P(-0.3333 \leq Z \leq 0.0833) \\ &= \Phi(0.0833) - \Phi(-0.3333) \\ &= 0.5332 - 0.3694 \\ &= 0.1638. \end{aligned}$$

where we look up the value of  $\Phi(z) = P(Z \leq z)$  in a table of standard normal curve areas.

Alternatively, we can use the `r` code:

```
pnorm(5.25, mean = 5, sd = 3) - pnorm(4, mean = 5, sd = 3)
```

```
[1] 0.1637654
```

**TODO:** plot area under normal curve (interior) ◇

## 1.2 t distribution

Student's *t* distribution gets its peculiar name as it was first published under the pseudonym “Student”. This bit of obfuscation was to protect the identity of his employer, and thereby vital trade secrets, in a highly competitive and lucrative industry.

**Definition 1.3.** A continuous rv  $X$  has a **t distribution** with parameter  $\nu > 0$ , if  $X$  has pdf

$$f(x; \nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{x^2}{\nu}\right)^{-\frac{\nu+1}{2}}, \quad -\infty < x < \infty.$$

We write  $X \sim t(\nu)$ .

### 1.2.1 Properties of $t$ distributions

1. The density for  $t(\nu)$  is a bell-shaped curve centered at 0.
2. The density for  $t(\nu)$  is more spread out than the standard normal density (i.e., it has “fatter tails” than the normal).
3. As  $\nu \rightarrow \infty$ , the spread of the corresponding  $t(\nu)$  density converges to the standard normal density (i.e., the spread of the  $t(\nu)$  density decreases relative to the standard normal).

If  $X \sim t(\nu)$ , then  $E[X] = 0$  for  $\nu > 1$  (otherwise the mean is undefined).

## 1.3 $\chi^2$ distribution

The  $\chi^2$  distribution arises as the distribution of a sum of the squares of  $\nu$  independent standard normal rvs.

**Definition 1.4.** A continuous rv  $X$  has a  $\chi^2$  **distribution** with parameter  $\nu \in \mathbf{N}_>$ , if  $X$  has pdf

$$f(x; \nu) = \frac{1}{2^{\nu/2} \Gamma(\nu/2)} x^{(\nu/2)-1} e^{-x/2},$$

with support  $x \in (0, \infty)$  if  $\nu = 1$ , otherwise  $x \in [0, \infty)$ . We write  $X \sim \chi^2(\nu)$ .

The pdf  $f(x; \nu)$  of the  $\chi^2(\nu)$  distribution depends on a positive integer  $\nu$  referred to as the df. The density  $f(x; \nu)$  is positively skewed, i.e., the right tail is longer and hence the mass is concentrated to the left of the figure. The distribution becomes more symmetric as  $\nu$  increases. We denote critical values of the  $\chi^2(\nu)$  distribution by  $\chi_{\alpha, \nu}^2$ .



Unlike the normal and  $t$  distributions, the  $\chi^2$  distribution is not symmetric. This means that the critical values e.g.  $\chi_{.99, \nu}^2$  and  $\chi_{.01, \nu}^2$  are **not** equal. Hence, it will be necessary to look up both values for CIs based on  $\chi^2$  critical values.

If  $X \sim \chi^2(\nu)$ , then  $E[X] = \nu$  and  $\text{Var}[X] = 2\nu$ .

## 1.4 F distribution

The F distribution arises as a test statistic when comparing population variances and in ANOVA.

**Definition 1.5.** A continuous rv  $X$  has an **F distribution** with df parameters  $\nu_1$  and  $\nu_2$ , if  $X$  has pdf

$$f(x; \nu_1, \nu_2) = \frac{\Gamma\left(\frac{n+m}{2}\right) n^{n/2} m^{m/2}}{\Gamma\left(\frac{n}{2}\right) \Gamma\left(\frac{m}{2}\right)} \frac{x^{n/2-1}}{(m + nx)^{(n+m)/2}}.$$

**Theorem 1.1.** If  $X_1 \sim \chi^2(\nu_1)$  and  $X_2 \sim \chi^2(\nu_2)$  are independent rvs, then the rv

$$F = \frac{X_1/\nu_1}{X_2/\nu_2} \sim F(\nu_1, \nu_2),$$

that comprises the ratio of two  $\chi^2$  rvs divided by their respective df has an  $F(\nu_1, \nu_2)$  distribution.

## Chapter 2

# Basics of statistical inferences

We discuss point estimation, confidence intervals, and hypothesis testing in Sections 2.1, 2.2, and 2.3, respectively. These three tools will form the basis for making inferences about a population.

### 2.1 Point estimation

Statistical inference seeks to draw conclusions about the characteristics of a population from data. For example, suppose we are botanists interested in taxonomic classification of iris flowers. Let  $\mu$  denote the true average petal length (in cm) of the *Iris setosa* (AKA the bristle-pointed iris). The parameter  $\mu$  is a characteristic of the whole population of the *setosa* species. Before we collect data, the petal lengths of  $m$  independent *setosa* flowers are denoted by rvs  $X_1, X_2, \dots, X_m$ . Any function of the  $X_i$ 's, such as the sample mean,

$$\bar{X} = \frac{1}{m} \sum_{i=1}^m X_i, \quad (2.1)$$

or the sample variance,

$$S^2 = \frac{1}{m-1} \sum_{i=1}^m (X_i - \bar{X})^2,$$

is also a rv.

Suppose we actually find and measure the petal length of 50 independent *setosa* flowers resulting in observations  $x_1, x_2, \dots, x_{50}$ ; the distribution (counts) of 50 such petal length measurements are displayed in Figure 2.1. The sample mean  $\bar{x}$  for petal length can then be used to draw a conclusion about the (true) value of the population mean  $\mu$ . Based on the data in Figure 2.1 and using (2.1), the value of the sample mean is  $\bar{x} = 1.462$ . The value  $\bar{x}$  provides a “best guess” or point estimate for the true value of  $\mu$  based on the  $m = 50$  samples.



The botanist Edgar Anderson's **Iris Data** contains 50 obs. of four features (sepal length [cm], sepal width [cm], petal length [cm], and petal width [cm]) for each of three plant species (*setosa*, *virginica*, *versicolor*) for 150 obs. total. This data set can be accessed in `r` by loading `library(datasets)` and then calling `data(iris)`.

**Definition 2.1.** A **point estimate** of a parameter  $\theta$  (recall: a fixed, unknown quantity) is a single number that we regard as a sensible value for  $\theta$ . Consider iid  $X_1, X_2, \dots, X_m \sim F(\theta)$ . A **point estimator**  $\hat{\theta}_m$  of  $\theta$  is obtained by selecting a suitable statistic  $g$ ,

$$\hat{\theta}_n = g(X_1, \dots, X_m).$$

A point estimate  $\hat{\theta}_m$  can then be computed from the estimator using sample data.

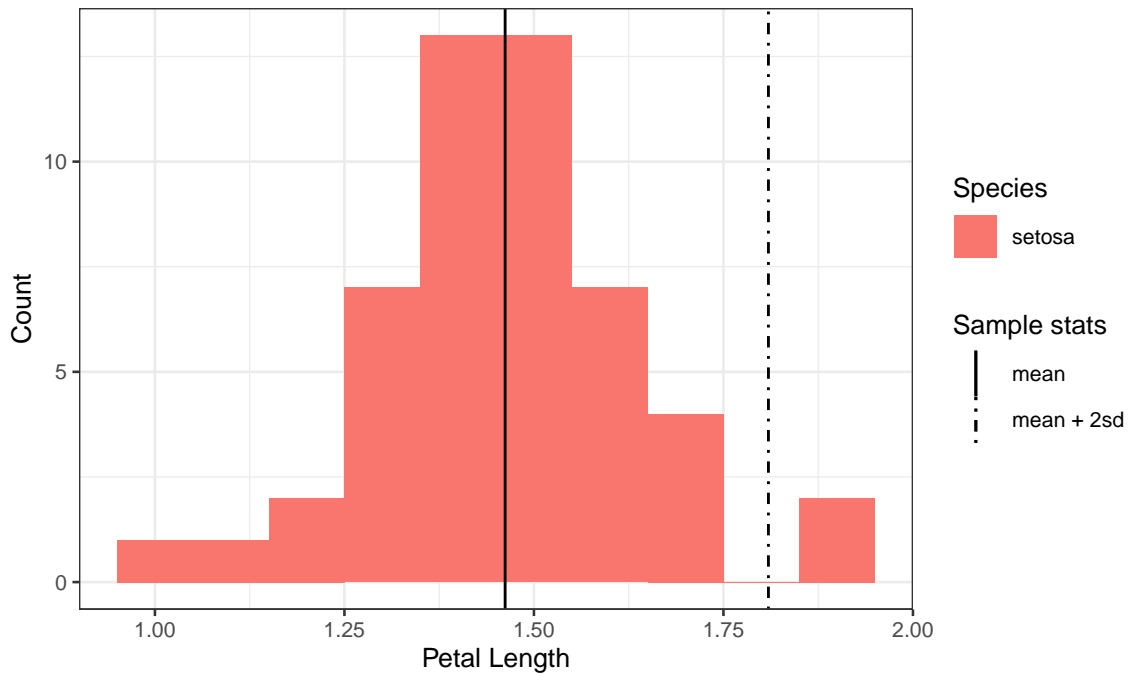


Figure 2.1: The distribution (counts) of  $m = 50$  *setosa* petal length measurements.



The symbol  $\hat{\theta}_m$  (or simply  $\hat{\theta}$  when the sample size  $m$  is clear from context) is typically used to denote both the estimator and the point estimate resulting from a given sample. Note that writing, e.g.,  $\hat{\theta} = 42$  does not indicate how the point estimate was obtained. Therefore, it is essential to report both the estimator and the resulting point estimate.

Definition 2.1 does not say how to select an appropriate statistic. For the *setosa* example, the sample mean  $\bar{X}$  is suggested as a good estimator of the population mean  $\mu$ . That is,  $\hat{\mu} = \bar{X}$  or “the point estimator of  $\mu$  is the sample mean  $\bar{X}$ ”. Here, while  $\mu$  and  $\sigma^2$  are fixed quantities representing characteristics of the population,  $\bar{X}$  and  $S^2$  are rvs with sampling distributions. If the population is *normally distributed* or if the *sample is large* then the sampling distribution for  $\bar{X}$  has a known form:  $\bar{X}$  is normal with mean  $\mu_{\bar{X}} = \mu$  and variance  $\sigma_{\bar{X}}^2 = \sigma^2/m$ , i.e.,

$$\bar{X} \sim N(\mu, \sigma^2/m),$$

where  $m$  is the sample size and  $\mu$  and  $\sigma$  are the (typically unknown) population parameters.

**Example 2.1.** Let us consider the heights (measured in inches) of 31 black cherry trees (sorted, for your enjoyment) in Table 2.1.

Table 2.1: Observations of  $m = 31$  felled black cherry trees.

Height [in]
63, 64, 65, 66, 69, 70, 71, 72, 72, 74, 74, 75, 75, 75, 76, 76, 77, 78, 79, 80, 80, 80, 80, 80, 81, 81, 82, 83, 85, 86, 87



The **Cherry Tree Data** contains 31 obs. of three features (diameter, height, and volume) and can be accessed in `r` by loading `library(datasets)` and then calling `data(trees)`.

The quantile-quantile plot in Figure 2.2, that compares the quantiles of this data to the quantiles of a normal dis-

tribution, is fairly straight.<sup>1</sup> Therefore, we assume that the distribution of black cherry tree heights is (at least approximately) normal with a mean value  $\mu$ ; i.e., that the population of heights is distributed  $N(\mu, \sigma^2)$  where  $\mu$  is a parameter to be estimated and  $\sigma^2$  is unknown. The observations  $X_1, \dots, X_{31}$  are then assumed to be a random sample from this normal distribution, i.e., iid

$$X_1, \dots, X_{31} \sim N(\mu, \sigma^2).$$

Consider the following three different estimators and the resulting point estimates for  $\mu$  based on the 31 samples in Table 2.1.

- Estimator (sample mean)  $\bar{X}$  as in (2.1) and estimate  $\bar{x} = \sum x_i/n = 2356/31 = 76$ .
- Estimator (average of extreme heights)  $\tilde{X} = [\min(X_i) + \max(X_i)]/2$  and estimate  $\tilde{x} = (63 + 87)/2 = 75$ .
- Estimator (10% trimmed mean – i.e., in this instance exclude the smallest and largest three values)  $\bar{X}_{\text{tr}(10)}$  and estimate  $\bar{x}_{\text{tr}(10)} = (2356 - 63 - 64 - 65 - 87 - 86 - 85)/25 = 76.24$ .

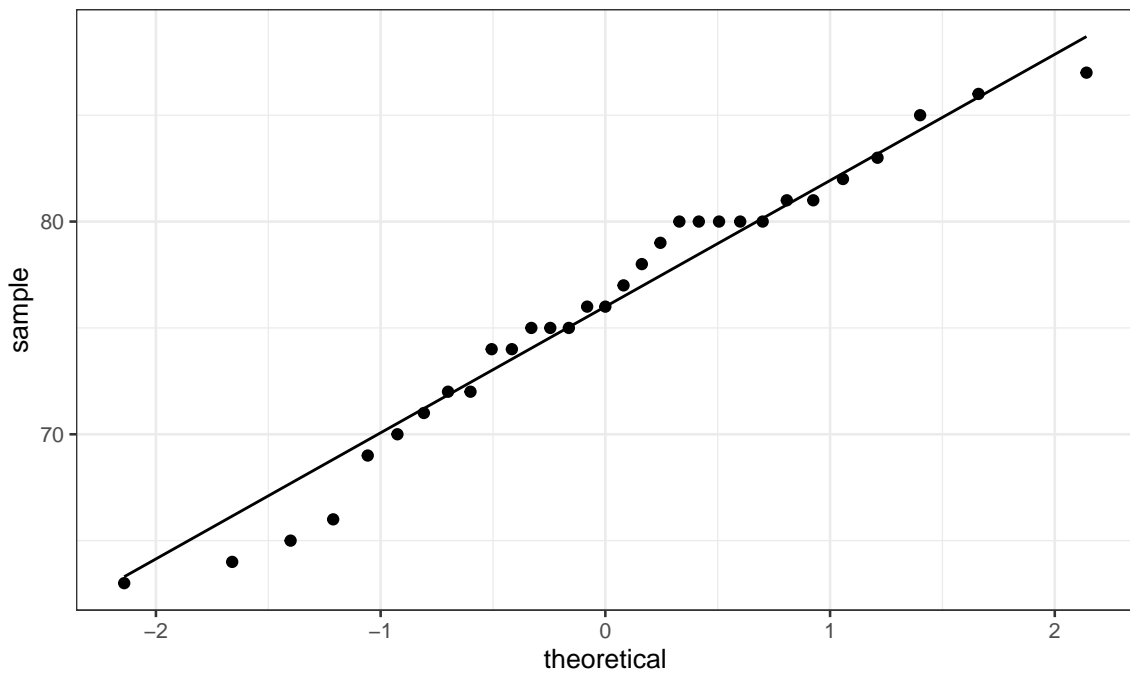


Figure 2.2: Normal quantile-quantile plot for the **Cherry Tree Data**.

Each estimator above uses a different notion of center for the sample data, i.e., a different statistic. An interesting question to think about is: which estimator will tend to produce estimates closest to the true parameter value? Will the estimators work universally well for all distributions?  $\diamond$

In addition to reporting a point estimate together with its estimator, some indication of its precision should be given. One measure of the precision of an estimate is its standard error.

**Definition 2.2.** The **standard error** of an estimator  $\hat{\theta}$  is the standard deviation

$$\sigma_{\hat{\theta}} = \sqrt{\text{Var}(\hat{\theta})}.$$

Often, the standard error depends on unknown parameters and must also be estimated. The **estimated standard error** is denoted by  $\hat{\sigma}_{\hat{\theta}}$  or simply  $s_{\hat{\theta}}$ .<sup>2</sup>

<sup>1</sup>How do we tell whether a population is normal? Constructing a normal quantile-quantile plot is one way of assessing whether a normality assumption is reasonable; such a plot compares the quantiles of the sample data  $x_i$  against the (theoretical) standard normal quantiles. If the sample data is consistent with a sample from a normal distribution, then the points will lie on a straight line (more or less). Below we display the QQ plot comparing quantiles of cherry tree heights from 2.1 to normal quantiles.

<sup>2</sup>The standard error is sometimes denoted  $\text{se} = \text{se}(\hat{\theta})$  and the estimated standard error by  $\widehat{\text{se}}$ .

## 2.2 Confidence intervals

An alternative to reporting a point estimate for a parameter is to report an interval estimate suggesting an entire range of plausible values for the parameter of interest. A confidence interval is an interval estimate that makes a probability statement about the degree of reliability, or the confidence level, of the interval. The first step in computing a confidence interval is to select the confidence level  $\alpha$ . A popular choice is a 95% confidence interval which corresponds to level  $\alpha = 0.05$ .

**Definition 2.3.** A  $100(1 - \alpha)\%$  **confidence interval** for a parameter  $\theta$  is a *random* interval  $C_m = (L_m, U_m)$ , where  $L_m = \ell(X_1, \dots, X_m)$  and  $U_m = u(X_1, \dots, X_m)$  are functions of the data, such that

$$P_\theta(L_m < \theta < U_m) = 1 - \alpha, \quad (2.2)$$

for all  $\theta \in \Theta$ .

My favorite interpretation of a confidence interval is due to [Wasserman, 2004, p 92]:

On day 1, you collect data and construct a 95 percent confidence interval for a parameter  $\theta_1$ . On day 2, you collect new data and construct a 95 percent confidence interval for an unrelated parameter  $\theta_2$ . On day 3, you collect new data and construct a 95 percent confidence interval for an unrelated parameter  $\theta_3$ . You continue this way constructing confidence intervals for a sequence of unrelated parameters  $\theta_1, \theta_2, \dots$ . Then 95 percent of your intervals will trap the true parameter value. There is no need to introduce the idea of repeating the same experiment over and over.

This interpretation makes clear that a confidence interval is not a probability statement about the parameter  $\theta$ . In Definition 2.3, note that  $\theta$  is fixed ( $\theta$  is not a rv) and the interval  $C_m$  is random. After data has been collected and a point estimator has been calculated, the resulting CIs either contain the true parameter value or they do not, as illustrated in Figure 2.3.

## 2.3 Hypothesis testing

Sections 2.1 and 2.2 reviewed how to estimate a parameter by a single number (point estimate) or range of plausible values (confidence interval), respectively. Next we discuss methods for determining which of two contradictory claims, or **hypotheses**, about a parameter is correct.

**Definition 2.4.** The **null hypothesis**, denoted by  $H_0$ , is a claim that we initially assume to be true by default. The **alternative hypothesis**, denoted by  $H_a$ , is an assertion that is contradictory to  $H_0$ .

Typically, we shall consider hypothesis concerning a parameter  $\theta \in \Theta$  taking values in a parameter space. The statistical hypothesis are contradictory in that  $H_0$  and  $H_a$  divide  $\Theta$  into two disjoint sets. For example, for a statistical hypothesis regarding the *equality* of a parameter  $\theta$  with a fixed quantity  $\theta_0$ , the null and alternative hypotheses will usually take one of the following forms in Table 2.2.

Table 2.2: Typical null hypothesis and corresponding alternative hypothesis.

Null hypothesis	Alternative hypothesis	Test form
$H_0 : \theta = \theta_0$	$H_a : \theta \neq \theta_0$	two-sided test
$H_0 : \theta \leq \theta_0$	$H_a : \theta > \theta_0$	one-sided test
$H_0 : \theta \geq \theta_0$	$H_a : \theta < \theta_0$	one-sided test

These pairs of hypothesis are associated with either a one-sided or two-sided test; what this means will become clear in the sequel. The value  $\theta_0$ , called the **null value**, separates the alternative from the null.

**Definition 2.5.** A **hypothesis test** asks if the available data provides sufficient evidence to reject  $H_0$ . If the observations disagree with  $H_0$ , then we reject the null hypothesis. If the sample evidence does not strongly contradict  $H_0$ , then we continue to believe  $H_0$ . The two possible conclusions of a hypothesis test are: *reject  $H_0$*  or *fail to reject  $H_0$* .<sup>3</sup>

<sup>3</sup>We comment that *fail to reject  $H_0$*  is sometimes phrased *retain  $H_0$*  or (perhaps less accurately) *accept  $H_0$* . Why not just *accept* the null and move on with our lives? Well, if I search the Highlands for the Scottish wildcat (critically endangered) and fail to find any, does that prove they do not exist?



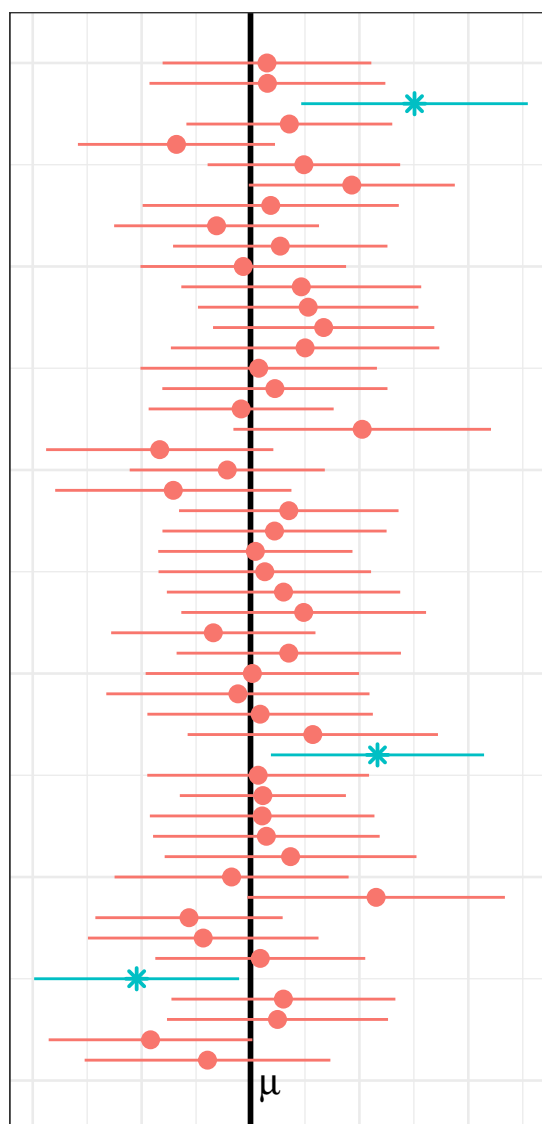


Figure 2.3: Fifty 95% CIs for a population mean  $\mu$ . After a sample is taken, the computed interval estimate either contains  $\mu$  or it does not (asterisk identify intervals that do not include  $\mu$ ). When drawing such a large number of 95% CIs, we would anticipate that approximately 5% (ca. 2 or 3) would fail to cover the true parameter  $\mu$ .

A procedure for carrying out a hypothesis test is based on specifying two additional items: a test statistic and a corresponding rejection region. A **test statistic**  $T$  is a function of the sample data (like an estimator). The decision to reject or fail to reject  $H_0$  will involve computing the test statistic. The **rejection region**  $R$  is the collection of values of the test statistic for which  $H_0$  is to be rejected in favor of the alternative, e.g.,

$$R = \{x : T(x) > c\},$$

where  $c$  is referred to as a **critical value**. If a given sample falls in the rejection region, then we reject  $H_0$ . That is, if  $X \in R$  (e.g., the calculated test statistic exceeds some critical value), then we reject  $H_0$ . The alternative is that  $X \notin R$  and in this case we fail to reject the null.

When carrying out a hypothesis test, two types of errors can be made. The basis for choosing a rejection region involves considering these errors.

**Definition 2.6.** A **type I** error occurs if  $H_0$  is rejected when  $H_0$  is actually true. A **type II** error is made if we fail to reject  $H_0$  when  $H_0$  is actually false.

If the maximal type I error of a test is fixed at an acceptably small value, then the type II error decreases as the sample size increases. In particular, a conclusion is reached in a hypothesis test by selecting a **significance level**  $\alpha$  for the test linked to the maximal type I error rate. Typically,  $\alpha = 0.10, 0.05, 0.01$ , or  $0.001$  is selected for the significance level.

**Definition 2.7.** A  **$P$ -value** is the probability, calculated assuming  $H_0$  is true, of obtaining a value of the test statistic at least as contradictory to  $H_0$  as the value calculated from the sample data.

Smaller  $P$ -values indicate stronger evidence against  $H_0$  in favor of  $H_a$ . If  $P \leq \alpha$  then we reject  $H_0$  at significance level  $\alpha$ . If  $P \geq \alpha$  we fail to reject  $H_0$  at significance level  $\alpha$ .



The  $P$ -value is a probability calculated assuming that  $H_0$  is true. However, the  $P$ -value is **not** the probability that:

1.  $H_0$  is TRUE,
2.  $H_0$  is FALSE, or
3. a wrong conclusion is reached.

**Proposition 2.1.** *The hypothesis test procedure that*

$$\begin{cases} \text{rejects } H_0 & \text{if } P \leq \alpha \\ \text{fails to reject } H_0 & \text{otherwise} \end{cases}$$

*has*  $P(\text{type I error}) = \alpha$ .

**Example 2.2.** Churchill claims that he will receive half the votes for the House of Commons seat for the constituency of Dundee.<sup>4</sup> If we do not believe Churchill's claim and we are doubtful of his popularity, then we would seek to test an alternative hypothesis. How should we write down our research hypotheses?

If we let  $p$  be the fraction of the population voting for Churchill, then we have the null hypothesis,

$$H_0 : p = 0.5,$$

and the alternative hypothesis (we believe Churchill is less popular than he claims),

$$H_a : p < 0.5.$$

Support for the alternative hypothesis is obtain by showing lack of support for it's converse hypothesis (the null hypothesis).  $\diamond$

<sup>4</sup>Sir Winston Churchill was Member of Parliament for Dundee from 1908–1922. [W]

**Example 2.3.** Suppose that  $m = 15$  voters are selected from Dundee and  $X$ , the number favoring Churchill, is recorded. Based on observing  $X$ , we construct a rejection region  $R = \{x : x \leq k\}$ . If  $k$  is small compared to  $m$ , then the rejection region would provide pretty strong evidence to reject  $H_0$ . How should one choose the rejection region?

Assume now that  $m = 15$  voters are polled and that we select  $k = 2$  to have a rejection region  $R = \{x \leq 2\}$ . For this choice of  $k$ , the rejection region  $R$  provides strong support to reject  $H_0$ . If we assume the null hypothesis is true, then we would expect that approximately half of the 15 voters (ca. 7) would plump for Churchill. Observing  $x = 0$ ,  $x = 1$  or  $x = 2$  (the values that would place us in the rejection region) would provide strong evidence *against*  $H_0$ .

We can calculate the probability of a type I error. From the definition of type I error,

$$\begin{aligned}\alpha &= P(\text{type I error}) \\ &= P(\text{rejecting } H_0 \text{ when } H_0 \text{ is true}) \\ &= P(X \in R \text{ when } H_0 \text{ is true}) \\ &= P(X \leq 2 \text{ when } p = 0.5).\end{aligned}$$

Since  $X \sim \text{Binom}(15, 0.50)$ ,<sup>5</sup> we calculate that  $\alpha = 0.00369$ . Thus, for this particular choice of rejection region  $R$ , the risk of concluding that Churchill will lose if in fact he is the winner is very small.

For this rejection region, how good is the test at protecting us from type II errors, i.e., concluding that Churchill is the winner if in fact he will lose? Suppose that Churchill receive 25 of the votes ( $p = 0.25$ ). The probability of a type II error  $\beta$ ,

$$\begin{aligned}\beta &= P(\text{type II error}) \\ &= P(\text{fail to reject } H_0 \text{ when } H_0 \text{ false}) \\ &= P(X \notin R \text{ when } H_0 \text{ false}) \\ &= P(X > 2 \text{ when } p = 0.3).\end{aligned}$$

For  $X \sim \text{Binom}(15, 0.25)$ , we calculate  $\beta = 0.764$ . If we use  $R = \{x \leq 2\}$  then our test will lead us to conclude that Churchill is the winner with probability 0.764 even if  $p$  is as low as 0.25!

If we repeat these calculations for  $R^* = \{x \leq 5\}$ , we find  $\alpha = 0.151$  versus  $\beta = 0.148$ , even if  $p$  is as low as 0.25, which is a much better balance between type I and type II errors.  $\diamond$



To summarize, the elements of a statistical test are:

1. Null hypothesis ( $H_0$ )
2. Alternative hypothesis ( $H_a$ )
3. Test statistic
4. Rejection region
5. Significance level ( $\alpha$ )

---

<sup>5</sup> $X$  is a binomial random variable because it can be modeled as  $m$  independent Bernoulli trials each with probability  $p$  of success (i.e. votes Churchill) as long as the sample size  $m$  is much smaller than the population of Dundee. If we had the means to canvas nearly the whole population, what goes wrong conceptually?



## Chapter 3

# Inferences based on a single sample

In a few situations we can derive the sampling distribution for the statistic of interest and use this as the basis for constructing confidence intervals and hypothesis tests. Presently we estimate population means  $\mu$  in Section 3.1, population proportions  $p$  in Section 3.2, and population variances  $\sigma^2$  in Section 3.3 in some special cases.

### 3.1 Estimating means

If the parameter of interest is the population mean  $\theta = \mu$ , then what can be said about the distribution of the sample mean estimator  $\hat{\theta} = \bar{X}$  in (2.1)? We will consider three cases,

1. normal population with known  $\sigma^2$ ,
2. any population with unknown  $\sigma^2$ , when the sample size  $m$  is large,
3. normal population with unknown  $\sigma^2$ , when the sample size  $m$  is small,

where the form of the confidence interval and hypothesis test statistic for  $\mu$  can be derived using the approximate normality of the sample mean.

In general, the confidence intervals for the mean based on normality theory will have the form:

$$\text{point estimate } \mu \pm (\text{critical value of reference dist.}) \cdot (\text{precision of point estimate}), \quad (3.1)$$

where the reference distribution will be the standard normal (for 1. and 2.) and the Student's  $t$  distribution (for 3.). The critical value corresponds to the value under the reference distribution that yields the two-sided (symmetric) tail areas summing to  $1 - \alpha$ .

#### 3.1.1 Mean of a normal population with known variance

When sampling from a normal population with known mean and variance, the estimator for the sample mean is also normal with mean  $\mu$  and variance  $\sigma^2/m$  where  $m$  is the sample size. Standardizing,

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{m}} \sim N(0, 1) \quad (3.2)$$

we see that

$$P\left(-z_{\alpha/2} < \frac{\bar{X} - \mu}{\sigma/\sqrt{m}} < z_{\alpha/2}\right) = 1 - \alpha.$$

Based on knowing the sampling distribution of the estimator, we state the following CI.

**Definition 3.1.** A  $100(1 - \alpha)\%$  **confidence interval** for the mean  $\mu$  of a normal population when the value of  $\sigma^2$  is known is given by

$$\left(\bar{x} - z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{m}}, \bar{x} + z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{m}}\right), \quad (3.3)$$

or  $\bar{x} \pm z_{\alpha/2} \cdot \sigma/\sqrt{m}$ , where  $m$  is the sample size.

The CI for the mean (3.9) can be expressed (cf. (3.1)) as

$$\text{point estimate } \mu \pm (z \text{ critical value}) \cdot (\text{standard error of mean}).$$

The  $z$  critical value is related to the tail areas under the standard normal curve; we need to find the  $z$ -score having a cumulative probability equal to  $1 - \alpha$  according to Definition 2.3.

**Example 3.1.** Consider 400 samples from a normal population with a known standard deviation  $\sigma = 17000$  with mean  $\bar{x} = 20992$  (as depicted in 3.1). How do we construct a 95% confidence interval for  $\mu$ ?

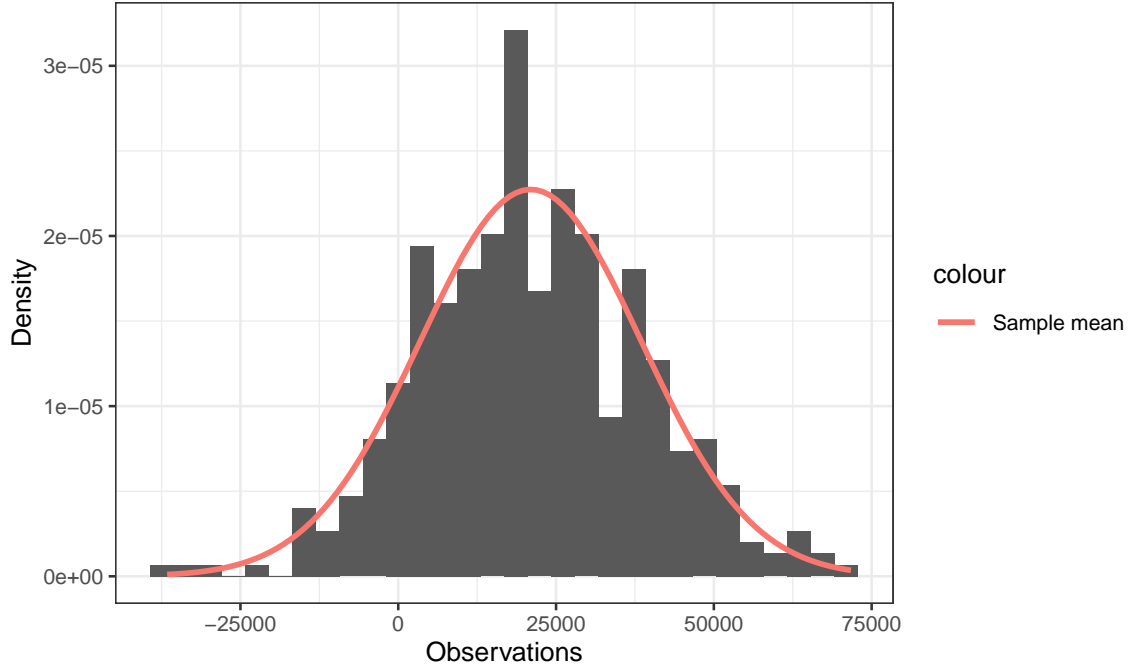


Figure 3.1: 400 samples from a normal population with known variance  $\sigma = 17000$  together with the corresponding (normal) sampling distribution for the observed mean.

For  $\alpha = 0.05$ , the critical value  $z_{0.025} = 1.96$ ; this value can be found by looking in a table of critical  $z$  values or using the `r` code `qnorm(1 - .05/2)`. From Definition 3.1,

$$\begin{aligned} \left( \bar{x} - z_{\alpha/2} \frac{\sigma}{\sqrt{m}}, \bar{x} + z_{\alpha/2} \frac{\sigma}{\sqrt{m}} \right) &= \left( 20992 - 1.96 \frac{17000}{\sqrt{400}}, 20992 + 1.96 \frac{17000}{\sqrt{400}} \right) \\ &= (19326, 22658). \end{aligned}$$

The data above was generated with a true population parameter  $\mu = 21500$ , and, incidentally, the CI actually contains the parameter value.  $\diamond$

As noted in (3.1) and (3.9), the width of a CI is related to the estimator's precision. The confidence level (or reliability) is inversely related to this precision. When the population is normal and the variance is known, then an appealing strategy is to determine the sample size necessary to achieve a desired confidence level and precision. A general formula for the sample size  $m^*$  necessary to achieve an interval width  $w$  is obtained at confidence level  $\alpha$  is obtained by equating  $w$  to  $2z_{\alpha/2} \cdot \sigma / \sqrt{m^*}$  and then solving for  $m^*$ .

**Proposition 3.1.** The sample size  $n$  required to achieve a CI for  $\mu$  with width  $w$  at level  $\alpha$  is given by,

$$m^* = \left( 2z_{\alpha/2} \cdot \frac{\sigma}{w} \right)^2.$$

From Proposition 3.1, we see that the smaller the desired  $w$  then the larger  $m^*$  must be (and subsequently, the more effort that must be allocated to data collection).

**Example 3.2.** In Example 3.1 we identified a 95% confidence interval for a normal population with known variance. The range (width) of that interval was  $22658 - 19326 = 3332$ . By how much would  $m$  need to increase to halve the interval width?

Using Proposition 3.1,

$$m = \left(2 \cdot 1.96 \cdot \frac{17000}{1666}\right)^2 = (40)^2 = 1600.$$

Thus, we find that for the same level  $\alpha = 0.05$ , we would need to quadruple our original sample size to halve the interval. It is expensive to remove uncertainty!  $\diamond$

Suppose now that we would like to consider a hypothesis test for the population mean, such as  $H_0 : \mu = \mu_0$ . Starting from (3.2) and assuming that the null hypothesis is true, we find

$$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{m}}.$$

The statistic  $Z$  measures the distance (measured in units of  $\text{sd } \bar{X}$ ) between  $\bar{X}$  and its expected value under the null hypothesis. We will use the statistic  $Z$  to determine if there is substantial evidence against  $H_0$  i.e. if the distance is too far in a direction consistent with  $H_a$ .

**Proposition 3.2.** Assume that we take a sample of size  $m$  from a normal population with known variance  $\sigma^2$ .

For the null hypothesis  $H_0 : \mu = \mu_0$ , we consider the test statistic

$$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{m}}. \quad (3.4)$$

If the alternative is  $H_a : \mu > \mu_0$ , then  $P = 1 - \Phi(z)$ .

If the alternative is  $H_a : \mu < \mu_0$ , then  $P = \Phi(z)$ .

If the alternative is  $H_a : \mu \neq \mu_0$ , then  $P = 2(1 - \Phi(|z|))$ .

We recall that  $\Phi(z)$  is the area in the lower tail of the standard normal density, i.e., to the *left* of the calculated value of  $z$ . Thus  $1 - \Phi(z)$  is the area in the upper tail and  $2(1 - \Phi(|z|))$  is the sum of the area in the tails (corresponding to  $\pm z$ ).

**Example 3.3.** Let's return to the data in Example 3.1, where we sample from a normal population with a known standard deviation  $\sigma = 17000$ . Suppose that someone claims the true mean is  $\mu_0 = 20000$ . Does our sample mean  $\bar{x} = 20992$  based on  $m = 400$  samples provide evidence to contradict this claim at the  $\alpha = 0.05$  level?

The first thing to record is our parameter of interest  $\mu$ , the true population mean. The null hypothesis, which we assume to be true, is

$$H_0 : \mu = 20000,$$

and the alternative hypothesis is

$$H_a : \mu \neq 20000,$$

since we are concerned with a deviation in either direction from  $\mu_0$ .

Since the population is normal with known variance, we compute the test statistic:

$$z = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{m}} = \frac{20992 - 20000}{17000/\sqrt{400}} = 1.167.$$

That is, the sample mean  $\bar{x}$  we observed is about 1 standard deviation above what we would expect under  $H_0$ . Consulting 3.2, we see that a two-tailed test is indicated for this particular  $H_a$ , and that the  $P$ -value is the area,<sup>1</sup>

$$P = 2(1 - \Phi(1.167)) = 2(0.1216052) = 0.2432.$$

Thus, since  $P = 0.2432 > 0.05 = \alpha$ , we fail to reject  $H_0$  at the level 0.05. The data does not support the claim that the true population mean differs from the value 20000 at the 0.05 level.  $\diamond$

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<sup>1</sup>Note  $\Phi(z)$  is found by calling `pnorm(z)` in `r`.

### 3.1.2 Mean of a population with unknown variance (large-sample)

Consider samples  $X_1, \dots, X_m$  from a population with mean  $\mu$  and variance  $\sigma^2$ . Provided that  $m$  is large enough, the Central Limit Theorem implies that the estimator for the sample mean  $\bar{X}$  in (2.1) has *approximately* a normal distribution. Then

$$P\left(-z_{\alpha/2} < \frac{\bar{X} - \mu}{\sigma/\sqrt{m}} < z_{\alpha/2}\right) \approx 1 - \alpha, \quad (3.5)$$

since the transformed variable has approximately a standard normal distribution. Thus, computing a point estimate based on a large  $m$  of samples yields a CI for the population parameter  $\mu$  at an *approximate* confidence level  $\alpha$ . However, it is often the case that the variance is unknown. When  $m$  is large, replacing the population variance  $\sigma^2$  by the sample variance  $S^2$  in (2.1) will not typically introduce too much additional variability.

**Proposition 3.3.** *For large sample size  $m$ , an approximate  $100(1 - \alpha)\%$  confidence interval for the mean  $\mu$  of any population when the variance is unknown is given by*

$$\left(\bar{x} - z_{\alpha/2} \cdot \frac{s}{\sqrt{m}}, \bar{x} + z_{\alpha/2} \cdot \frac{s}{\sqrt{m}}\right), \quad (3.6)$$

or  $\bar{x} \pm z_{\alpha/2} \cdot s/\sqrt{m}$ .

The CI for the mean (3.6) applies regardless of the shape of the population distribution so long as the number of samples is large. A rule of thumb is that  $m > 40$  is sufficient. In words, the CI (3.6) can be expressed (cf. (3.1)) as

point estimate  $\mu \pm (z \text{ critical value}) \cdot (\text{estimated standard error of mean})$ .

Typically, a large-sample CI for a general parameter  $\theta$  holds that is similar in nature to (3.6) for any estimator  $\hat{\theta}$  that satisfies: (1) approximately normal in distribution, (2) approximately unbiased, and (3) an expression for the standard error is available.

To conduct a large-sample hypothesis test regarding the population mean  $\mu$ , we consider the test statistic

$$Z = \frac{\bar{X} - \mu_0}{S/\sqrt{m}} \quad (3.7)$$

under the null hypothesis. When the number of samples  $m$  is large (say  $m > 40$ ) then  $Z$  will be approximately normal. Substituting this test statistic  $Z$  for (3.4), we follow Proposition 3.2 to determine how to calculate the  $P$ -value.

### 3.1.3 Mean of a normal population with unknown variance

In Section 3.1.1, we considered samples  $X_1, \dots, X_n$  from a normal population with a known  $\mu$  and  $\sigma^2$ . In contrast, here we consider samples from a normal population and assume the population parameters  $\mu$  and  $\sigma^2$  are unknown. If the number of samples is large, the discussion in Section 3.1.2 indicates that the rv  $Z = (\bar{X} - \mu)\sqrt{n}/S$  has approximately a standard normal distribution. However, if  $n$  is not sufficiently large then the transformed variable will be more spread out than a standard normal distribution.

**Theorem 3.1.** *For the sample mean  $\bar{X}$  based on  $n$  samples from a normal distribution with mean  $\mu$ , the rv*

$$T = \frac{\bar{X} - \mu}{S} \sqrt{n} \sim t(n-1), \quad (3.8)$$

that is,  $T$  has Student's  $t$  distribution with  $\nu = n - 1$  degrees of freedom (df).

This leads us to consider a CI for the population parameter  $\mu$  that is based on critical values of the  $t$  distribution.

**Proposition 3.4.** *A  $100(1 - \alpha)\%$  confidence interval for the mean  $\mu$  of a normal population when the value of  $\sigma^2$  is unknown is given by*

$$\left(\bar{x} - t_{\alpha/2, n-1} \cdot \frac{s}{\sqrt{n}}, \bar{x} + t_{\alpha/2, n-1} \cdot \frac{s}{\sqrt{n}}\right), \quad (3.9)$$

or  $\bar{x} \pm t_{\alpha/2, n-1} \cdot s/\sqrt{n}$ . Here  $\bar{x}$  and  $s$  are the sample mean and sample standard deviation, respectively.



In contrast to Proposition 3.1, it is difficult to select the sample size  $n$  to control the width of the t-based CI as the width involves the unknown (before the sample is acquired)  $s$  and because  $n$  also enters through  $t_{\alpha/2, n-1}$ .

**TODO:** add example

**Proposition 3.5. TODO:** rule of thumb normal CI

**TODO:** add example using rule of thumb

## 3.2 Estimating proportions

Consider a population of size  $N$  in which a proportion  $p$  of the population satisfies a given property. The  $p \in (0, 1)$  is a parameter characterizing the population, with distribution  $F(p)$ ,<sup>2</sup> that we might be interested in estimating. A sample,  $X_1, \dots, X_n \sim F(p)$ , of size  $n$  from the population contains a proportion,

$$\hat{p} = \frac{1}{n} \sum_{i=1}^n X_i, \quad (3.10)$$

satisfying the given property. The estimator  $\hat{p}$  varies with the sample and for large  $n$  its sampling distribution has the following properties:

$$\mu_{\hat{p}} = \mathbf{E}[X_i] = p$$

and

$$\sigma_{\hat{p}}^2 = \frac{\text{Var}[X_i]}{n} = \frac{p(1-p)}{n}, \quad (3.11)$$

provided that  $n$  is small relative to  $N$  (a rule of thumb is  $n \leq 0.05N$ ).<sup>3</sup> Moreover, by invoking the Central Limit Theorem we have the distribution of  $\hat{p}$  is approximately normal for sufficiently large  $n$  as (3.10) is a sample mean. Indeed, this normal approximation works well for moderately large  $n$  as long as  $p$  is not too close to zero or one; a rule of thumb is that  $np > 5$  and  $n(1-p) > 5$ .

**Proposition 3.6.** For large samples  $n$ , a  $100(1 - \alpha)\%$  confidence interval for the parameter  $p$  is given by

$$\hat{p} \pm z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}. \quad (3.12)$$

This follows from Proposition 3.3 by observing that (3.10) is a sample mean and replacing the standard error  $\sigma_{\hat{p}}$  from (3.11) by the estimated standard error,

$$\widehat{\text{se}}(\hat{p}) = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}};$$

recall the  $s$  in (3.6) is the sample variance for the *population* and  $s/\sqrt{n} = \text{se}$  is the standard error of the point estimator.

**Example 3.4. TODO:** Examples of sampling distribution for  $p$   $\diamond$

**Example 3.5. TODO:** Example confidence interval for  $p$   $\diamond$

**Example 3.6. TODO:** Example hypothesis test  $\diamond$

## 3.3 Estimating variances

Next we consider estimates of the population variance (and standard deviation) when the population is assumed to have a normal distribution. In this case, the sample variance  $S^2$  in (2.1) provides the basis for inferences. Consider iid samples  $X_1, \dots, X_n \sim \mathbf{N}(\mu, \sigma^2)$ . We provide the following theorem without proof.

<sup>2</sup>Here we write  $F$  for a general distribution, but what special distribution might this be?

<sup>3</sup>Note that if  $n$  is large relative to  $N$  ( $n > 0.05N$ ) then the variance (3.11) must be adjusted by a factor (related to the hypergeometric distribution):

$$\sigma_{\hat{p}}^2 = \frac{p(1-p)}{n} \frac{N-n}{N-1},$$

where for fixed  $n$  the factor converges to 1 as  $N \rightarrow \infty$ .

**Theorem 3.2.** For the sample variance  $S^2$  based on  $n$  samples from a normal distribution with variance  $\sigma$ , the rv

$$V = \frac{(n-1)S^2}{\sigma^2} = \frac{\sum_i (X_i - \bar{X})^2}{\sigma^2} \sim \chi_{n-1}^2,$$

that is,  $V$  has a  $\chi^2$  distribution with  $v = n - 1$  df.

Based on Theorem 3.2,

$$P\left(\chi_{1-\alpha/2, n-1}^2 < \frac{(n-1)S^2}{\sigma^2} < \chi_{\alpha/2, n-1}^2\right) = 1 - \alpha,$$

i.e., the area captured between the right and left tail critical  $\chi^2$  values is  $1 - \alpha$ . The expression above can be further manipulated to obtain an interval for the unknown parameter  $\sigma^2$ :

$$P\left(\frac{(n-1)s^2}{\chi_{\alpha/2, n-1}^2} < \sigma^2 < \frac{(n-1)s^2}{\chi_{1-\alpha/2, n-1}^2}\right) = 1 - \alpha,$$

where we substitute the computed value of the point estimate  $s^2$  for the estimator into the limits to give a CI for  $\sigma^2$ . If we take square roots of the inequality above, we obtain a CI for the population standard deviation  $\sigma$ .

**Proposition 3.7.** A  $100(1 - \alpha)\%$  confidence interval for the variance of a normal population is

$$\left((n-1)s^2/\chi_{\alpha/2, n-1}^2, (n-1)s^2/\chi_{1-\alpha/2, n-1}^2\right).$$

A  $100(1 - \alpha)\%$  confidence interval for the standard deviation  $\sigma$  of a normal population is given by taking the square roots of the lower and upper limits in (3.7).

**Example 3.7. TODO:** Example CI for variance (using the tree data?)  $\diamond$

## Chapter 4

# Inferences based on two samples

We consider inferences—estimators, confidence intervals, and hypothesis testing—for comparing means, proportions, and variances based on two independent samples from different populations, respectively, in Sections 4.1, 4.3, 4.4. We also consider inferences when the samples are not independent, so-called paired samples, in Section 4.2.

### 4.1 Comparing means

Let us assume that we have two normal populations with iid samples

$$X_1, \dots, X_m \sim N(\mu_X, \sigma_X^2)$$

and

$$Y_1, \dots, Y_n \sim N(\mu_Y, \sigma_Y^2)$$

and, moreover, that the  $X$  and  $Y$  samples are independent of one another. When comparing the means of two populations, the quantity of interest is the difference:  $\mu_X - \mu_Y$ .

**Proposition 4.1.** *If we consider the sample means  $\bar{X}$  and  $\bar{Y}$ , then the mean of the variable  $\bar{X} - \bar{Y}$  is,*

$$\mu_{\bar{X}-\bar{Y}} = \mathbf{E} [\bar{X} - \bar{Y}] = \mu_X - \mu_Y ,$$

*and the variance is,*

$$\sigma_{\bar{X}-\bar{Y}}^2 = \text{Var} [\bar{X} - \bar{Y}] = \frac{\sigma_X^2}{m} + \frac{\sigma_Y^2}{n} .$$

Proposition 4.1 follows directly from the definition of the sample mean in (2.1) and properties of expectation and variance. If our parameter of interest is

$$\theta = \mu_1 - \mu_2 ,$$

then its estimator,

$$\hat{\theta} = \bar{X} - \bar{Y} ,$$

is normally distributed with mean and variance given by Proposition 4.1. If the samples sizes  $m$  and  $n$  are large, then the estimator is approximately normally distributed by the Central Limit Theorem regardless of the population. We now discuss CIs and hypothesis tests for comparing population means  $\theta = \mu_X - \mu_Y$ . We consider three cases when comparing means:

1. normal populations when the variances  $\sigma_X^2$  and  $\sigma_Y^2$  are known,
2. any populations with unknown variances  $\sigma_X^2$  and  $\sigma_Y^2$ , when the sample sizes  $m$  and  $n$  are large,
3. normal populations when the variances  $\sigma_X^2$  and  $\sigma_Y^2$  are unknown, when the sample sizes  $m$  and  $n$  are small,

noting that the development largely reflects that of Section 3.1.

### 4.1.1 Comparing means of normal populations when variances are known

When  $\sigma_X^2$  and  $\sigma_Y^2$  are known, standardizing  $\bar{X} - \bar{Y}$  yields the standard normal variable:

$$Z = \frac{\bar{X} - \bar{Y} - (\mu_X - \mu_Y)}{\sqrt{\frac{\sigma_X^2}{m} + \frac{\sigma_Y^2}{n}}} \sim N(0, 1). \quad (4.1)$$

Inferences proceed by treating the parameter of interest  $\theta$  as a single sample using (4.1).

**Proposition 4.2.** A  $100(1 - \alpha)\%$  CI for the parameter  $\theta = \mu_X - \mu_Y$  based on samples of size  $m$  from a normal population  $N(\mu_X, \sigma_X^2)$  and of size  $n$  from  $N(\mu_Y, \sigma_Y^2)$  with known variances, is given by

$$(\bar{x} + \bar{y}) \pm z_{\alpha/2} \cdot \sqrt{\frac{\sigma_X^2}{m} + \frac{\sigma_Y^2}{n}}.$$

**Proposition 4.3.** For null hypothesis  $H_0 : \mu_X - \mu_Y = \theta_0$ , the test statistic to consider is:

$$z = \frac{\bar{x} - \bar{y} - \theta_0}{\sqrt{\frac{\sigma_X^2}{m} + \frac{\sigma_Y^2}{n}}}$$

### 4.1.2 Comparing means when the sample sizes are large

When the samples are large, then the assumptions about normality of the populations and knowledge of the variances  $\sigma_X^2$  and  $\sigma_Y^2$  can be relaxed. For sufficiently large  $m$  and  $n$ , the difference of the sample means,  $\bar{X} - \bar{Y}$ , has approximately a normal distribution for any underlying population distributions by the Central Limit Theorem. Moreover, if  $m$  and  $n$  are large enough, then replacing the population variances with the sample variances  $S_X^2$  and  $S_Y^2$  will not increase the variability of the estimator or the test statistic too much.

**Proposition 4.4.** For  $m$  and  $n$  sufficiently large, an approximate  $100(1 - \alpha)\%$  CI for  $\mu_X - \mu_Y$  for two samples from populations with any underlying distribution is given by

$$(\bar{x} + \bar{y}) \pm z_{\alpha/2} \cdot \sqrt{\frac{s_X^2}{m} + \frac{s_Y^2}{n}}$$

**Proposition 4.5.** For null hypothesis  $H_0 : \mu_X - \mu_Y = \theta_0$ , the test statistic to consider is:

$$z = \frac{\bar{x} - \bar{y} - \theta_0}{\sqrt{\frac{s_X^2}{m} + \frac{s_Y^2}{n}}}$$

### 4.1.3 Comparing means of normal populations when variances are unknown and the sample size is small

If  $\sigma_X$  and  $\sigma_Y$  are unknown and either sample is small (e.g.,  $m < 30$  or  $n < 30$ ), but both populations are normally distributed, then we can use Student's  $t$  distribution to make inferences. We provide the following theorem without proof.

**Theorem 4.1.** When both population distributions are normal, the standardized variable

$$T = \frac{\bar{X} - \bar{Y} - (\mu_X - \mu_Y)}{\sqrt{\frac{S_X^2}{m} + \frac{S_Y^2}{n}}} \sim t(\nu)$$

where the  $df \nu$  is estimated from the data. Namely,  $\nu$  is given by (round  $\nu$  down to the nearest integer):

$$\nu = \frac{\left(\frac{s_X^2}{m} + \frac{s_Y^2}{n}\right)^2}{\frac{(s_X^2/m)^2}{m-1} + \frac{(s_Y^2/n)^2}{n-1}} = \frac{\left(\frac{s_X^2}{m} + \frac{s_Y^2}{n}\right)^2}{\frac{s_X^4}{m-1} + \frac{s_Y^4}{n-1}} \quad (4.2)$$

where  $s_X^2$  and  $s_Y^2$  are point estimators of the sample variances; alternatively, we see that the formula (4.2) can also be written in terms of the standard error of the sample means:

$$s_{\bar{X}} = \frac{s_X}{\sqrt{m}} \quad \text{and} \quad s_{\bar{Y}} = \frac{s_Y}{\sqrt{n}}.$$

The formula (4.2) for the data-driven choice of  $\nu$  calls for the computation of the standard error of the sample means.

**Proposition 4.6.** A  $100(1 - \alpha)\%$  CI for  $\mu_X - \mu_Y$  for two samples of size  $m$  and  $n$  from normal populations where the variances are unknown is given by

$$(\bar{x} - \bar{y}) \pm t_{\alpha/2, \nu} \sqrt{\frac{s_X^2}{m} + \frac{s_Y^2}{n}},$$

where we recall that  $t_{\alpha/2, \nu}$  is the  $\alpha/2$  critical value of  $t(\nu)$  with  $\nu$  given by (4.2).

**Proposition 4.7.** For the null hypothesis  $H_0 = \mu_X - \mu_Y = \theta_0$ , the test statistic to consider is:

$$t = \frac{(\bar{x} - \bar{y}) - \theta_0}{\sqrt{\frac{s_X^2}{m} + \frac{s_Y^2}{n}}}.$$

If the normal populations have the same variance (i.e., the populations differ only in *location* not in *spread*), then matters simplify. If the variances of the normal populations are unknown but are the same (i.e.,  $\sigma_X^2 = \sigma_Y^2$ ), then deriving CIs and test statistics for comparing the means can be simplified by considering a combined or pooled estimator for (the single parameter)  $\sigma^2$ . If we have two samples from populations with variance  $\sigma^2$ , then each sample provides an estimate for  $\sigma^2$ . That is,  $S_X^2$ , based on the  $m$  observations of the first sample, is one estimator for  $\sigma^2$  and another is given by  $S_Y^2$ , based on  $n$  observations of the second sample. The correct way to combine these two estimators into a single estimator for the sample variance is to consider the **pooled estimator** of  $\sigma^2$ ,

$$S_p^2 = \frac{m-1}{m+n-2} S_X^2 + \frac{n-1}{m+n-2} S_Y^2. \quad (4.3)$$

The pooled estimator is a weighted average that adjusts for differences between the sample sizes  $m$  and  $n$ .<sup>1</sup>

**Proposition 4.8.** A  $100(1 - \alpha)\%$  CI for  $\mu_X - \mu_Y$  for two samples of size  $m$  and  $n$  from normal populations where the variance  $\sigma^2$  is unknown is given by

$$(\bar{x} - \bar{y}) \pm t_{\alpha/2, m+n-2} \cdot \sqrt{s_p^2 \left( \frac{1}{m} + \frac{1}{n} \right)},$$

where we recall that  $t_{\alpha/2, m+n-2}$  is the  $\alpha/2$  critical value of the  $t(\nu)$  with  $\nu = m + n - 2$  df.

Similarly, one can consider a pooled  $t$  test, i.e., a hypothesis test based on the pooled estimator for the variance as opposed to the two-sample  $t$  test in Proposition 4.7. If you have reasons to believe that  $\sigma_X^2 = \sigma_Y^2$ , these pooled  $t$  procedures are appealing because  $\nu$  is very easy to compute.



Pooled  $t$  procedures are not robust if the assumption of equalized variance is violated. Theoretically, you could first carry out a statistical test  $H_0 : \sigma_X^2 = \sigma_Y^2$  on the equality of variances and then use a pooled  $t$  procedure if the null hypothesis is not rejected. However, there is no free lunch: the typical  $F$  test for equal variances (see Section 4.4) is sensitive to normality assumptions. The two sample  $t$  procedures, with the data-driven choice of  $\nu$  in (4.2), are therefore recommended unless, of course, you have a very compelling reason to believe  $\sigma_X^2 = \sigma_Y^2$ .

<sup>1</sup> If  $m \neq n$ , then the estimator with *more* samples will contain *more* information about the parameter  $\sigma^2$ . Thus, the simple average  $(S_X^2 + S_Y^2)/2$  wouldn't really be fair, would it?

## 4.2 Comparing paired samples

The preceding analysis for comparing population means was based on the assumption that a random sample  $X_1, \dots, X_m$  is drawn from a distribution with mean  $\mu_X$  and that a completely independent random sample  $Y_1, \dots, Y_n$  is drawn from a distribution with mean  $\mu_Y$ . Some situations, e.g., comparing observations before and after a treatment or exposure, necessitate the consideration of paired values.

Consider a random sample of iid pairs

$$(X_1, Y_1), \dots, (X_n, Y_n)$$

with  $\mathbf{E}[X_i] = \mu_X$  and  $\mathbf{E}[Y_i] = \mu_Y$ . If we are interested in making inferences about the difference  $\mu_X - \mu_Y$  then the paired differences

$$D_i = X_i - Y_i, \quad i = 1, \dots, n,$$

constitute a sample with mean  $\mu_D = \mu_X - \mu_Y$  that can be treated using single-sample CIs and tests, e.g., see Section 3.1.3.

## 4.3 Comparing proportions

Consider a population containing a proportion  $p_X$  of individuals satisfying a given property. For a sample of size  $m$  from this population, we denote the sample proportion by  $\hat{p}_X$ . Likewise, we consider a population containing a proportion  $p_Y$  of individuals satisfying the same given property. For a sample of size  $n$  from this population, we denote the sample proportion by  $\hat{p}_Y$ . We assume the samples from the  $X$  and  $Y$  populations are independent. The natural estimator for the difference in population proportions  $p_X - p_Y$  is the difference in the sample proportions  $\hat{p}_X - \hat{p}_Y$ .

Provided the samples are much smaller than the population sizes (i.e., the populations are about 20 times larger than the samples),

$$\mu_{(\hat{p}_X - \hat{p}_Y)} = \mathbf{E}[\hat{p}_X - \hat{p}_Y] = p_X - p_Y,$$

and

$$\sigma_{(\hat{p}_X - \hat{p}_Y)}^2 = \text{Var}[\hat{p}_X - \hat{p}_Y] = \frac{p_X(1 - p_X)}{m} + \frac{p_Y(1 - p_Y)}{n},$$

by considering the fact that the count of individuals satisfying the given property in each population will be independent draws from  $\text{Binom}(m, p_X)$  and  $\text{Binom}(n, p_Y)$ , respectively. Further, if  $m$  and  $n$  are large (e.g.,  $m \geq 30$  and  $n \geq 30$ ), then  $\hat{p}_X$  and  $\hat{p}_Y$  are (approximately) normally distributed. Standardizing  $\hat{p}_X - \hat{p}_Y$ ,

$$Z = \frac{\hat{p}_X - \hat{p}_Y - (p_X - p_Y)}{\sqrt{\frac{p_X(1 - p_X)}{m} + \frac{p_Y(1 - p_Y)}{n}}} \sim \mathbf{N}(0, 1).$$

A CI for  $\hat{p}_X - \hat{p}_Y$  then follows from the large-sample CI considered in Section 3.1.2.

**Proposition 4.9.** *An approximate  $100(1 - \alpha)\%$  CI for  $p_X - p_Y$  is given by*

$$\hat{p}_X - \hat{p}_Y \pm z_{\alpha/2} \sqrt{\frac{\hat{p}_X(1 - \hat{p}_X)}{m} + \frac{\hat{p}_Y(1 - \hat{p}_Y)}{n}},$$

and, as a rule of thumb, can be reliably used if  $m\hat{p}_X$ ,  $m(1 - \hat{p}_X)$ ,  $n\hat{p}_Y$ , and  $n(1 - \hat{p}_Y)$  are greater than or equal to 10.

Proposition 4.9 does not pool the estimators for the population proportions. However, if we are considering a hypothesis test concerning the equality of the population proportions with the null hypothesis

$$H_0 : p_X - p_Y = 0,$$

then we are assuming that  $p_X = p_Y$  (unless the data suggests otherwise). Therefore as a matter of consistency we should replace the standard error in (4.9) with a pooled estimator for the standard error of the population proportion,

$$\hat{p} = \frac{m}{m+n} \hat{p}_X + \frac{n}{m+n} \hat{p}_Y.$$

**Proposition 4.10.** *For the null hypothesis  $H_0 : p_X - p_Y = 0$ , the test statistic to consider is:*

$$z = \frac{\hat{p}_X - \hat{p}_Y}{\sqrt{\hat{p}(1 - \hat{p}) \left( \frac{1}{m} + \frac{1}{n} \right)}}$$

## 4.4 Comparing variances

For a random sample

$$X_1, \dots, X_m \sim N(\mu_X, \sigma_X^2)$$

and an independent random sample

$$Y_1, \dots, Y_n \sim N(\mu_Y, \sigma_Y^2),$$

the rv

$$F = \frac{S_X^2/\sigma_X^2}{S_Y^2/\sigma_Y^2} \sim F(m-1, n-1), \quad (4.4)$$

that is,  $F$  has an  $F$  distribution with df  $\nu_1 = m-1$  and  $\nu_2 = n-1$ . The statistic  $F$  in (4.4) comprises the *ratio* of variances  $\sigma_X^2/\sigma_Y^2$  and not the difference; therefore, the plausibility of  $\sigma_X^2 = \sigma_Y^2$  will be based on how much the ratio differs from 1.

**Proposition 4.11.** *For the null hypothesis  $H_0 : \sigma_X^2 = \sigma_Y^2$ , the test statistic to consider is:*

$$f = \frac{s_X^2}{s_Y^2}$$

and the  $P$ -values are determined by the  $F(m-1, n-1)$  curve where  $m$  and  $n$  are the respective sample sizes.

A  $100(1-\alpha)\%$  CI for the ratio  $\sigma_X^2/\sigma_Y^2$  is based on forming the probability,

$$P(F_{1-\alpha/2, \nu_1, \nu_2} < F < F_{\alpha/2, \nu_1, \nu_2}) = 1 - \alpha,$$

where  $F_{\alpha/2, \nu_1, \nu_2}$  is the  $\alpha/2$  critical value from the  $F(\nu_1 = m-1, \nu_2 = n-1)$  distribution. Substituting (4.4) with point estimates for  $F$  and manipulating the inequalities it is possible to isolate the ratio  $\sigma_X^2/\sigma_Y^2$ ,

$$P\left(\frac{1}{F_{\alpha/2, \nu_1, \nu_2}} \frac{s_X^2}{s_Y^2} < \frac{\sigma_X^2}{\sigma_Y^2} < \frac{1}{F_{1-\alpha/2, \nu_1, \nu_2}} \frac{s_X^2}{s_Y^2}\right) = 1 - \alpha.$$

**Proposition 4.12.** *A  $100(1-\alpha)\%$  CI for the ratio of population variances  $\sigma_X^2/\sigma_Y^2$  is given by*

$$\left(F_{\alpha/2, m-1, n-1}^{-1} s_X^2/s_Y^2, F_{1-\alpha/2, m-1, n-1}^{-1} s_X^2/s_Y^2\right).$$





## Chapter 5

# Analysis of variance (ANOVA)

Analysis of variance, shortened as ANOVA, is a collection of statistical models and estimation procedures for analyzing the variation among different groups. In particular, a single-factor ANOVA provides a hypothesis test regarding the equality of two or more population means, thereby generalizing the one-sample and two-sample  $t$  tests considered in Sections 3.1.3 and 4.1.3.

### 5.1 Single factor ANOVA test

Suppose that we have  $k$  normally distributed populations<sup>1</sup> with different means  $\mu_1, \dots, \mu_k$  and equal variances  $\sigma^2$ . We denote the rv for the  $j$ th measurement taken from the  $i$ th population by  $X_{ij}$  and the corresponding sample observation by  $x_{ij}$ . For samples of size  $m_1, \dots, m_k$ , we denote the sample means

$$\bar{X}_i = \frac{1}{m_i} \sum_{j=1}^{m_i} X_{ij},$$

and sample variances

$$S_i^2 = \frac{1}{m_i - 1} \sum_{j=1}^{m_i} (X_{ij} - \bar{X}_i)^2,$$

for each  $i = 1, \dots, k$ ; likewise, we denote the associated point estimates for the sample means  $\bar{x}_1, \dots, \bar{x}_k$  and the sample variances  $s_1^2, \dots, s_k^2$ . The average over all observations  $m = \sum m_i$ , called the **grand mean**, is denoted by

$$\bar{X} = \frac{1}{m} \sum_{i=1}^k \sum_{j=1}^{m_i} X_{ij}.$$

The sample variances  $s_i^2$ , and hence the sample standard deviations, will generally vary even when the  $k$  populations share the same variance; a rule of thumb is that the equality of variances is reasonable if the largest  $s_i$  is not much more than two times the smallest.

We wish to test the equality of the population means, given by the null hypothesis,

$$H_0 : \mu_1 = \mu_2 = \dots = \mu_k,$$

versus the alternative hypothesis,

$$H_a : \text{at least two } \mu_i \text{ differ.}$$

Note that if  $k = 3$  then  $H_0$  is true only if all three means are the same, i.e.,  $\mu_1 = \mu_2 = \mu_3$ , but there are a number of ways which the alternative might hold:  $\mu_1 \neq \mu_2 = \mu_3$  or  $\mu_1 = \mu_2 \neq \mu_3$  or  $\mu_1 = \mu_3 \neq \mu_2$  or  $\mu_1 \neq \mu_2 \neq \mu_3$ .

The test procedure is based on comparing a measure of difference in variation among the sample means, i.e., the variation between  $x_i$ 's, to a measure of variation within each sample.

---

<sup>1</sup>In the context of ANOVA, these  $k$  populations are often referred to as **treatment distributions**.

**Definition 5.1.** The mean square for treatments is

$$\text{MSTr} = \frac{1}{k-1} \sum_{i=1}^k m_i (\bar{X}_i - \bar{X})^2,$$

and the mean square error is

$$\text{MSE} = \frac{1}{m-k} \sum_{i=1}^k (m_i - 1) S_i^2.$$

The MSTr and MSE are statistics that measure, respectively, the variation among sample means and the variation within samples. We will also use MSTr and MSE to denote calculated values of these statistics.

**Proposition 5.1.** The test statistic

$$F = \frac{\text{MSTr}}{\text{MSE}}$$

is the appropriate test statistic for the single-factor ANOVA problem involving  $k$  populations (or treatments) with a random sample of size  $m_1, \dots, m_k$  from each. When  $H_0$  is true,

$$F \sim F(v_1 = k - 1, v_2 = m - k).$$

In the present context a large test statistic value is more contradictory to  $H_0$  than a smaller value, therefore the test is upper-tailed, i.e., consider the area  $F_\alpha$  to the right of the critical value  $F_{\alpha, v_1, v_2}$ . We reject  $H_0$  if the value of the test statistic  $F > F_\alpha$ .

**Example 5.1.** Consider the average salary data from local councils in Table 5.1. Is the expected average salary in each nation the same at the 5% level?

Table 5.1: \*\*Average Salary Data\*\* reported from 20 local councils.

Nation	Average salaries ('000 £)	Size $(m_i)$	Sample Mean $(\bar{x}_i)$	Sample SD $(s_i)$
England	17, 12, 18, 13, 15, 12	6	14.5	2.588
N Ireland	11, 7, 9, 13	4	10.0	2.582
Scotland	15, 10, 13, 14, 13	5	13.0	1.871
Wales	10, 12, 8, 7, 9	5	9.2	1.924



Table 5.1 presents the **Average Salary Data** (in thousands of pounds) reported from 20 local councils classified by nation (England, N Ireland, Scotland, and Wales). The sample means together with the sample standard deviations are summarized in the table as well as presented using box plots in Figure 5.1.

For  $\alpha = 0.05$ , we compute the upper-tail area  $F_{0.05}$  i.e. to the right of the critical value  $F_{0.05, 3, 16}$  by consulting a statistical table or by using `r` to find  $F_{0.05} = 3.2388715$ .

```
qf(1-.05, df1 = 4-1, df2 = 20-4) # alt: qf(.05, df1 = 4-1, df2 = 20-4, lower.tail = FALSE)
```

```
[1] 3.238872
```

The grand mean is

$$\bar{x} = \frac{17 + 12 + 18 + \dots + 8 + 7 + 9}{20} = 11.9,$$

and hence the variation among sample means is given by,

$$\begin{aligned} \text{MSTr} &= \frac{1}{4-1} (m_1(\bar{x}_1 - \bar{x})^2 + \dots + m_4(\bar{x}_4 - \bar{x})^2) \\ &= (6(14.5 - 11.9)^2 + 4(10.0 - 11.9)^2 + 5(13.0 - 11.9)^2 + 5(9.2 - 11.9)^2) / 3 \\ &= 32.5. \end{aligned}$$

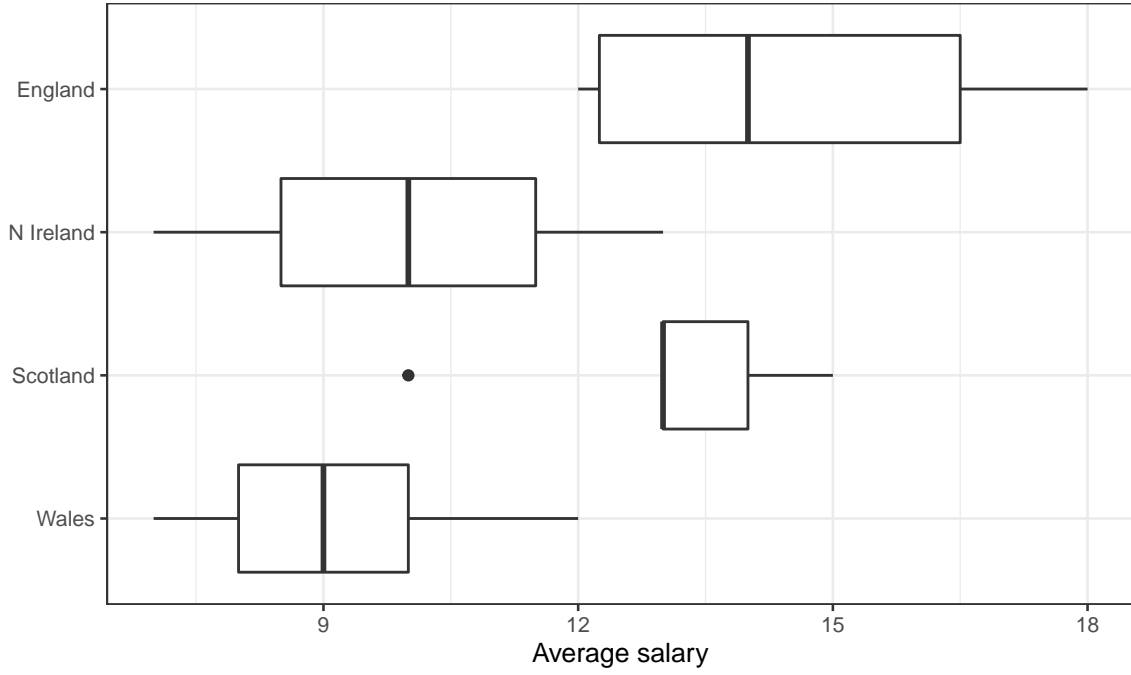


Figure 5.1: Box plots of the average mean salary data in Table 5.1 indicate five summary statistics: the median, two hinges (first and third quartiles) and two whiskers (extending from the hinge to the most extreme data point within  $1.5 \cdot \text{IQR}$ ).

The mean square error is

$$\begin{aligned} \text{MSE} &= \frac{1}{20 - 4} ((m_1 - 1)s_1^2 + \dots + (m_4 - 1)s_4^2) \\ &= \frac{5(2.588)^2 + 3(2.582)^2 + 4(1.871)^2 + 4(1.924)^2}{16} \\ &= 5.14366 \end{aligned}$$

yielding the test statistic value

$$F = \frac{\text{MSTr}}{\text{MSE}} = \frac{32.5}{5.14366} = 6.3184581.$$

Since  $F > F_\alpha$  we reject  $H_0$ . The data does not support the hypothesis that the mean salaries in each nation are identical at the 5% level.  $\diamond$

## 5.2 Confidence intervals

In Section 4.1 we gave a CI for comparing population means that involved the difference  $\mu_X - \mu_Y$ . In some settings, we would like to give CIs for more complicated functions of population means  $\mu_i$ . Let

$$\theta = \sum_{i=1}^k c_i \mu_i,$$

for constants  $c_i$ . As we assume the  $X_{ij}$  are normally distributed with  $\mathbf{E}[X_{ij}] = \mu_i$  and  $\text{Var}[X_{ij}] = \sigma^2$ , the estimator

$$\hat{\theta} = \sum_{i=1}^k c_i \bar{X}_i,$$

is normally distributed with

$$\text{Var}[\hat{\theta}] = \sum_{i=1}^k c_i^2 \text{Var}[\bar{X}_i] = \sigma^2 \sum_{i=1}^k \frac{c_i^2}{m_i}.$$

Estimating  $\sigma^2$  by the MSE and forming  $\hat{\sigma}_{\hat{\theta}}$  results in a  $t$  variable

$$\frac{\hat{\theta} - \theta}{\hat{\sigma}_{\hat{\theta}}}.$$

**Proposition 5.2.** A  $100(1 - \alpha)\%$  CI for  $\sum c_i \mu_i$  is given by

$$\sum_{i=1}^k c_i \bar{x}_i \pm t_{\alpha/2, m-k} \sqrt{\text{MSE} \sum_{i=1}^k \frac{c_i}{m_i}}.$$

**Example 5.2.** Determine a 90% CI for the difference in mean average salary for councils in Scotland and England, based on the data available in Table 5.1

For  $\alpha = 0.10$ , the critical value  $t_{0.05, 16} = 1.7458837$  is found by looking in a table of  $t$  critical values or by using `r`:

```
qt(1-0.1/2, df = 20 - 4) # alt: qt(0.1/2, 16, lower.tail = FALSE)
```

```
[1] 1.745884
```

Then for the function  $\bar{x}_2 - \bar{x}_1$ ,

$$\begin{aligned} (\bar{x}_{Eng} - \bar{x}_{Sco}) \pm t_{0.05, 16} \sqrt{\text{MSE} \sqrt{\frac{1}{m_{Eng}} + \frac{1}{m_{Sco}}}} \\ = (14.5 - 13.0) \pm 1.7458837 \sqrt{5.14366} \sqrt{\frac{1}{6} + \frac{1}{5}} \\ = 1.5 \pm 2.3976575. \end{aligned}$$

Thus a 90% confidence interval for  $\mu_{Eng} - \mu_{Sco}$  is  $(-0.8977, 3.898)$ .  $\diamond$



How does the result in Example 5.2 compare to the  $t$  method in Section 4.1.3?

# Chapter 6

## Linear regression

**Regression analysis** allows us to study the relationship among two or more rvs. Typically, we are interested in the relationship between a **response** or **dependent** rv  $Y$  and a **covariate**  $X$ .<sup>1</sup> The relationship between  $X$  and  $Y$  will be explained through a **regression function**,

$$r(x) = \mathbf{E}[Y \mid X = x] = \int y f(y \mid x) dy.$$

In particular, we shall assume that  $r$  is linear,

$$r(x) = \beta_0 + \beta_1 x, \quad (6.1)$$

and estimate the intercept  $\beta_0$  and slope  $\beta_1$  of this linear model from sample data

$$(Y_1, X_1), \dots, (Y_m, X_m) \sim F_{Y,X}.$$

### 6.1 Simple linear regression models

The simplest regression is when  $X_i$  is one-dimensional and  $r(x)$  is linear as in (6.1). A linear regression posits the expected value of  $Y_i$  is a linear function of the data  $X_i$ , but that  $Y$  deviates from its expected value by a random amount for fixed  $x_i$ .

**Definition 6.1.** The **simple linear regression model** relates a random response  $Y_i$  to a set of independent variables  $X_i$ ,

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i, \quad (6.2)$$

where the intercept  $\beta_0$  and slope  $\beta_1$  are unknown parameters and the **random deviation** or **random error**  $\epsilon_i$  is a rv assumed to satisfy:

1.  $\mathbf{E}[\epsilon_i \mid X_i = x_i] = 0$ ,
2.  $\text{Var}[\epsilon_i \mid X_i = x_i] = \sigma^2$  does not depend on  $x_i$ ,
3.  $\epsilon_i$  and  $\epsilon_j$  are independent for  $i, j = 1, \dots, m$ .

From the assumptions on  $\epsilon_i$ , the linear model (6.2) implies

$$\mathbf{E}[Y_i \mid X_i = x_i] = \beta_0 + \beta_1 x_i.$$

Thus, if  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are estimators of  $\beta_0$  and  $\beta_1$ , then the **fitted line** is

$$\hat{r}(x) = \hat{\beta}_0 + \hat{\beta}_1 x$$

and the **predicted** or **fitted value**  $\hat{Y}_i = \hat{r}(X_i)$  is an estimator for  $\mathbf{E}[Y_i \mid X_i = x_i]$ . The **residuals** are defined to be

$$\hat{\epsilon}_i = Y_i - \hat{Y}_i = Y_i - (\hat{\beta}_0 + \hat{\beta}_1 X_i). \quad (6.3)$$

---

<sup>1</sup>The covariates  $X$  are also called **predictor variables**, **explanatory variables**, **independent variables**, and/or **features** depending on who you are talking to.

The **residual sums of squares**,<sup>2</sup>

$$\text{RSS} = \sum_{i=1}^m \hat{\epsilon}_i^2, \quad (6.4)$$

measures how well the regression line  $\hat{r}$  fits the data  $(Y_1, X_1), \dots, (Y_m, X_m)$ . The **least squares estimates** of  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are the values that minimize the RSS in (6.4).

**Theorem 6.1.** The *least squares estimates* for  $\hat{\beta}_1$  and  $\hat{\beta}_0$  are given by, respectively,

$$\hat{\beta}_1 = \frac{\sum_{i=1}^m (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^m (X_i - \bar{X})^2} = \frac{S_{xy}}{S_{xx}}, \quad (6.5)$$

and

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}. \quad (6.6)$$

Equation (6.4) is a function of  $\hat{\beta}_0$  and  $\hat{\beta}_1$  from the definition of the residuals (6.3). Then (6.5) and (6.6) follow by equating the partial derivatives of (6.4) to zero. The  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are the unique solution to this linear system.

**Example 6.1.** In Figure 6.1, we consider the **Cherry Tree Data** (see Table 2.1 and discussion). We fit a least squares regression of the volume of timber (response variable) to the diameter of the tree (independent variable). As you would expect, the volume of timber yielded from a tree increases with its diameter.

The `r` code below can be used to calculate the least squares regression and residuals.

```
data(trees)
y <- trees$Volume
x <- trees$Girth # NB: this is diameter; data mislabeled!
fit <- lm(y ~ x)
e <- resid(fit)
yhat <- predict(fit)
```

The `fit` data frame contains the estimates for  $\hat{\beta}_0$  and  $\hat{\beta}_1$ :

```
fit$coefficients
```

```
(Intercept)      x
-36.943459    5.065856
```

In Figure 6.1, the regression line is `yhat` plotted against `x` and the error bars indicate the least squares residuals, i.e., the difference  $y - \text{yhat}$ . The residuals are presented a second way in Figure 6.2. ◇

## 6.2 Estimating $\sigma^2$ for linear regressions

The parameter  $\sigma^2$  (the variance of the random deviation) determines the variability in the regression model.

**Theorem 6.2.** An unbiased estimate of  $\sigma^2$  is given by

$$\hat{\sigma}^2 = s^2 = \frac{\text{RSS}}{m-2} = \frac{1}{m-2} \sum_{i=1}^m (y_i - \hat{y}_i)^2. \quad (6.7)$$

In Figure 6.3, we present a least squares regression of timber volume on both tree diameter and height (for the **Cherry Tree Data**). As expected, the regressions indicate the volume increases with both covariates. Estimates for the variance of the random deviation (6.7) in both regression models,  $\sigma_D^2$  and  $\sigma_H^2$ , respectively, are computed to be  $s_D^2 = 18.08$  and  $s_H^2 = 179.48$ . Thus, we see that small variances lead to observations of  $(x_i, y_i)$  that sit tightly around the regression line, in contrast to large variances that lead to a large cloud of points.



In Theorem 6.2, the number in the denominator is the df associated with the RSS and  $s^2$ . To calculate RSS you must estimate two parameters  $\beta_0$  and  $\beta_1$  which results in the loss of two df. Hence the  $m-2$ .

<sup>2</sup>The RSS is sometimes referred to as the **error sum of squares** and abbreviated SSE (no, that isn't a typo).

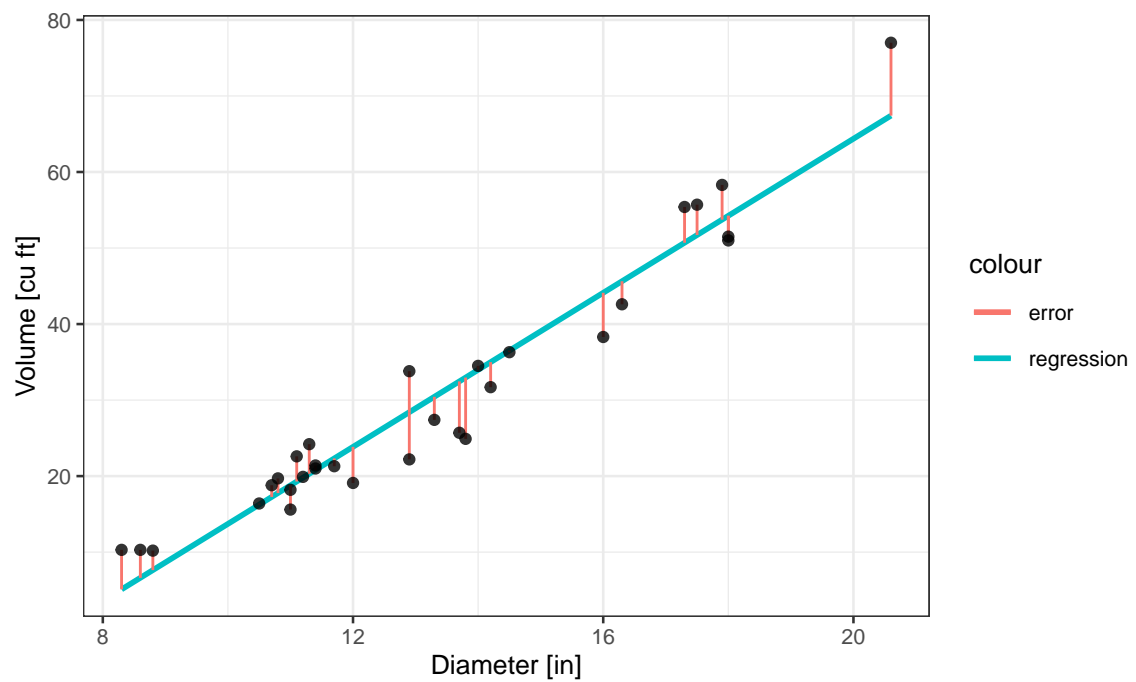


Figure 6.1: Linear regression (or least squares fit) of Volume to Diameter from the **Cherry Tree Data**. The vertical bars between the observed data point and the regression line indicate the error in the fit (the least squares residual).

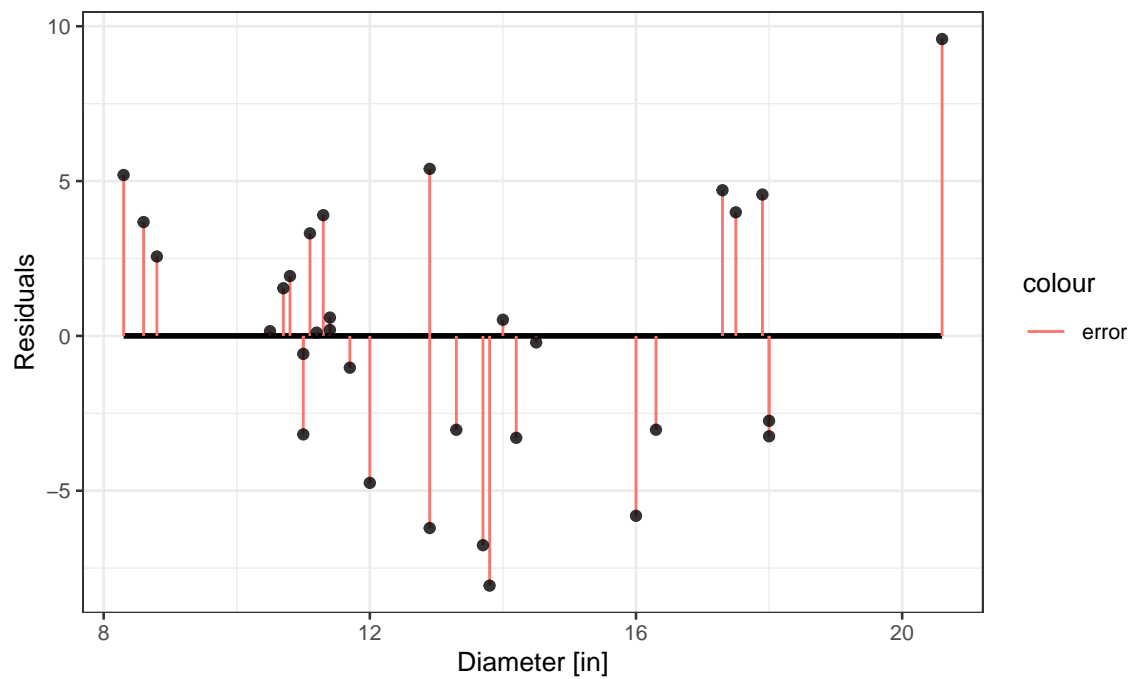


Figure 6.2: The residuals of the least squares fit of Volume to Diameter plotted in Figure 6.1.

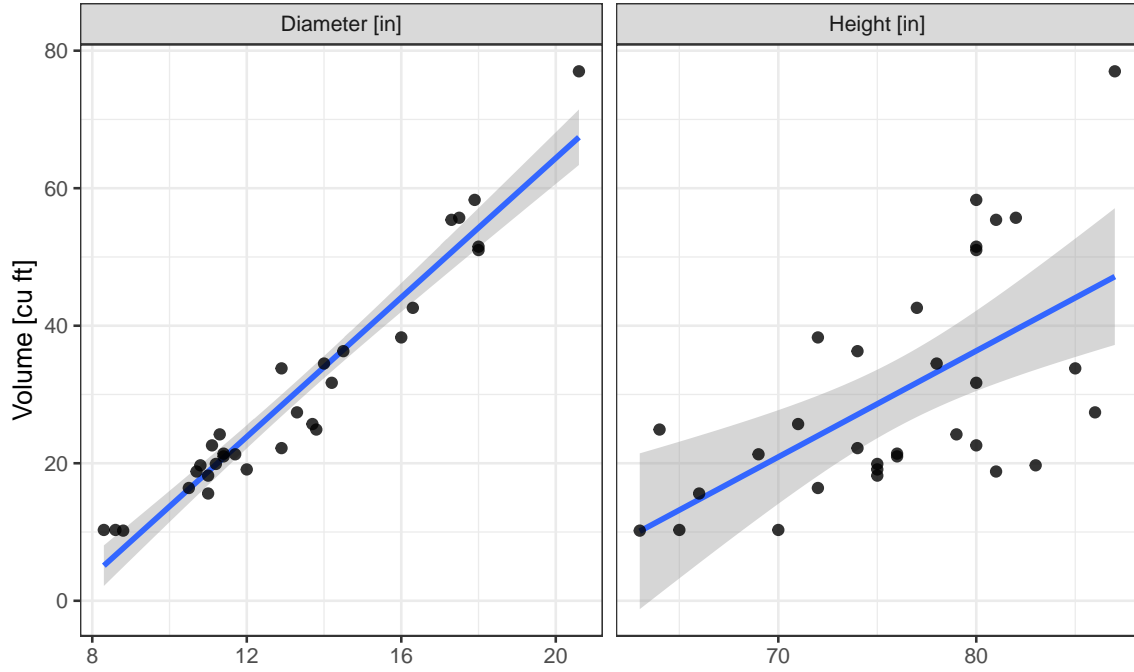


Figure 6.3: For the **Cherry Tree Data**, we estimate the variance to be  $s_D^2 = 18.08$  (for Diameter) and  $s_H^2 = 179.48$  (for Height); small variances lead to observations of  $(x_i, y_i)$  that sit tightly around the regression line, in contrast to large variances that lead to a large cloud of points.

We note for the purposes of making inferences, the statistic

$$S^2 = \frac{\text{RSS}}{m-2}$$

is an unbiased estimator of  $\sigma^2$  and the random variable

$$\frac{(m-2)S^2}{\sigma^2} \sim \chi^2(m-2).$$

Moreover, the statistic  $S^2$  is independent of both  $\hat{\beta}_0$  and  $\hat{\beta}_1$ .

### 6.3 Inferences for least-squares estimators

If  $\epsilon_i$  in (6.2) is assumed to be normally distributed, then we can derive the sampling distributions of the estimators  $\hat{\beta}_0$  and  $\hat{\beta}_1$ . Hence, we can use these sampling distributions to make inferences about the parameters  $\beta_0$  and  $\beta_1$ .

Provided iid  $\epsilon_i \mid X_i \sim N(0, \sigma^2)$ , the least-squares estimators possess the following properties.

1. Both  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are normally distributed.
2. Both  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are unbiased, i.e.,  $\mathbf{E}[\hat{\beta}_i] = \beta_i$  for  $i = 0, 1$ .
3.  $\text{Var}[\hat{\beta}_0] = c_{00}\sigma^2$  where  $c_{00} = \sum_{i=1}^m x_i^2 / (mS_{xx})$ .
4.  $\text{Var}[\hat{\beta}_1] = c_{11}\sigma^2$  where  $c_{11} = 1/S_{xx}$ .
5.  $\text{Cov}[\hat{\beta}_0, \hat{\beta}_1] = c_{01}\sigma^2$  where  $c_{01} = -\bar{x}/S_{xx}$ .

These properties can be determined by working directly from (6.5) and (6.6).

**Proposition 6.1.** To test the null hypothesis  $H_0 : \beta_i = \beta_{i0}$  against the alternatives

$$H_a : \begin{cases} \beta_i > \beta_{i0} & \text{upper-tail RR} \\ \beta_i < \beta_{i0} & \text{lower-tail RR} \\ \beta_i \neq \beta_{i0} & \text{two-tailed RR} \end{cases}$$



Test statistic:

$$T = \frac{\hat{\beta}_i - \beta_{i0}}{S\sqrt{c_{ii}}}$$

where  $t_\alpha$  is based on  $m - 2$  df.

**Proposition 6.2.** A  $100(1 - \alpha)\%$  CI for  $\beta_i$  is given by

$$\hat{\beta}_i \pm t_{\alpha/2, m-2} S\sqrt{c_{ii}}.$$

## 6.4 Correlation

Let  $(X_1, Y_1), \dots, (X_m, Y_m)$  denote a random sample from a bivariate normal distribution with  $\mathbf{E}[X_i] = \mu_X$ ,  $\mathbf{E}[Y_i] = \mu_Y$ ,  $\text{Var}[X_i] = \sigma_X^2$ ,  $\text{Var}[Y_i] = \sigma_Y^2$ , and correlation coefficient  $\rho$ . The sample correlation coefficient is given by,

$$r = \frac{\sum_{i=1}^m (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^m (X_i - \bar{X})^2 \sum_{i=1}^m (Y_i - \bar{Y})^2}},$$

which can be rewritten in terms of  $S_{xx}$ ,  $S_{xy}$ , and  $S_{yy}$ :

$$r = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}} = \hat{\beta}_1 \sqrt{\frac{S_{xx}}{S_{yy}}},$$

using (6.5) and we see that  $r$  and  $\hat{\beta}_1$  have the same sign. A  $|r|$  close to 1 means that the regression line is a good fit to the data and, similarly, an  $|r|$  close to 0 means a poor fit to the data.

**\*\*TODO\*\*:** insert plots for correlation coefficients and interpretation

Once a model is fit, it can be used to predict a value of  $y$  for a given  $x$ . However, the model only gives the most likely value of  $y$ ; a corresponding **prediction interval** is usually more appropriate.

**Proposition 6.3.** A  $100(1 - \alpha)\%$  **prediction interval** for an actual value of  $Y$  when  $x = x^*$  is given by

$$(\hat{\beta}_0 + \hat{\beta}_1 x^*) \pm t_{\alpha/2, m-2} S \sqrt{1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}.$$



The prediction interval is not the same as the confidence interval for expected  $Y$ . Note that the length of the *confidence interval* for  $\mathbf{E}[Y]$  when  $x = x^*$  is given by

$$2 \cdot t_{\alpha/2} S \sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}$$

whereas the length for the *prediction interval* of  $Y$  is

$$2 \cdot t_{\alpha/2} S \sqrt{1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}.$$

Thus the prediction intervals for an actual value of  $Y$  are longer than the confidence intervals for  $\mathbf{E}[Y]$  if both are determined for the same value  $x^*$ .

The linear model

$$\mathbf{E}[Y | X = x] = \beta_0 + \beta_1 x,$$

assumes that the conditional expectation of  $Y$  for a fixed value of  $X$  is a linear function of the  $x$  value. If we assume that  $(X, Y)$  has a bivariate normal distribution, then

$$\beta_1 = \frac{\sigma_Y}{\sigma_X} \rho,$$

and thus, for the simple hypothesis tests we have considered (Table 2.2), statistical tests for  $\beta$  and  $\rho$  are equivalent.



# Chapter 7

## Categorical data

### 7.1 Multinomial experiments

Suppose we have a population that is divided into  $k > 2$  distinct categories. We consider an experiment where we select  $m$  individuals (or objects) from the population and categorize each one. We denote the proportion of the population in the  $i$ th category by  $p_i$ . If the sample size  $m$  is much smaller than the population size  $M$  (so that the  $m$  trials are independent), this experiment will be approximately *multinomial* with success probability  $p_i$  for each category,  $i = 1, \dots, k$ .

Before the experiment is performed, we denote the number (or count) of the trials resulting in category  $i$  by the rv  $N_i$ . The expected number of trials that result in category  $i$  is given by

$$\mathbf{E}[N_i] = mp_i, \quad i = 1, \dots, k. \quad (7.1)$$

After the experiment is performed, we denote the corresponding observed value by  $n_i$ . Since the trials result in distinct categories,

$$\sum_{i=1}^k N_i = \sum_{i=1}^k n_i = m,$$

which indicates that, for a given  $m$ , we only need to observe  $k - 1$  of the variables to be able to work out what the  $k$ th variable should be.

### 7.2 Goodness-of-fit for a single factor

We are interested in making inferences about the proportion parameters  $p_i$ . Specifically, we will consider the null hypothesis,

$$H_0 : p_1 = p_{10}, p_2 = p_{20}, \dots, p_k = p_{k0}, \quad (7.2)$$

that completely specifies a value  $p_{i0}$  for each  $p_i$ .<sup>1</sup> The alternative hypothesis  $H_a$  will state that  $H_0$  is not true, i.e., that at least one  $p_i$  is different from the value  $p_{i0}$  claimed under the null  $H_0$ .

Provided the null hypothesis in (7.2) is true, the expected values (7.1) can be written in terms of the expected frequencies,

$$\mathbf{E}[N_i] = mp_{i0}, \quad i = 1, \dots, k.$$

Often the  $n_i$ , referred to as the **observed cell counts**, and the corresponding  $mp_{i0}$ , referred to as the **expected cell counts**, are tabulated, for example, as in Table 7.1.

The test procedure assesses the discrepancy between the value of the observed and expected cell counts. This discrepancy, or **goodness of fit**, is measured by the squared deviations divided by the expected count.<sup>2</sup>

<sup>1</sup>Here for  $i = 1, \dots, k$  we use the notation  $p_{i0}$  to denote the value of  $p_i$  claimed under the null hypothesis.

<sup>2</sup>The division by the expected cell counts is to account for possible differences in the relative magnitude of the observed/expected counts.

Table 7.1: Observed and expected cell counts.

Category	$i=1$	$i=2$	$\cdots$	$i=k$	Row total
Observed	$n_{1\cdot}$	$n_{2\cdot}$	$\cdots$	$n_{k\cdot}$	$m$
Expected	$mp_{10}$	$mp_{20}$	$\cdots$	$mp_{k0}$	$m$

**Theorem 7.1.** For  $mp_i \geq 5$  for  $i = 1, \dots, k$ , the rv

$$V = \sum_{i=1}^k \frac{(N_i - mp_i)^2}{mp_i} \sim \chi^2(k-1),$$

that is,  $V$  has approximately a  $\chi^2$  distribution with  $v = k - 1$  df.

**Proposition 7.1.** For the null hypothesis

$$H_0 : p_1 = p_{10}, p_2 = p_{20}, \dots, p_k = p_{k0},$$

and alternative

$$H_a : p_i \neq p_{i0} \text{ for at least one } i,$$

the test statistic to consider is:

$$V = \sum_{i=1}^k \frac{(n_i - mp_{i0})^2}{mp_{i0}},$$

provided, as a rule of thumb,  $mp_{i0} \geq 5$  for all  $i = 1, \dots, k$ .



Things are much more complicated if the category probabilities are not completely specified.

### 7.3 Test for independence of factors

In Section 7.2 we considered the categorization of a population into a single factor. We now consider a single population where each individual is categorized into two factors with  $I$  distinct categories for the first factor and  $J$  distinct categories for the second factor. That is, each individual from the population belongs to exactly one of the  $I$  categories of the first factor and exactly one of the  $J$  categories of the second factor. We want to determine whether or not there is any dependency between the two factors.

For a sample of  $m$  individuals, we denote by  $n_{ij}$  the count of the  $m$  samples that fall both in category  $i$  of the first factor and category  $j$  of the second factor, for  $i = 1, \dots, I$  and  $j = 1, \dots, J$ . A **contingency (data) table** with  $I$  rows and  $J$  columns (i.e.,  $IJ$  cells) will be used to record the  $n_{ij}$  counts (in the obvious way).<sup>3</sup> Let  $p_{ij}$  be the proportion of individuals in the population who belong in category  $i$  of factor 1 and category  $j$  of factor 2. Then, the probability that a randomly selected individual falls in category  $i$  of factor 1 is found by summing over all  $j$ :

$$p_i = \sum_{j=1}^J p_{ij},$$

and likewise, the probability that a randomly selected individual falls in category  $j$  of factor 2 is found by summing over all  $i$ :

$$p_j = \sum_{i=1}^I p_{ij}.$$

The null hypothesis that we will be interested in adopting is

$$H_0 : p_{ij} = p_i \cdot p_j \quad \forall (i, j),$$

<sup>3</sup>Contingency is another word for dependency in this context.

that is, that an individual's category in factor 1 is independent of the category in factor 2.

Following the same program as for the single category goodness-of-fit test, we note that, assuming the null hypothesis (7.3) is true, then the expected count in cell  $i, j$  is

$$\mathbf{E}[N_{ij}] = np_{ij} = mp_i p_j;$$

and we estimate  $p_i$  and  $p_j$  by the appropriate sample proportion:

$$\hat{p}_i = \frac{n_i}{m}, \quad n_i = \sum_j n_{ij} \quad (\text{row total}),$$

and

$$\hat{p}_j = \frac{n_j}{m}, \quad n_j = \sum_i n_{ij} \quad (\text{col total}).$$

Thus, the expected cell count is given by

$$\hat{e}_{ij} = m\hat{p}_i\hat{p}_j = \frac{n_i n_j}{m},$$

and we assess the goodness of fit between the observed cell count  $n_{ij}$  and the expected cell count  $\hat{e}_{ij}$ .

**Proposition 7.2.** *Null hypothesis  $H_0 : p_{ij} = p_i p_j$  for all  $i = 1, \dots, I, j = 1, \dots, J$ . Alternative hypothesis  $H_a : H_0$  is not true. Test statistic:*

$$V = \sum_{i=1}^I \sum_{j=1}^J \frac{(n_{ij} - \hat{e}_{ij})^2}{\hat{e}_{ij}}$$

*Rule of thumb,  $\hat{e}_{ij} \geq 5$  for all  $i, j$ , and when  $H_0$  is true then the test statistic has approximately  $\chi^2((I-1)(J-1))$  distribution. Upper tail.*



## Chapter 8

# Quality Control

Quality control is an area of applied statistics that seeks to make interventions to maintain or improve the outcome of industrial processes. Random variations in output processes might negatively impact the quality of a product. We would like to identify the sources of random variations in output processes that might have *assignable causes*. **Control charts** are a tool that help us to recognize when industrial processes are no longer controlled so that one might then seek to identify assignable causes.

The basic elements of control charting involve specifying a control region and then analyzing time-series data. We will specify a base-line value along with an upper and lower limit of control and assume that a process is under control unless a test statistic suggests otherwise.<sup>1</sup> To construct a control chart, one collects data about a process at fixed points of time and calculates the running value of quality statistic. If the quality statistic exceeds the upper or lower control limits, the process is deemed to be out of control and the quality of the product is assumed to be negatively impacted.

The process of creating a control chart is best illustrated through an extended example, like Example 8.1 provided below.

**Example 8.1.** Here we consider the typical  $3\sigma$  control charting for a process mean  $\bar{X}$  based on estimated parameters. That is, we assume the generating process  $X$  is normally distributed with unknown parameters  $\mu$  and  $\sigma^2$ . We seek to estimate the mean  $\bar{X}$ . Our control region is specified to be three standard deviations; that is, the process is in-control if it remains within three standard deviations of a baseline value.

The **Beer Data** contains measurements of the features OG, ABV, pH, and IBU for 50 batches of each of three types of product (Premium Lager, IPA, and Light Lager). We are interested in the IPA's pH value, which influences saccharification. We assume that 3 batches of IPA are produced per day and we prepare the data as follows.

```
ipa <- beer %>%
  select(Batch_Id, pH, Beer) %>%
  filter(Beer == "IPA") %>%
  rename(Day = Batch_Id)
ipa$Day[1:48] <- rep(1:16, each = 3)
ipa <- ipa[1:48,]
m <- 3      # three batches per day
k <- 16     # number of days
```

We first observe that the pH measurements are (at least approximately) normal, as can be seen from the quantile-quantile plot in Figure 8.1.

```
ggplot(ipa, aes(sample = pH)) + stat_qq() + stat_qq_line()
```

We consider the data for pH readings from three batches of IPA taken over sixteen days ( $k = 16$ ) presented in Table 8.1. The Table includes the sample mean per day  $\bar{x}$ , the sample standard deviation  $s$ , and the range of values  $\max x_i - \min x_i$  per day (each based on  $m = 3$  batches).

---

<sup>1</sup>The default position here will be reminiscent of hypothesis testing.

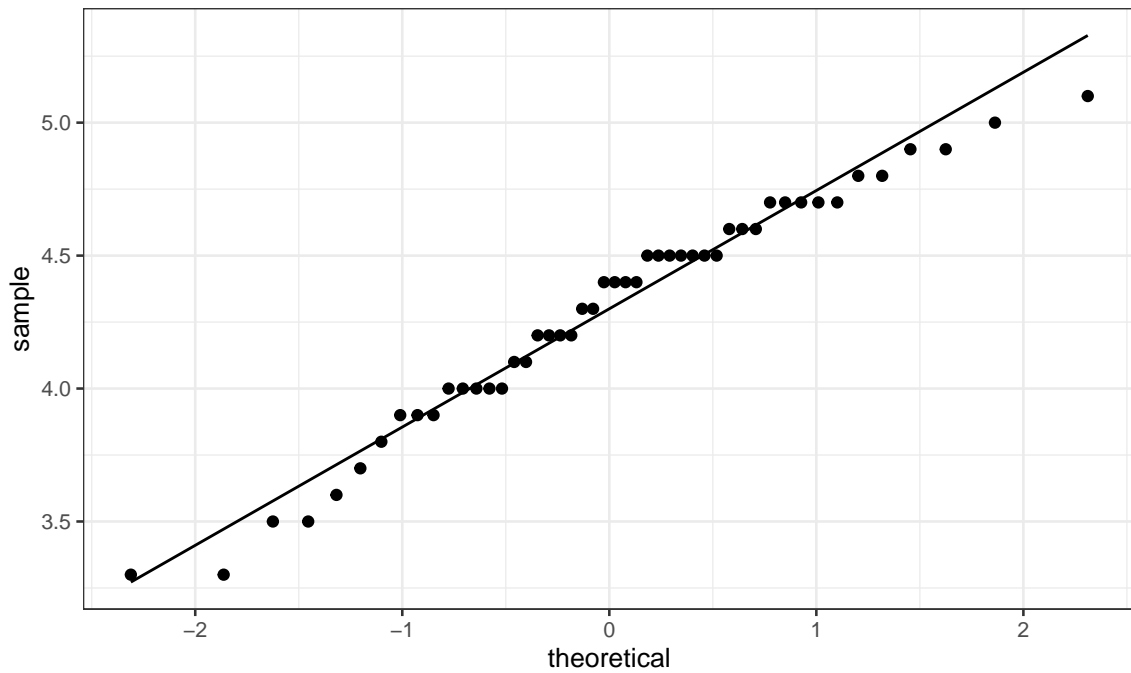


Figure 8.1: Normal quantile-quantile plot of observed pH measurements of the IPA batches in Table 8.1.

```
ipa_stat <- ipa %>%
  group_by(Day) %>%
  summarise(observations = list(pH), mean = signif(mean(pH), digits = 4),
            sd = signif(sd(pH), digits = 4), range = max(pH) - min(pH))
kbl(ipa_stat, align = "llccc",
     caption = "Observations and summary statistics for the **Beer Data**.",
     col.names = c('Day', "pH Observations", '$\\overline{x}$', '$s$', 'Range'),
     booktabs = T) %>%
  kable_styling(latex_options = c("striped", "hold_position"))
```

Table 8.1: Observations and summary statistics for the \*\*Beer Data\*\*.

Day	pH Observations	$\overline{x}$	$s$	Range
1	4.7, 4.5, 4.9	4.700	0.20000	0.4
2	4.0, 4.6, 4.5	4.367	0.32150	0.6
3	4.7, 3.3, 4.6	4.200	0.78100	1.4
4	3.9, 3.5, 4.2	3.867	0.35120	0.7
5	4.0, 4.7, 3.6	4.100	0.55680	1.1
6	4.4, 4.5, 4.1	4.333	0.20820	0.4
7	4.5, 3.9, 4.8	4.400	0.45830	0.9
8	4.0, 4.9, 4.7	4.533	0.47260	0.9
9	4.3, 4.4, 4.8	4.500	0.26460	0.5
10	5.0, 4.5, 3.5	4.333	0.76380	1.5
11	3.8, 3.7, 3.9	3.800	0.10000	0.2
12	5.1, 4.5, 4.5	4.700	0.34640	0.6
13	4.7, 4.4, 4.1	4.400	0.30000	0.6
14	4.0, 4.4, 4.6	4.333	0.30550	0.6
15	4.0, 3.3, 4.2	3.833	0.47260	0.9
16	4.2, 4.2, 4.3	4.233	0.05774	0.1



We estimate of the mean

$$\hat{\mu} = \frac{1}{k} \sum_{i=1}^k \bar{x}_i,$$

by averaging the means found for the  $k$  days and, similarly, estimate the mean of the sample standard deviation,

$$\bar{s} = \frac{1}{k} \sum_{i=1}^k s_i,$$

by averaging the sample standard deviations for the  $k$  days. It can be shown that

$$\hat{\sigma} = \frac{\bar{S}}{a_m}$$

is an unbiased estimator of  $\sigma$  where

$$a_m = \frac{\sqrt{2}\Gamma(m/2)}{\sqrt{m-1}\Gamma((n-1)/2)}.$$

Thus, we compute the  $3\sigma$  upper and lower control limits, respectively,

$$\text{UCL} = \hat{\mu} + 3 \frac{\bar{s}}{a_m \sqrt{m}}$$

and

$$\text{LCL} = \hat{\mu} - 3 \frac{\bar{s}}{a_m \sqrt{m}}.$$

The computations in `r` follow, along with the resulting **control chart** in Figure 8.2.

```
a <- function(m){ sqrt(2) * gamma(m/2) / (sqrt(m-1) * gamma((m-1)/2)) }
muhat = sum(ipa_stat$mean) / k
sbar = sum(ipa_stat$sd) / k
lcl = muhat - 3*sbar / (a(m) * sqrt(m))
ucl = muhat + 3*sbar / (a(m) * sqrt(m))

ggplot(ipa_stat, aes(x = Day)) + geom_point(aes(y = mean)) +
  geom_hline(aes(yintercept = muhat, color = "Mean"), size = 1) +
  geom_hline(aes(yintercept = lcl, color = "LCL"), size = 1.5) +
  geom_hline(aes(yintercept = ucl, color = "UCL"), size = 2) + ylab("pH")
```

From Figure 8.2, we observe for each day the process is in-control as the observed mean pH values fall within the control limits (LCL, UCL). If this were not the case, then our initial assumption, that process is in-control, would be violated. The violation of the assumption would require that we seek to identify an assignable cause for the variation. If a cause could be identified, then the we would need to recompute our control limits with the observations that were out of control removed.  $\diamond$

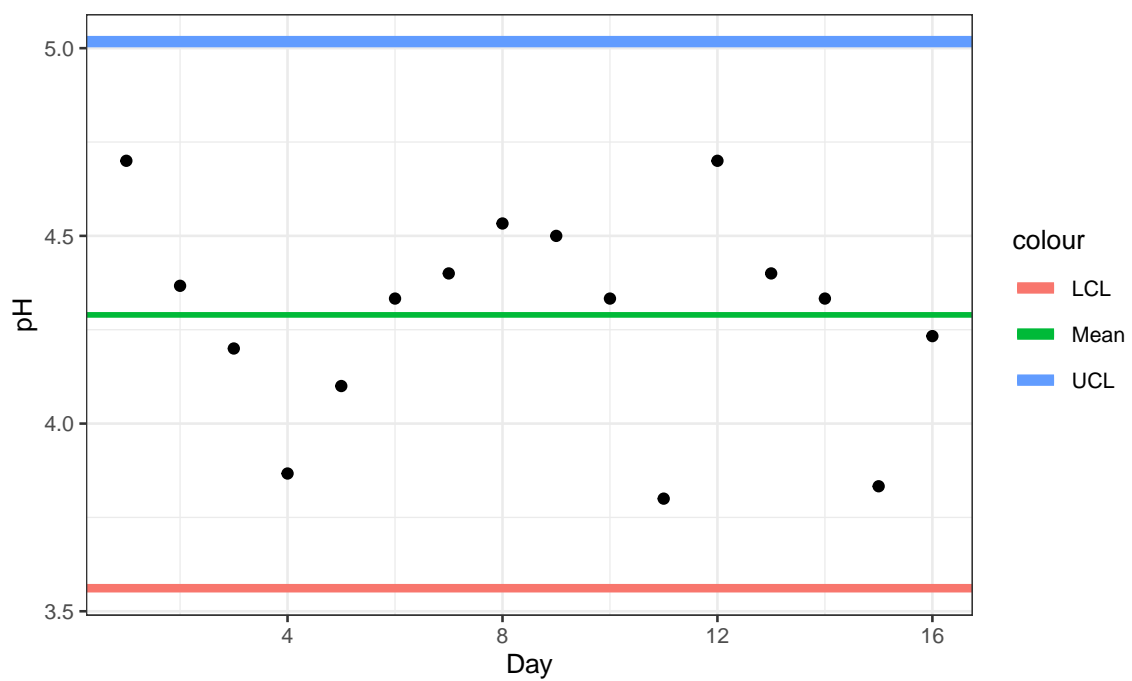


Figure 8.2: The  $3\sigma$  **control chart** illustrates that with respect to pH the brewing process is in-control over the selected timeframe as the observations fall within the (LCL, UCL) control interval.

# References



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