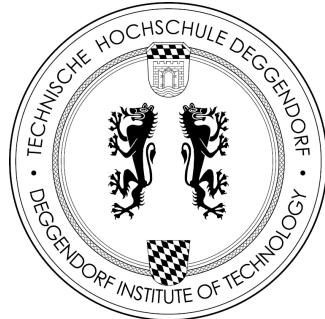


DEGGENDORF INSTITUTE OF TECHNOLOGY



Advanced Statistical Methods and Optimization

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Preface

This is the script for the lecture “Advanced Statistical Methods and Optimization” at the DIT/Campus Cham. I do realize, that this body of knowledge has been repeated over and over, but have decided to do my own nonetheless so I can add my own flavor to the realms of statistics. Please note that this material is copyrighted, you are not allowed to copy, at least ask for permission - you are likely to get it.

Tim Weber, Oct. 2024

1 Basic Concepts

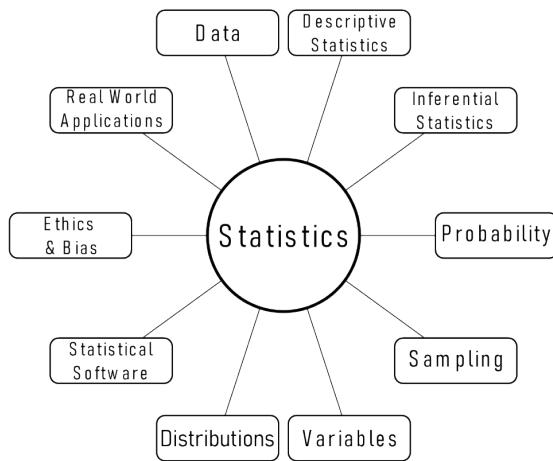


Figure 1.1: The necessary statistical ingredients.

Statistics is a fundamental field that plays a crucial role in various disciplines, from science and economics to social sciences and beyond. It's the science of collecting, organizing, analyzing, interpreting, and presenting data. In this introductory overview, we'll explore some key concepts and ideas that form the foundation of statistics:

1. **Data:** At the heart of statistics is data. Data can be anything from numbers and measurements to observations and information collected from experiments, surveys, or observations. In statistical analysis, we work with two main types of data: quantitative (numerical) and qualitative (categorical).
2. **Descriptive Statistics:** Descriptive statistics involve methods for summarizing and organizing data. These methods help us understand the basic characteristics of data, such as measures of central tendency (mean, median, mode) and measures of variability (range, variance, standard deviation).
3. **Inferential Statistics:** Inferential statistics is about making predictions, inferences, or decisions about a population based on a sample of data. This involves hypothesis testing, confidence intervals, and regression analysis, among other techniques.

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4. **Probability:** Probability theory is the foundation of statistics. It deals with uncertainty and randomness. We use probability to describe the likelihood of events occurring in various situations, which is essential for making statistical inferences.
5. **Sampling:** In most cases, it's impractical to collect data from an entire population. Instead, we often work with samples, which are smaller subsets of the population. The process of selecting and analyzing samples is a critical aspect of statistical analysis.
6. **Variables:** Variables are characteristics or attributes that can vary from one individual or item to another. They can be categorized as dependent (response) or independent (predictor) variables, depending on their role in a statistical analysis.
7. **Distributions:** A probability distribution describes the possible values of a variable and their associated probabilities. Common distributions include the normal distribution, binomial distribution, and Poisson distribution, among others.
8. **Statistical Software:** In the modern era, statistical analysis is often conducted using specialized software packages like R, Python (with libraries like NumPy and Pandas), SPSS, or Excel. These tools facilitate data manipulation, visualization, and complex statistical calculations.
9. **Ethics and Bias:** It's essential to consider ethical principles in statistical analysis, including issues related to data privacy, confidentiality, and the potential for bias in data collection and interpretation.
10. **Real-World Applications:** Statistics has a wide range of applications, from medical research to marketing, finance, and social sciences. It helps us make informed decisions and draw meaningful insights from data in various fields.

1.1 Probability

1.1.1 Overview

Probability theory is a fundamental concept in the field of statistics, serving as the foundation upon which many statistical methods and models are built.

1.1.2 What is Probability?

Probability is a mathematical concept that quantifies the uncertainty or randomness of events. It provides a way to measure the likelihood of different outcomes occurring in a given situation. In essence, probability is a numerical representation of our uncertainty.

1.1.3 Basic Probability Terminology

- **Experiment:** An experiment is any process or procedure that results in an outcome. For example, rolling a fair six-sided die is an experiment.
- **Outcome:** An outcome is a possible result of an experiment. When rolling a die, the outcomes are the numbers 1 through 6.
- **Sample Space (S):** The sample space is the set of all possible outcomes of an experiment. For a fair six-sided die, the sample space is $\{1, 2, 3, 4, 5, 6\}$.
- **Event (E):** An event is a specific subset of the sample space. It represents a particular set of outcomes that we are interested in. For instance, “rolling an even number” is an event for a six-sided die, which includes outcomes $\{2, 4, 6\}$.

1.1.4 Probability Notation

In probability theory, we use notation to represent various concepts:

- **P(E):** Probability of event E occurring.
- **P(A and B):** Probability of both events A and B occurring.
- **P(A or B):** Probability of either event A or event B occurring.
- **P(E'): Complement of event E:** Probability of the complement of event E, which is the probability of E not occurring.

1.1.5 The Fundamental Principles of Probability

There are two fundamental principles of probability:

- **The Addition Rule:** It states that the probability of either event A or event B occurring is given by the sum of their individual probabilities, provided that the events are mutually exclusive (i.e., they cannot both occur simultaneously).

$$P(A \text{ or } B) = P(A) + P(B) \quad (1.1)$$

- **The Multiplication Rule:** It states that the probability of both event A and event B occurring is the product of their individual probabilities, provided that the events are independent (i.e., the occurrence of one event does not affect the occurrence of the other).

$$P(A \text{ and } B) = P(A) * P(B) \quad (1.2)$$

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1.1.6 Example: Rolling a Fair Six-Sided Die

Consider rolling a fair six-sided die.

- Sample Space (S): $\{1, 2, 3, 4, 5, 6\}$ (Figure 1.2)
- Event A: Rolling an even number = $\{2, 4, 6\}$ (Figure 1.2)
- Event B: Rolling a number greater than 3 = $\{4, 5, 6\}$ (Figure 1.2)

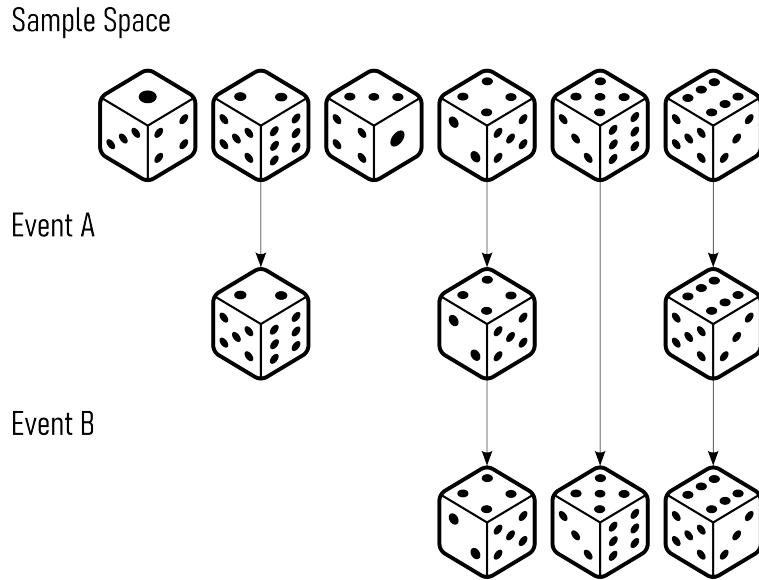


Figure 1.2: This example's sample space, as well as event A and event B.

Calculation of some probabilities:

- Probability of Event A ($P(A)$): $P(A) = \frac{\text{Number of outcomes in } A}{\text{Total number of outcomes in } S} = \frac{3}{6} = \frac{1}{2}$
- Probability of Event B ($P(B)$): $P(B) = \frac{3}{6} = \frac{1}{2}$
- Probability of both A and B ($P(A \text{ and } B)$): 4 and 6 satisfy both A and B, $P(A \text{ and } B) = \frac{2}{6} = \frac{1}{3}$

This example demonstrates the fundamental principles of probability and how they can be applied to real-world situations.

In the subsequent chapters of this course, more advanced concepts in probability theory will be explored, including conditional probability, random variables, probability distributions, and statistical inference.

1.1.7 Population Definition

In the field of statistics, a population refers to the entire group or collection of individuals, objects, or events under study. For example, when conducting a survey to examine the average income of households in a country, the population encompasses all the households within that country.

1.1.8 Random Sampling

To study a population, statisticians often employ random sampling techniques as it may not be feasible or practical to gather data from every member of the population. Probability principles come into play during the selection of a random sample, ensuring that the sampling process adheres to well-defined rules to represent the population adequately.

1.1.9 Sampling Distribution

Once a random sample is acquired, probability theory becomes instrumental in analyzing and characterizing various sample statistics, such as the sample mean and variance. The sampling distribution serves as a probability distribution, encompassing all possible values of sample statistics attainable through random sampling.

1.1.10 Inferential Statistics

Probability plays a pivotal role in drawing conclusions about the population based on the data obtained from the sample. Statistical methodologies, including hypothesis testing and constructing confidence intervals, rely on probability theory to assess the likelihood of specific outcomes and quantify the associated uncertainty.

1.1.11 Estimation

Probability is a key element in parameter estimation. For instance, when estimating population parameters like the mean or variance based on a sample, statisticians employ probability distributions such as the t-distribution or chi-squared distribution to create confidence intervals and determine margins of error.

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1.1.12 Hypothesis Testing

In hypothesis testing, probability is employed to ascertain whether observed differences or associations in sample data hold statistical significance. Probability calculations aid in evaluating whether the observed results are likely to be a product of random chance or if they genuinely reflect characteristics of the population.

1.1.13 Generalization

The primary objective of statistical analysis is to generalize findings from the sample to the entire population. Probability allows for quantifying the likelihood that the characteristics observed in the sample accurately represent the entire population, while also considering the inherent uncertainty associated with the sampling process.

1.1.14 Probability in action - The Galton Board

A Galton board, also known as a bean machine or a quincunx, is a mechanical device that demonstrates the principles of probability and the normal distribution. It was invented by Sir Francis Galton¹ in the late 19th century. The Galton board consists of a vertical board with a series of pegs or nails arranged in triangular or hexagonal patterns.

A Galton board, also known as a bean machine or a quincunx, is a mechanical device that demonstrates the principles of probability and the normal distribution. It was invented by Sir Francis Galton in the late 19th century. The Galton board consists of a vertical board with a series of pegs or nails arranged in triangular or hexagonal patterns.

1. **Initial Release:** At the top of the Galton board, a ball or particle is released. This ball can take one of two paths at each peg, either to the left or to the right. The decision at each peg is determined by chance, such as the flip of a coin or the roll of a die. This represents a random event.
2. **Multiple Trials:** As the ball progresses downward, it encounters several pegs, each of which randomly directs it either left or right. The ball continues to bounce off pegs until it reaches the bottom.
3. **Accumulation:** Over multiple trials or runs of the Galton board, you will notice that the balls accumulate in a pattern at the bottom. This pattern forms a bell-shaped curve, which is the hallmark of a normal distribution.

¹Sir Francis Galton (1822-1911): Influential English scientist, notable for his contributions to statistics and genetics.

1.2 Population

4. **Normal Distribution:** The accumulation of balls at the bottom resembles the shape of a normal distribution curve. This means that the majority of balls will tend to accumulate in the center, forming the peak of the curve, while fewer balls will accumulate at the extreme left and right sides.

The Galton board is a visual representation of the central limit theorem, a fundamental concept in probability theory. It demonstrates how random events, when repeated many times, tend to follow a normal distribution. This distribution is commonly observed in various natural phenomena and is essential in statistical analysis.

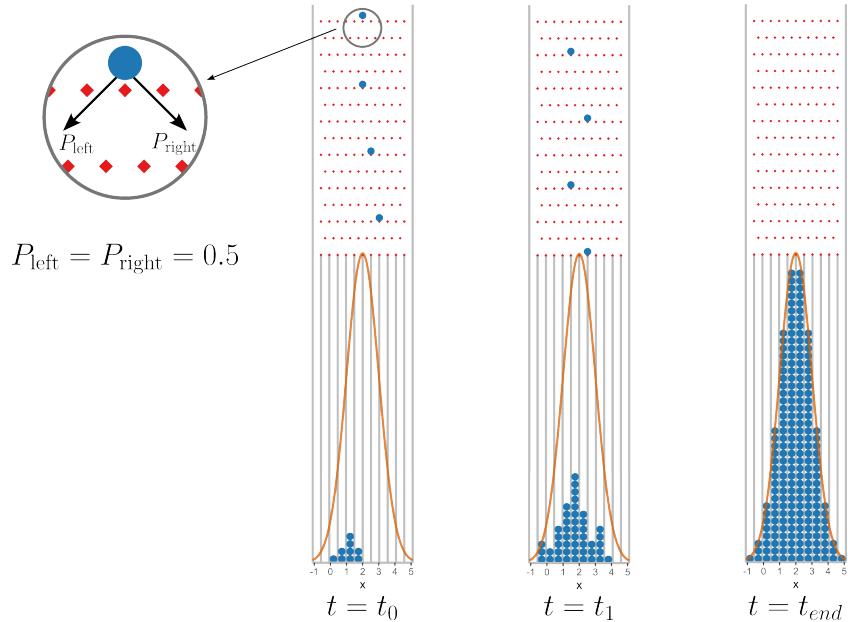


Figure 1.3: A Galton board in action.

1.2 Population

In statistics, a population is the complete set of individuals, items, or data points that are the subject of a study. Understanding populations and how to work with them is fundamental in statistical analysis, as it forms the basis for making meaningful inferences and drawing conclusions about the broader group being studied. It is the complete collection of all elements that share a common characteristic or feature and is of interest to the researcher. The population can vary widely depending on the research question or problem at hand. A populations *true mean* is depicted with μ_0 and the variance is depicted with σ_0^2 .

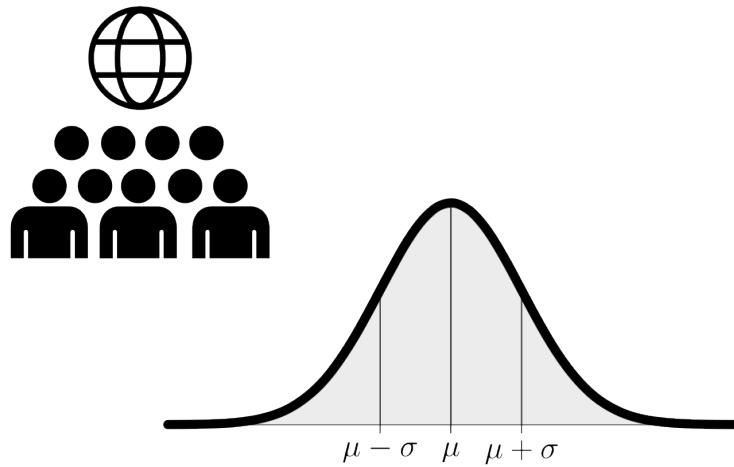


Figure 1.4: An example for a population.

1.3 Sample

The key principles behind a sample include its role as a manageable subset of data, which can be chosen randomly or purposefully. Ideally, it should be representative, reflecting the characteristics and diversity of the larger population. Statistical techniques are then applied to this sample to make inferences, estimate population parameters, or test hypotheses. The size of the sample matters, as a larger sample often leads to more precise estimates, but it should be determined based on research goals and available resources. Various sampling methods, such as random sampling, stratified sampling, or cluster sampling, can be employed depending on the research objectives and population characteristics. A samples *true mean* is depicted with \bar{x} and the variance is depicted with sd .

1.4 Descriptive Statistics

Descriptive Statistics: Descriptive statistics are used to summarize and describe the main features of a data set. They provide a way to organize, present, and analyze data in a meaningful and concise manner. Descriptive statistics do not involve making inferences or drawing conclusions beyond the data that is being analyzed. Instead, they aim to provide a clear and accurate representation of the data set. Some common techniques and measures used in descriptive statistics include:

1. Measures of Central Tendency:

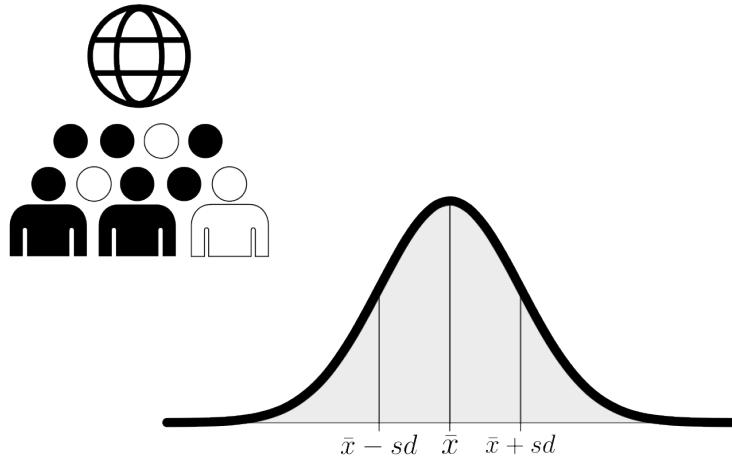


Figure 1.5: A sample drawn from the population.

- Mean (average)
 - Median (middle value)
 - Mode (most frequent value)
2. Measures of Variability or Dispersion:
- Range (difference between the maximum and minimum values)
 - Variance (average of the squared differences from the mean)
 - Standard Deviation (square root of the variance)
3. Frequency Distributions:
- Histograms
 - Density plots
 - Frequency tables
 - Bar charts
4. Summary Statistics:
- Percentiles
 - Quantiles

1.4.1 Histogram

An example for descriptive statistics is shown in Figure 1.6 as a histogram. It shows data from a company that produces pharmaceutical syringes, taken from Ramalho (2021).

1 Basic Concepts

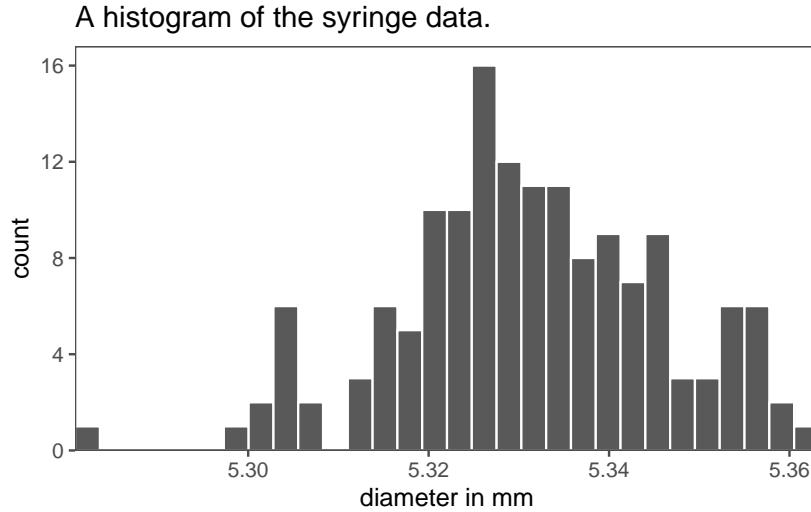


Figure 1.6: An example for descriptive statistics (histogramm)

During the production of those syringes, the so called *barrel diameter* is a critical parameter to the function of the syringe and therefore of special interest for the Quality Control.

A histogram as shown in Figure 1.6 shows the data of 150 measurements during the QC. On the **x-axis** the *barrel diameter* is shown, while the count of each *binned* diameter is shown on the **y-axis**. The binning and of data is a crucial parameter for such a plot, because it already changes the appearance and width of the bars. Binning is a trade-off between visibility and readability.

1.4.2 Density plot

Density plots are another way of displaying the statistical distribution of an underlying dataset. The biggest strength of those plots is, that no binning is necessary in order to show the data. The limitation of this kind of plot is the interpretability. An example of a density plot for the syringe data is shown in Figure 1.7. On the **x-axis** the syringe barrel diameter is shown (as in a histogram). The **y-axis** in contrast does not display the count of a binned category, but rather the Probability Density Function for the specific diameter. The grey area under the density curve depicts the probability of a syringe diameter to appear in the data. The complete area under the curve equals to 1 meaning that a certain diameter is sure to appear in the data.

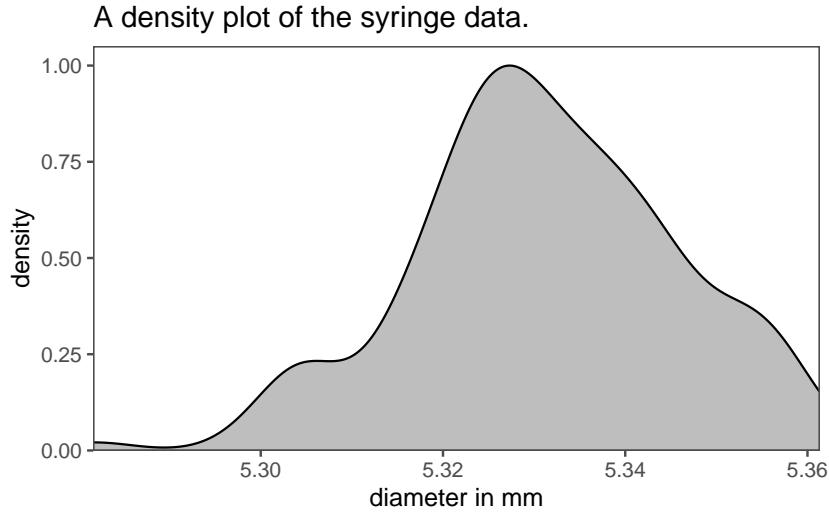


Figure 1.7: An example for a density plot for the syringe data (barrel diameter).

1.4.3 Boxplot

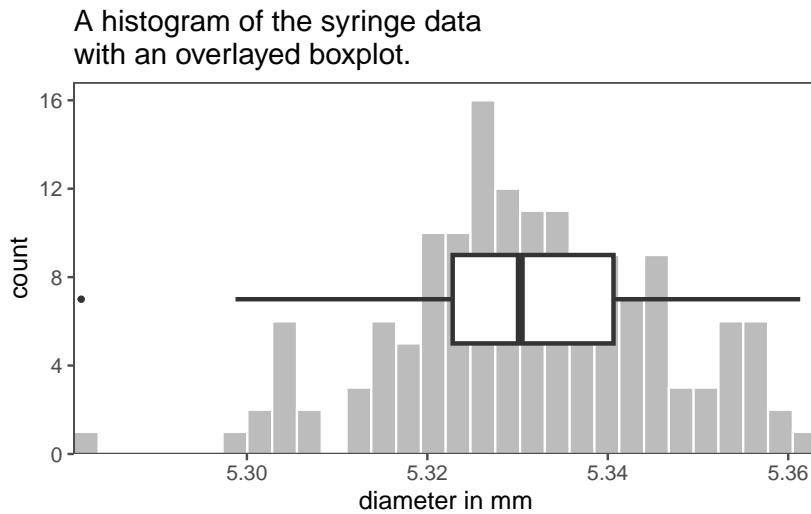


Figure 1.8: A boxplot of the same syringe data combined with the according histogram.

It is very common to include and inspect measures of central tendency in the graphical depiction of data. A **boxplot**, also known as a box-and-whisker plot, is a very common way of doing this. A **boxplot** is a graphical representation of a dataset's distribution. It displays the following key statistics:

1. Median (middle value).

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2. Quartiles (25^{th} and 75^{th} percentiles), forming a box.
3. Minimum and maximum values (whiskers).
4. Outliers (data points significantly different from the rest).

The syringe data in boxplot form is shown in Figure 1.8 as an overlay of the histogram plot before. Boxplots are useful for quickly understanding the central tendency, spread, and presence of outliers in a dataset, making them a valuable tool in data analysis and visualization.

1.4.4 Average, Standard deviation and Range

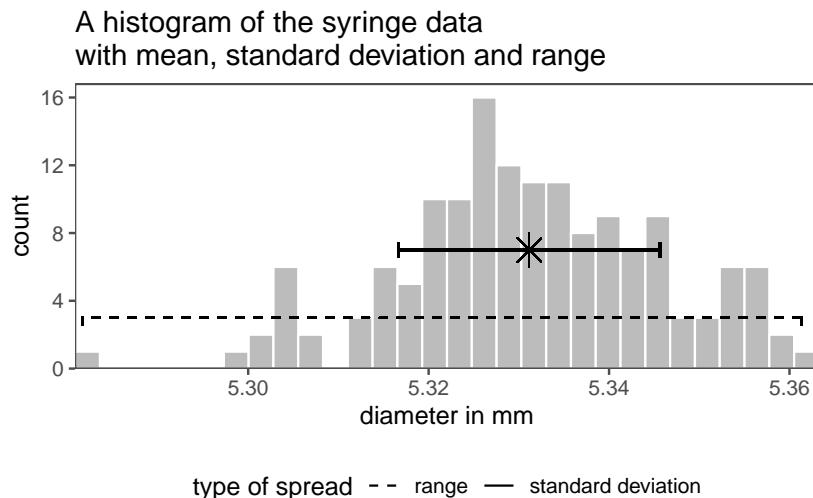


Figure 1.9: A histogram of the syringe data with mean, standard deviation and range.

Very popular measures of central tendency include the *average* (mean) and the *standard deviation* (variance) of a dataset. The computed mean from an actual dataset is depicted with \bar{x} and calculated via (1.3).

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (1.3)$$

With n being the number of datapoints and x_i being the datapoints. The *mean* is therefore the sum of all datapoints divided by the total number n of all datapoints. It is not to be confused with the true mean μ_0 of a population.

The computed *standard deviation* from an actual dataset is depicted with sd and calculated via (1.4).

$$sd = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (1.4)$$

The *standard deviation* can therefore be explained as the square root of the sum of all differences of each individual datapoints to the mean of a dataset divided by the number of datapoints. It is not to be confused with the true variance σ_0^2 of a population. The variance of a dataset can be calculated via (1.5).

$$\sigma = sd^2 \quad (1.5)$$

The *range* from an actual dataset is depicted with r and calculated via (1.6).

$$r = \max(x_i) - \min(x_i) \quad (1.6)$$

The *range* can therefore be interpreted as the range from minimum to maximum in a dataset.

1.5 Visualizing Groups

1.5.1 Boxplots

The methods described above are especially useful when it comes to visualizing groups in data. The data is discretized and the information density is increased. As with every discretization comes also a loss of information. It is therefore strongly advised to choose the right tool for the job.

If the underlying distribution of the data is unknown, a good start to visualize groups within data is usually a boxplot as shown in Figure 1.10. The syringe data from Ramalho (2021) contains six different groups, one for every sample drawn. Each sample consists of 25 observations in total. On the **x-axis** the *diameter* in mm is shown, the **y-axis** depicts the sample number. The **boxplots** are then drawn as described above (median, 25th and 75th percentile box, 5th and 95th whisker). The 25th and 75th percentile box is also known as the Interquartile Range

1 Basic Concepts

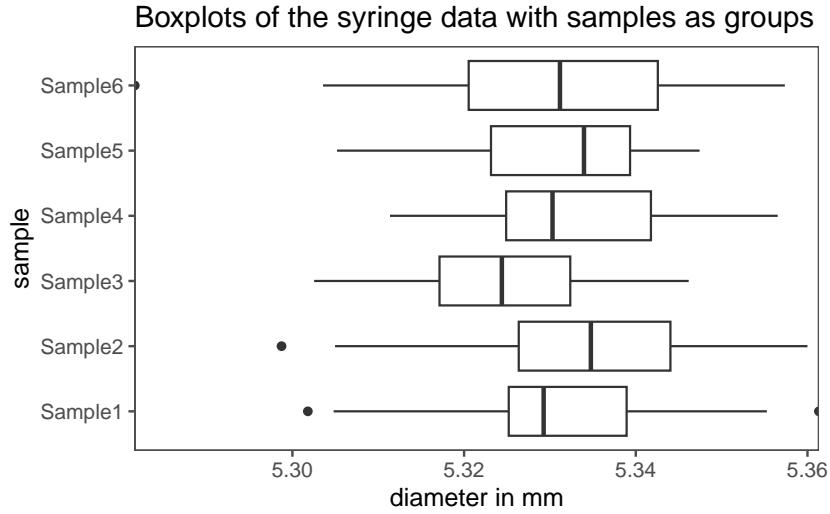


Figure 1.10: Boxplots of the syringe data with the samples as groups.

1.5.2 Mean and standard deviation plots

If the data follows a normal distribution, showing the mean and standard deviation for each group is also very common. For the syringe dataset, this is shown in Figure 1.11. The plot follows the same logic as for the boxplots (`x-axis-data`, `y-axis-data`), but the data itself shows the mean with a \times -symbol, as the length of the horizontal errorbars accords to $\bar{x} \pm sd(x)$.

1.5.3 Half-half plots

Boxplots and mean-and-standard-deviation plots sometimes hide some details within the data, that may be of interest or simply important. Half-half plots, as shown in Figure 1.12, incorporate different plot mechanisms. The left half shows a violin plot, which outlines the underlying distribution of the data using the PDF. This is very similar to a density plot. The right half shows the original data points and give the user a visible clue about the sample size in the data size. Note that the y-position of the points is jittered to counter *overplotting*. Details can be found in Tiedemann (2022).

1.5.4 Ridgeline plots

Figure 1.13 shows so called *ridgeline* plots as explained in Wilke (2022). They are in essence density plots that use the `y-axis` to differentiate between the groups. On the `x-axis` the density of the underlying dataset is shown. More info on the creation of these

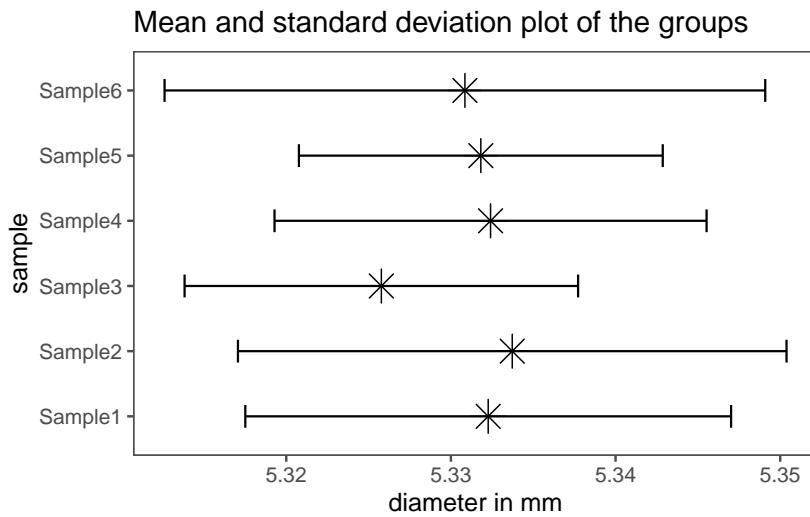


Figure 1.11: Mean and standard deviation plots of the groups in the dataset.

plots and graphics is available in Wickham (2016) as well as “The R Graph Gallery – Help and Inspiration for r Charts” (2022).

1.6 The drive shaft exercise

1.6.1 Introduction

A drive shaft is a mechanical component used in various vehicles and machinery to transmit rotational power or torque from an engine or motor to the wheels or other driven components. It serves as a linkage between the power source and the driven part, allowing the transfer of energy to propel the vehicle or operate the machinery.

1. Material Selection: Quality steel or aluminum alloys are chosen based on the specific application and requirements.
2. Cutting and Machining: The selected material is cut and machined to achieve the desired shape and size. Precision machining is crucial for balance and performance.
3. Welding or Assembly: Multiple sections may be welded or assembled to achieve the required length. Proper welding techniques are used to maintain structural integrity.
4. Balancing: Balancing is critical to minimize vibrations and ensure smooth operation. Counterweights are added or mass distribution is adjusted.

1 Basic Concepts

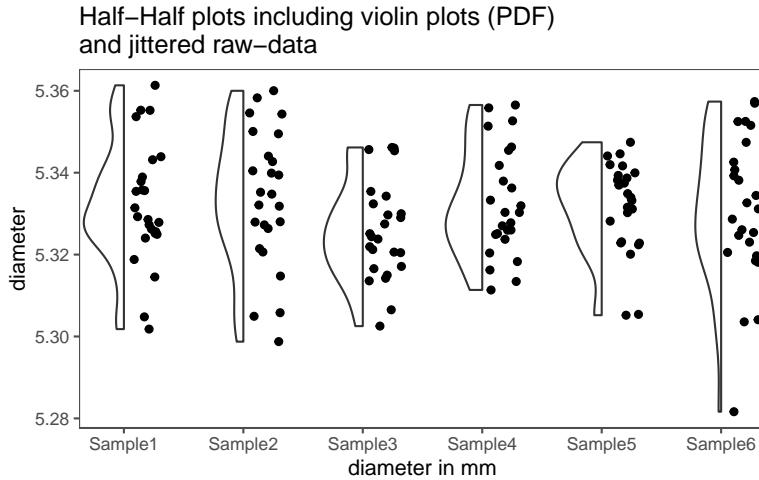


Figure 1.12: Half-half plots that incorporate different types of plots

5. Surface Treatment: Drive shafts are often coated or treated for corrosion resistance and durability. Common treatments include painting, plating, or applying protective coatings.
6. Quality Control: Rigorous quality control measures are employed to meet specific standards and tolerances. This includes dimensional checks, material testing, and defect inspections.
7. Packaging and Distribution: Once quality control is passed, drive shafts are packaged and prepared for distribution to manufacturers of vehicles or machinery.

The end diameter of a drive shaft is primarily determined by its torque capacity, length, and material selection. It needs to be designed to handle the maximum torque while maintaining structural integrity and flexibility as required by the specific application. For efficient load transfer, there are ball bearings mounted on the end diameter. Ball bearings at the end diameter of a drive shaft support its rotation, reducing friction. They handle axial and radial loads, need lubrication for longevity, and may include seals for protection. Proper alignment and maintenance are crucial for their performance and customization is possible to match specific requirements.

The end diameter of the drive shaft shall be $\varnothing 12 \pm 0.1\text{mm}$ (see Figure 1.14). This example will haunt us the rest of this lecture.

1.6.2 Visualizing all the Data

First, some descriptive statistics of $N = 500$ produced drive shafts are shown in Table 1.1 ($\bar{x}(sd)$, $\text{median}(IQR)$). This first table does not tell us an awful lot about the sample, apart from the classic statistical measures of central tendency and spread.

1.6 The drive shaft exercise

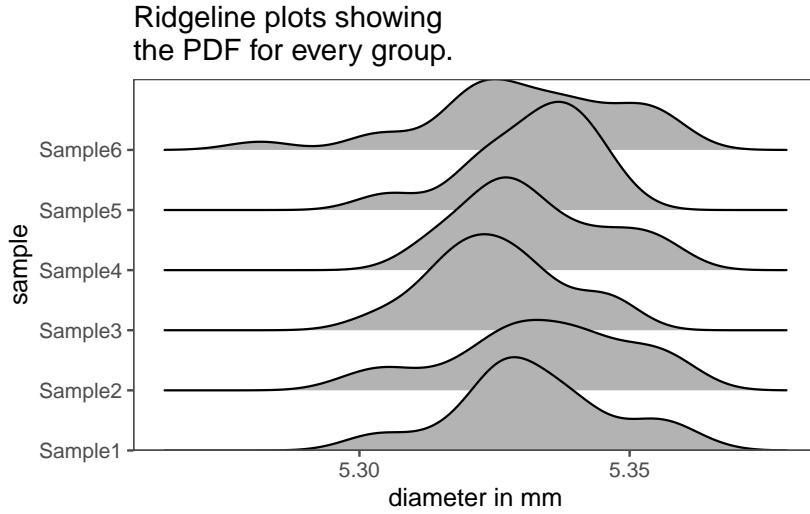


Figure 1.13: Ridgeline plots for distributions within groups.

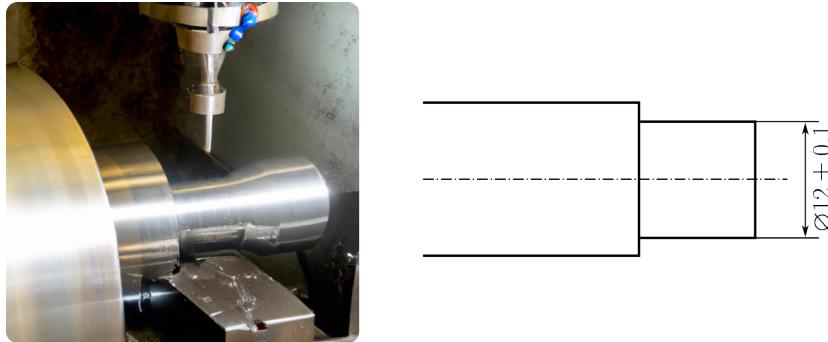


Figure 1.14: The drive shaft specification.

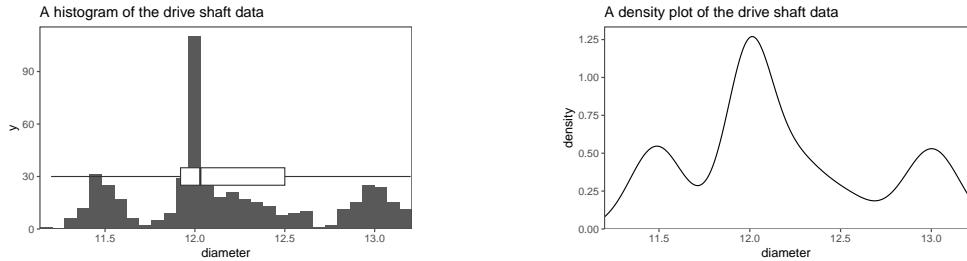
Table 1.1: The summary table of the drive shaft data

Variable	$N = 500^1$
diameter	12.17 (0.51), 12.03 (0.58)

¹Mean (SD), Median (IQR)

In Figure 1.15 the data and the distribution thereof is visualized using different modalities. The complete `drive shaft data` is shown as a histogram (Figure 1.15a) and as a density plot (Figure 1.15b). A single boxplot is plotted over the histogram data in Figure 1.15a, providing a link to Table 1.1 (median and IQR). One important conclusion may be drawn from those plots already: There may be more than one dataset hidden inside the data. We will explore this possibility further.

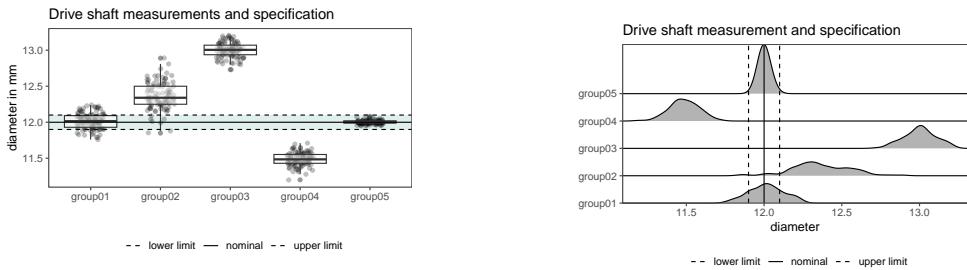
1 Basic Concepts



(a) The drive shaft data shown in a histogram. (b) The drive shaft data shown in a density plot.

Figure 1.15: The raw data of the measured drive shaft diameter.

1.6.3 Visualizing groups within the data



(a) The groups visualized as boxplots (including the specification) (b) The groups visualized as ridgeline plots

Figure 1.16: The raw data of the measured drive shaft diameter.

Fortunately for us, the groups that may be hidden within the data are marked in the original dataset and denoted as `group0x`. Unfortunately for us, it is not known (purely from the data) how these groups come about. Because we did get the dataset from a colleague, we need to investigate the *creation* of the dataset even further. This is an important point, for without knowledge about the history of the data, it is *impossible* or at least *unadvisable* to make valid statements about the data. We will go on with a table of summary statistics, see Table 1.2. Surprisingly, there are five groups hidden within the data, something we would not be able to spot from the raw data alone.

Table 1.2: The group summary table of the drive shaft data

Variable	N = 100 ¹
group01	12.02 (0.11), 12.02 (0.16)
group02	12.36 (0.19), 12.34 (0.25)
group03	13.00 (0.10), 13.01 (0.13)
group04	11.49 (0.09), 11.49 (0.12)

1.6 The drive shaft exercise

group05	12.001 (0.026), 12.000 (0.030)
---------	--------------------------------

¹Mean (SD), Median (IQR)

Again, the table is good to have, but not as engagingi for ourself and our co-workers to look at. In order to make the data more approachable, we will use some techniques shown in Section 1.5.

First in Figure 1.16a the raw data points are shown as points with overlayed boxplots. On the **x-axis** the groups are depicted, while the Parameter of Interest (in this case the *end diameter* of the drive shaft) is shown on the **y-axis**. Because we are interested how the manufactured drive shafts behave with respect to the specification limit, the **nominal** value as well as the **upper** and the **lower** specification limit is also shown in the plot as horizontal lines.

In Figure 1.16b the data is shown as ridgeline density plots. On the **x-axis** the diameter is depicted, while the **y-axis** shows two types of data. First, the groups 1 ... 5 are shown. For the individual groups, the probability is depicted as a line, therefore indicating which values are most probable in the given group. Again, because we are interested how the manufactured drive shafts behave .w.r.t the specification limit, the **nominal** value as well as the **upper** and the **lower** specification limit is also shown in the plot as vertical lines.

2 Statistical Distributions

2.1 Types of data

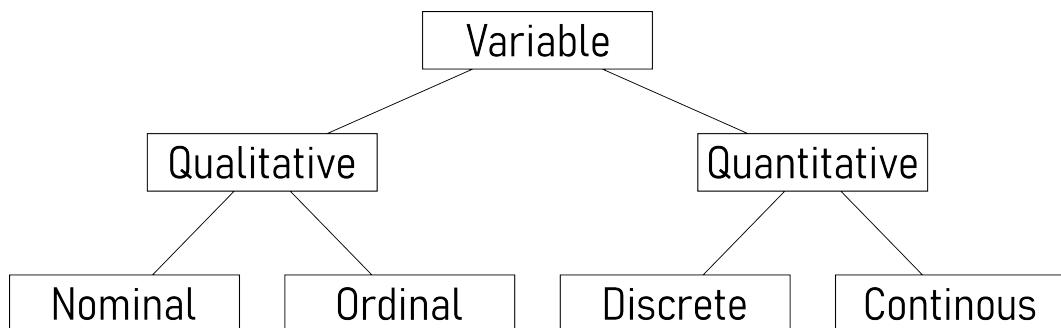


Figure 2.1: Data can be classified as different types.

1. Nominal Data:

- Description: Nominal data represents categories with no inherent order or ranking.
- Examples: Colors, gender, or types of fruits.
- Characteristics: Categories are distinct, but there is no meaningful numerical value associated.

2. Ordinal Data:

- Description: Ordinal data has categories with a meaningful order or ranking, but the intervals between them are not consistent or measurable.
- Examples: Educational levels (e.g., high school, bachelor's, master's), customer satisfaction ratings (e.g., low, medium, high).
- Characteristics: The order is significant, but the differences between categories are not precisely quantifiable.

3. Discrete Data:

- Description: Discrete data consists of separate, distinct values, often counted in whole numbers and with no intermediate values between them.
- Examples: Number of students in a class, number of cars in a parking lot.

2 Statistical Distributions

- Characteristics: The data points are distinct and separate; they do not have infinite possible values within a given range.

4. Continuous Data:

- Description: Continuous data can take any value within a given range and can be measured with precision.
- Examples: Height, weight, temperature.
- Characteristics: Values can be any real number within a range, and there are theoretically infinite possible values within that range.

2.1.1 Nominal Data

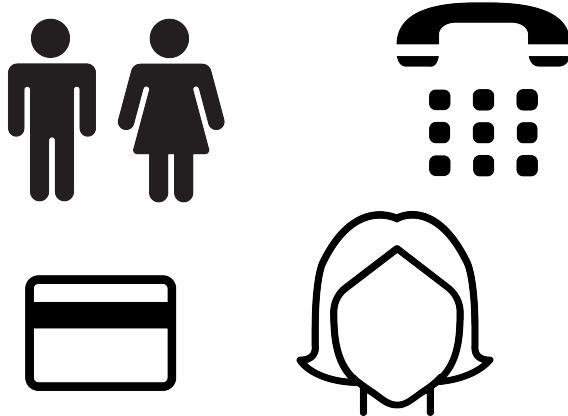


Figure 2.2: Some example for nominal data.

Nominal data is a type of data that represents categories or labels without any specific order or ranking. These categories are distinct and non-numeric. For example, colors, types of fruits, or gender (male, female, other) are nominal data. Nominal data can be used for classification and grouping, but mathematical operations like addition or subtraction do not make sense in this context.

2.1.2 Ordinal Data

Ordinal data represents categories that have a specific order or ranking. While the categories themselves may not have a consistent numeric difference between them, they can be arranged in a meaningful sequence. A common example of ordinal data is survey responses with options like “strongly agree,” “agree,” “neutral,” “disagree,” and “strongly disagree.” These categories indicate a level of agreement, but the differences between them may not be uniform or measurable.

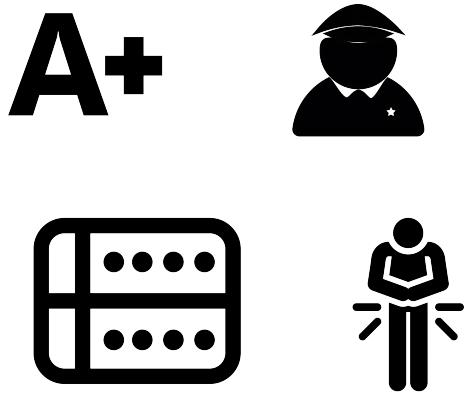


Figure 2.3: Some example for ordinal data.

2.1.3 Discrete Data

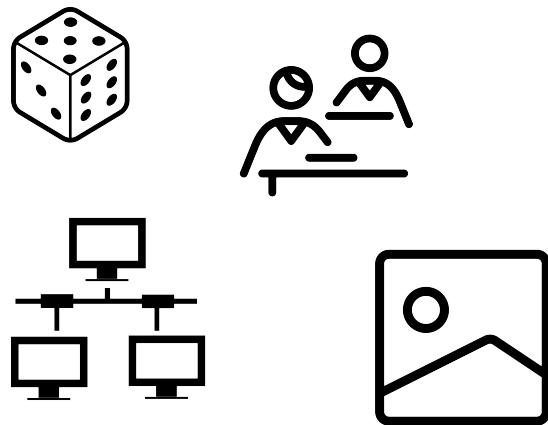


Figure 2.4: Some example for discrete data.

Discrete data consists of distinct, separate values that can be counted and usually come in whole numbers. These values can be finite or infinite, but they are not continuous. Examples include the number of students in a class, the count of cars in a parking lot, or the quantity of books in a library. Discrete data is often used in counting and can be represented as integers.

One quote in the literature about discrete data, shows how difficult the classification of data types can become (J. Bibby (1980)): "... All actual sample spaces are discrete, and all observable random variables have discrete distributions. The continuous distribution

2 Statistical Distributions

is a mathematical construction, suitable for mathematical treatment, but not practically observable. ...”

2.1.4 Continous Data

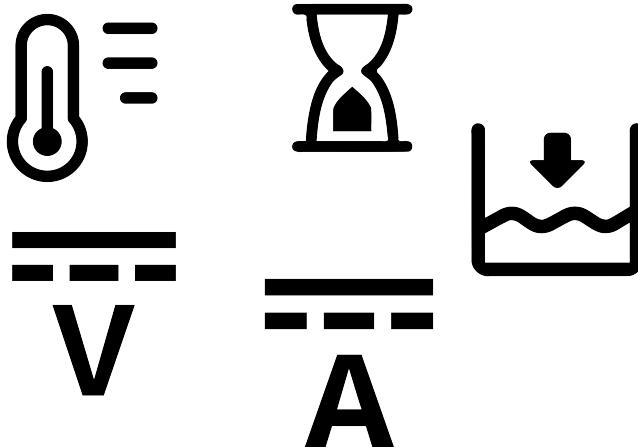


Figure 2.5: Some example for continous data.

Continuous data encompasses a wide range of values within a given interval and can take on any real number. There are infinite possibilities between any two points in a continuous dataset, making it suitable for measurements with high precision. Examples of continuous data include temperature, height, weight, and time. It is important to note that continuous data can be measured with decimals or fractions and is not limited to whole numbers.

2.2 The Normal Distribution

The normal distribution is a fundamental statistical concept that holds immense significance in the realms of engineering and production. It is often referred to as the Gaussian distribution or the bell curve, is a mathematical model that describes the distribution of data in various natural and human-made phenomena, see Johnson (1994). It forms a symmetrical curve when plotted, is centered around a mean (μ_0) and balanced on both sides (Figure 2.6). The spread or dispersion of the data points is characterized by σ_0^2 . Those two parameters completely define the normal distribution. A remarkable property of the normal distribution is the empirical rule, which states that approximately 68% of the data falls within one standard deviation from the mean, 95% falls within two standard deviations, and 99.7% falls within three standard deviations (Figure 2.6). The existence of the normal distribution in the real world is a result of the combination of

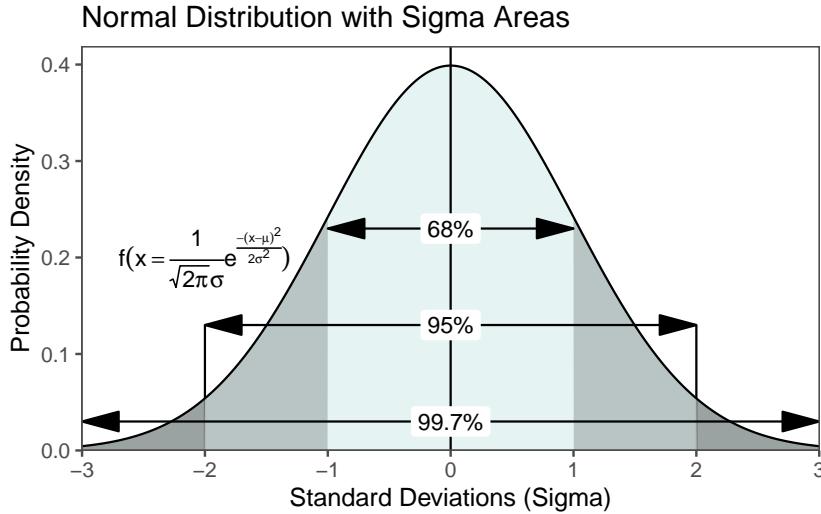


Figure 2.6: The standarized normal distribution

several factors, including the principles of statistics and probability, the Central Limit Theorem, and the behavior of random processes in nature and society.

2.2.1 Central Limit Theorem (CLT)

The primary reason for the existence of the normal distribution in many real-world datasets is the Central Limit Theorem (Taboga 2017). The CLT states that when you take a large enough number of random samples from any population, the distribution of the sample means will tend to follow a normal distribution, even if the original population distribution is not normal. This means that the normal distribution emerges as a statistical consequence of aggregating random data points. This is shown in Figure 2.7.

From $n = 10000$ uniformly disitrubuted data points (the *population*) ($\min = 1, \max = 100$) either 2, 10, 50 or 200 samples are taken randomly (the *samples*). For each of the samples the mean is calculated, resulting in 1000 mean values for each (2, 10, 50 or 200) sample size. In Figure 2.7 the results from this numerical study are shown. The larger the sample size, the closer the mean calculated \bar{x} is to the population mean (μ_0). The effect is especially large on the standard deviation, resulting in a smaller standard deviation the larger the sample size is.

2.2.2 Randomness and Independence

In nature and society, many processes involve a large number of random, independent, and additive factors. When these factors combine, their individual effects tend to follow

Central Limit Theorem Demonstration

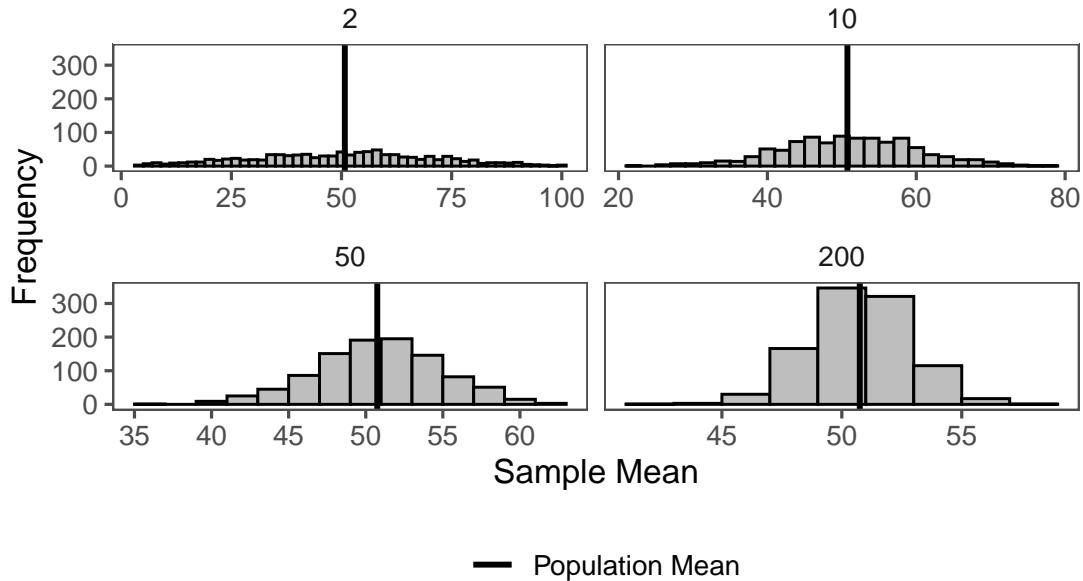


Figure 2.7: The central limit theorem in action.

a normal distribution, as predicted by the CLT. This principle is observed in various contexts, such as the behavior of particles in a gas (Brownian motion), the genetics of traits in populations, or the variability in the heights and weights of individuals in a population.

2.2 The Normal Distribution

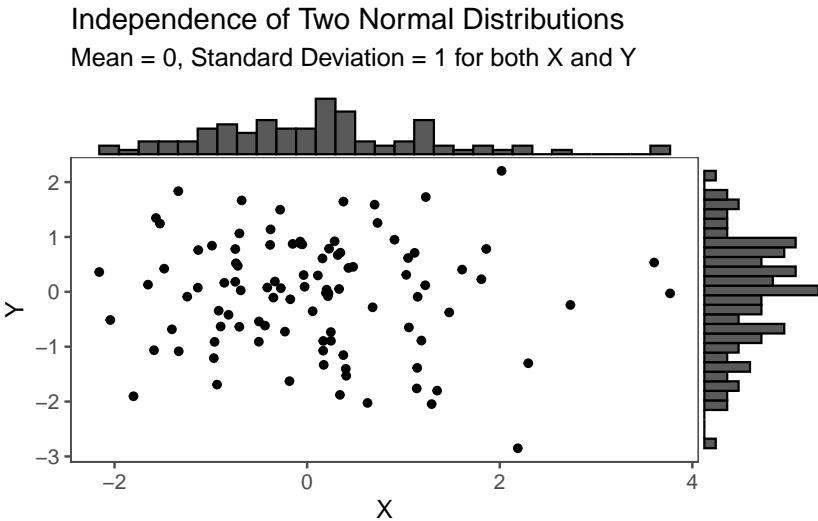


Figure 2.8: Two random and independent samples drawn from a normal distribution. They do not show any independence.

2.2.3 Law of Large Numbers

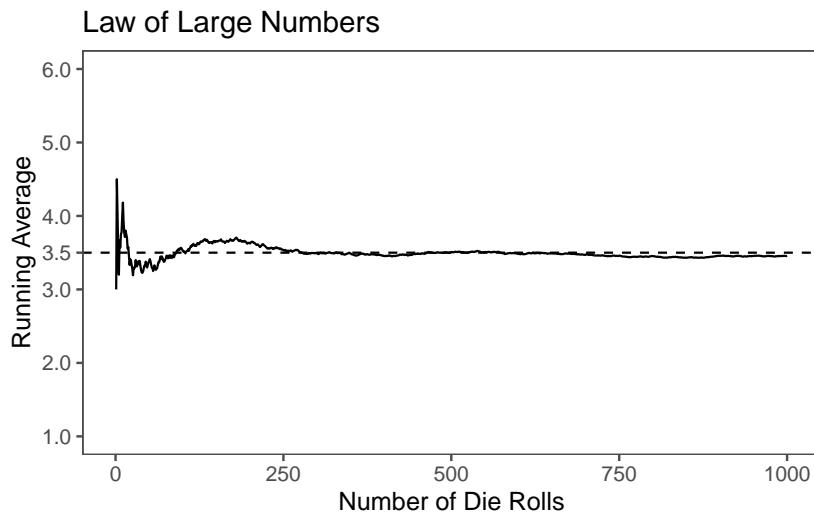


Figure 2.9: The Law of Large Numbers in Action with die rolls as an example.

The Law of Large Numbers states that as the size of a random sample increases, the sample average converges to the population mean. This law, along with the CLT, explains why the normal distribution frequently arises. When you take many small, independent, and identically distributed measurements and compute their averages, these averages

2 Statistical Distributions

tend to cluster around the true population mean, forming a normal distribution Johnson (1994).

The LLN at work is shown in Figure 2.9. A fair six-sided die is rolled 1000 times and the running average of the roll results after each roll is calculated. The resulting line plot shows how the running average approaches the expected value of 3.5, which is the average of all possible outcomes of the die. The line in the plot represents the running average. It fluctuates at the beginning but gradually converges toward the expected value of 3.5. To emphasize this convergence, a dashed line indicating the theoretical expected value which is essentially the expected value applied to each roll. This visualization demonstrates the Law of Large Numbers, which states that as the number of trials or rolls increases, the *sample mean* (running average in this case) approaches the *population mean* (expected value) with greater accuracy, showing the predictability and stability of random processes over a large number of observations.

2.2.4 The drive shaft exercise - Normal Distribution

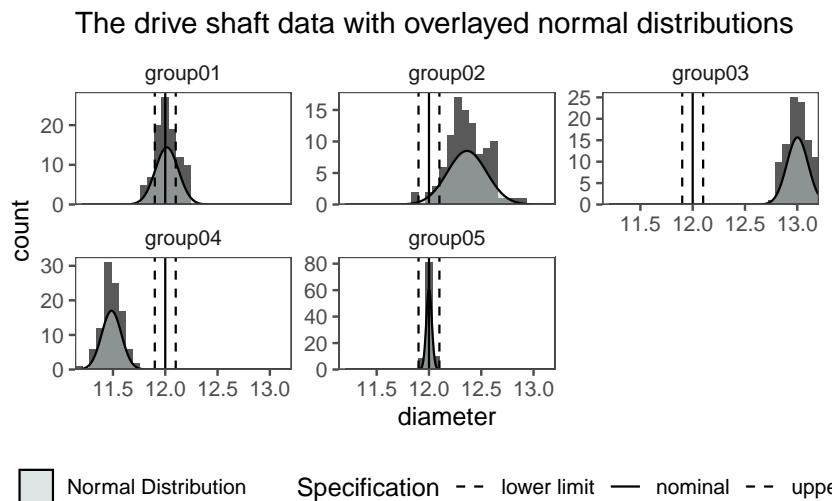


Figure 2.10: The drive shaft data with the respective normal distributions.

In Figure 2.10 the **drive shaft data** is shown for each group in a histogram. As an overlay, the respective *normal distribution* (with the groups \bar{x}, sd) is overlaid. If the data is normally distributed, is a different question.

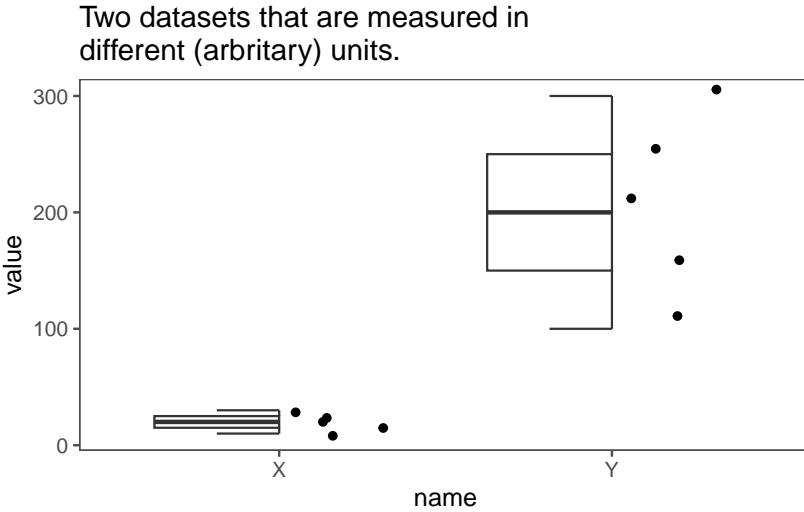


Figure 2.11: The original data of group X and group Y

2.3 Z - Standardization

The Z-standardization, also known as standard score or z-score, is a common statistical technique used to transform data into a standard normal distribution with a mean of 0 and a standard deviation of 1 (Taboga 2017). This transformation is useful for comparing and analyzing data that have different scales and units (2.1).

$$Z = \frac{x_i - \bar{x}}{sd} \quad (2.1)$$

How the z-score can be applied is shown in Figure 2.11 and Figure 2.12. The data for group X and group Y may be measured in different units (Figure 2.11). To answer the question, which of the values $x_i (i = 1 \dots 5)$ is more probable, the single data points are transformed to the respective z-score using (2.1). In Figure 2.12, the z-scores for both groups are plotted against each other. The perfect correlation of the datapoints shows, that for every x_i the same probability applies. Thus, the datapoints are comparable.

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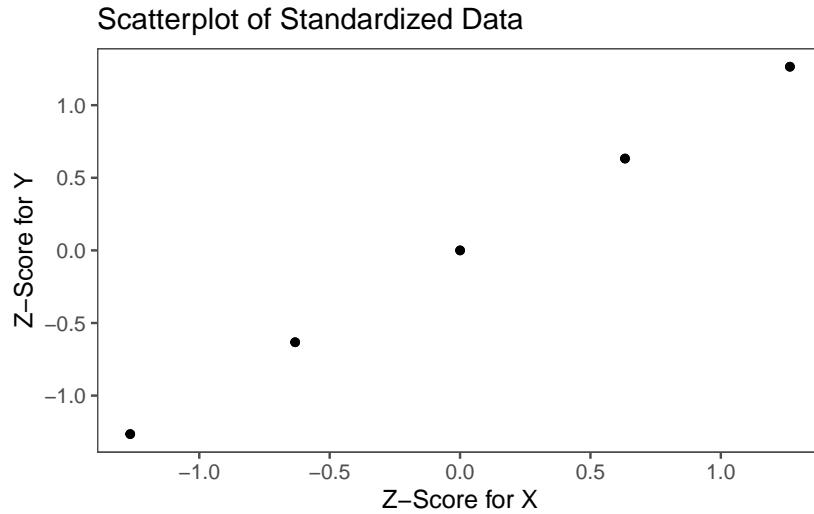


Figure 2.12: The correlation of the z-score shows, that every point x_i is equally probable

2.3.1 The drive shaft exercise - Z-Standardization

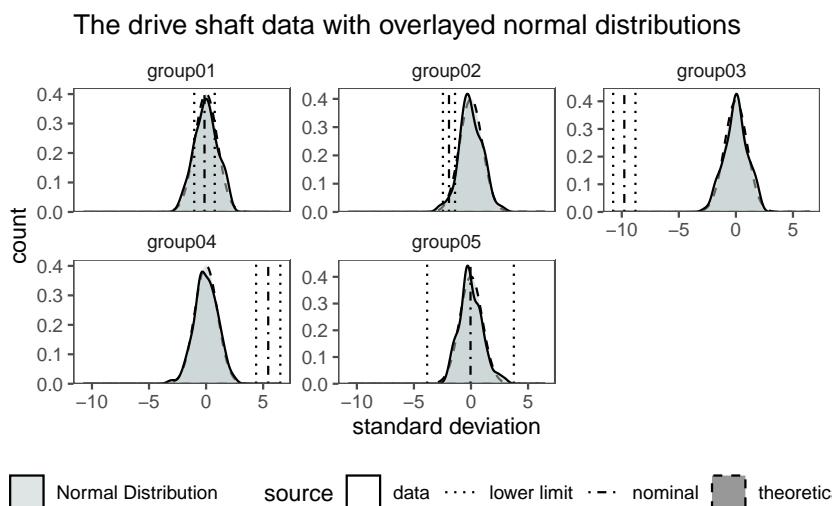


Figure 2.13: The standardized data of the drive shaft data.

In Figure 2.13 the standardized drive shaft data is shown. The mean of the data (\bar{x}) is now centered at 0 and the standard deviation is 1. For this case, the specification limits have also been transferred to the respective z-score (even though they can not be interpreted as such anymore). For every x_i the probability to be within a normal distribution is now known. When comparing this to the transferred specification limits,

2.3 Z - Standardization

it is clear to see that for `group01` “most” of the data points are within the limits in contrast to `group03` where none of the data points lies within the specification limits. When looking at `group03` we see, that the *nominal* specification limit is -9.78 standard deviations away from the centered mean of the datapoints. The probability of a data point being located there is $6.8605273 \times 10^{-23}$ which does not sound an awful lot. We will dwelove more into such investigation in another chapter, but this is a first step in the direction of inferential statistics.

2.4 Probability Density Function (PDF)

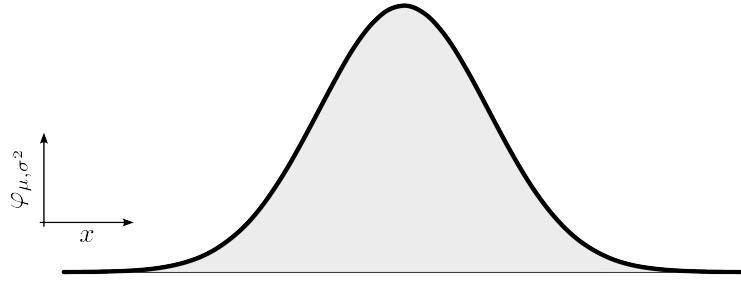


Figure 2.14: A visual representation of the PDF for the normal distribution.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \quad (2.2)$$

A probability density function (PDF) is a mathematical function that describes the *likelihood* of a continuous random variable taking on a particular value. Unlike discrete probability distributions, which assign probabilities to specific values of a discrete random variable, a PDF describes the relative likelihood of the variable falling within a particular range of values. The total area under the curve of a PDF over its entire range is equal to 1, indicating that the variable must take on some value within that range. In other words, the integral of the PDF over its entire domain equals 1. The probability of a continuous random variable falling within a specific interval is given by the integral of the PDF over that interval.

2.5 Cumulative Density Function (CDF)

A cumulative density function (CDF), also known as a cumulative distribution function, describes the probability that a random variable will take on a value less than or equal to a given point. It is the integral of the PDF from negative infinity to a certain value. The CDF provides a comprehensive view of the probability distribution of a random variable by showing how the probability accumulates as the value of the random variable increases. Unlike the PDF, which gives the probability density at a particular point, the CDF gives the cumulative probability up to that point.

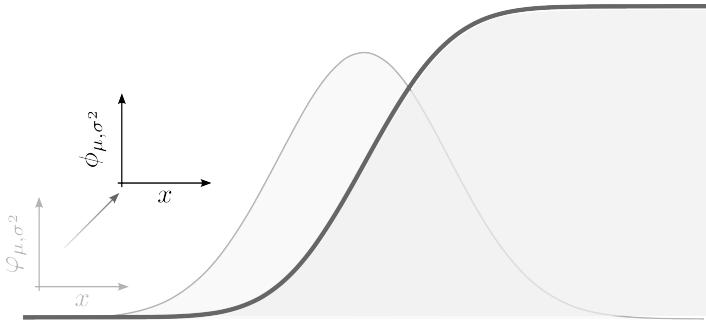


Figure 2.15: A visual representation of the CDF for the normal distribution.

$$z = \frac{x - \mu}{\sigma} \quad (2.3)$$

$$\varphi(x) = \frac{1}{2\pi} e^{-\frac{z^2}{2}} \quad (2.3)$$

$$\phi(x) = \int \frac{1}{2\pi} e^{-\frac{x^2}{2}} dx \quad (2.4)$$

$$\lim_{x \rightarrow \infty} \phi(x) = 1$$

$$\lim_{x \rightarrow -\infty} \phi(x) = 0$$

2.6 Likelihood and Probability

Likelihood refers to the chance or plausibility of a particular event occurring given certain evidence or assumptions. It is often used in statistical inference, where it indicates how well a particular set of parameters (or hypotheses) explain the observed data. Likelihood is a measure of how compatible the observed data are with a specific hypothesis or model.

Probability represents the measure of the likelihood that an event will occur. It is a quantification of uncertainty and ranges from 0 (indicating impossibility) to 1 (indicating certainty). Probability is commonly used to assess the chances of different outcomes in various scenarios.

In summary, while both likelihood and probability deal with the chance of events occurring, likelihood is often used in the context of comparing different *hypotheses or models* based on *observed data*, while probability is more broadly used to quantify the chances of *events happening in general*.

2 Statistical Distributions

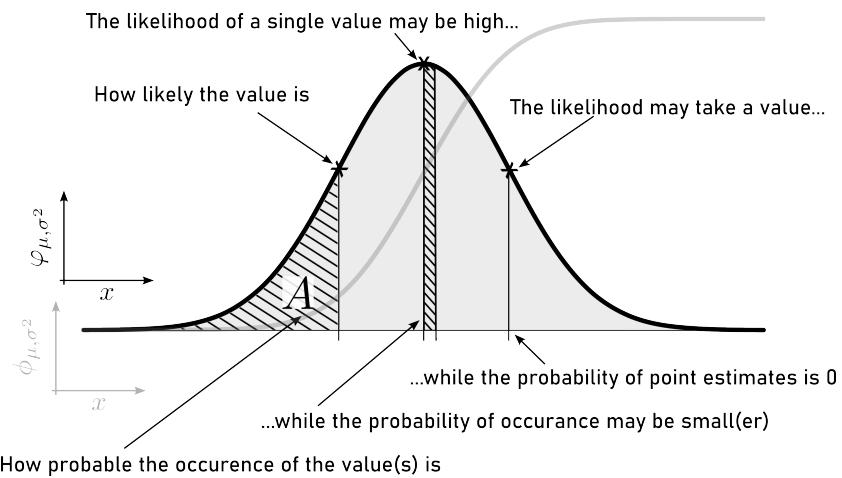


Figure 2.16: The subtle difference between likelihood and probability.

2.7 Chi² - Distribution

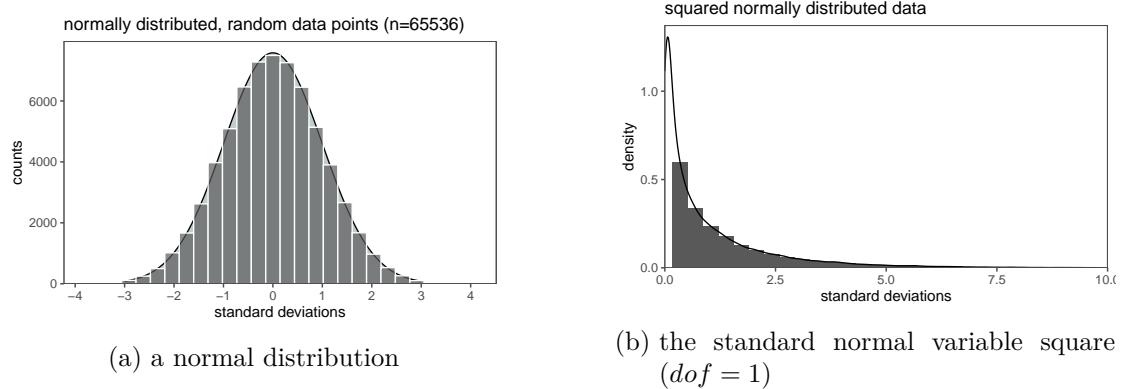


Figure 2.17: What a χ^2 distribution represents and how it relates to a the normal distribution.

The χ^2 distribution is a continuous probability distribution that is widely used in statistics (Taboga 2017). It is often used to test hypotheses about the independence of categorical variables.

$$\chi^2 = \sum_{k=1}^n \frac{(O_k - E_k)^2}{E_k} \quad (2.5)$$

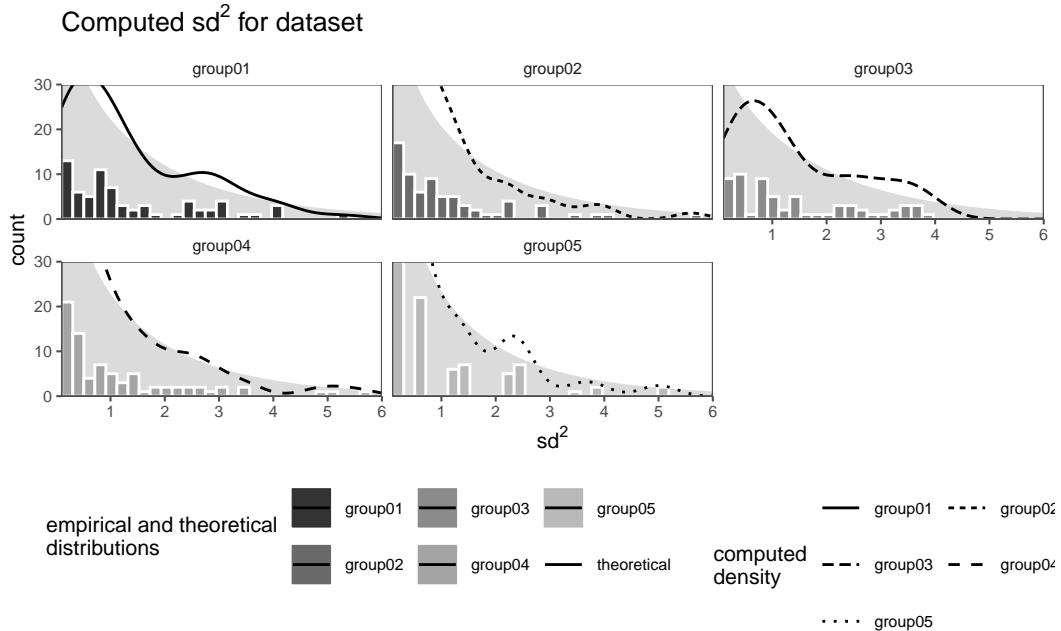
The connection between the chi-squared distribution and sample variance holds significant importance in statistics.

1. **Distribution of Sample Variance:** When calculating the sample variance from a dataset, it follows a chi-squared distribution. Specifically, for a random sample from a normally distributed population with mean μ_0 and variance σ_0^2 , the sample variance (adjusted for bias) divided by σ_0^2 follows a χ^2 distribution with $n - 1$ degrees of freedom, where n is the sample size.
2. **Hypothesis Testing:** In statistical analysis, hypothesis testing is a common technique for making inferences about populations using sample data. The χ^2 distribution plays a crucial role in hypothesis testing, especially when comparing variances between samples.
 - **χ^2 Test for Variance:** The χ^2 distribution is used to test whether the variance of a sample matches a hypothesized variance. This is applicable in various scenarios, such as quality control, to assess the consistency of a manufacturing process.
3. **Confidence Intervals:** When estimating population parameters like population variance, it's essential to establish confidence intervals. The χ^2 distribution aids in constructing these intervals, allowing researchers to quantify the uncertainty associated with their parameter estimates.
4. **Model Assessment:** In regression analysis, the χ^2 distribution is related to the F-statistic, which assesses the overall significance of a regression model. It helps determine whether the regression model is a good fit for the data.

In summary, the link between the chi-squared distribution and sample variance is fundamental in statistical analysis. It empowers statisticians and analysts to make informed decisions about population parameters based on sample data and evaluate the validity of statistical models. Understanding this relationship is essential for those working with data and conducting statistical investigations.

2.7.1 The drive shaft exercise - Chi² Distribution

In Figure 2.18 the squared standard deviation for every datapoint (from the standardized data) is shown as a histogram for every group with an overlaid (and scaled) density plot. In the background of every group the theoretical χ^2 -distribution with $dof = 1$ is plotted to visually compare the empirical distribution of the datapoints to the theoretical.

Figure 2.18: The χ^2 distribution of the drive shaft data.

2.8 t - Distribution

The t-distribution, also known as the Student's t-distribution (Student 1908), is a probability distribution that plays a significant role in statistics¹. It is a symmetric distribution with a bell-shaped curve, similar to the normal distribution, but with heavier tails. The key significance of the t-distribution lies in its application to inferential statistics, particularly in hypothesis testing and confidence interval estimation.

- 1. Small Sample Sizes:** When dealing with small sample sizes (typically less than 30), the t-distribution is used to make inferences about population parameters, such as the mean. This is crucial because the normal distribution assumptions are often violated with small samples.
- 2. Accounting for Variability:** The t-distribution accounts for the variability inherent in small samples. It provides wider confidence intervals and more conservative hypothesis tests compared to the normal distribution, making it more suitable for situations where sample size is limited.
- 3. Degrees of Freedom:** The shape of the t-distribution is determined by a parameter called degrees of freedom (df). As the df increases, the t-distribution approaches

¹William Sealy Gosset (June 13, 1876 - October 16, 1937) was a pioneering statistician known for developing the t-distribution, a key tool in modern statistical analysis.

2 Statistical Distributions

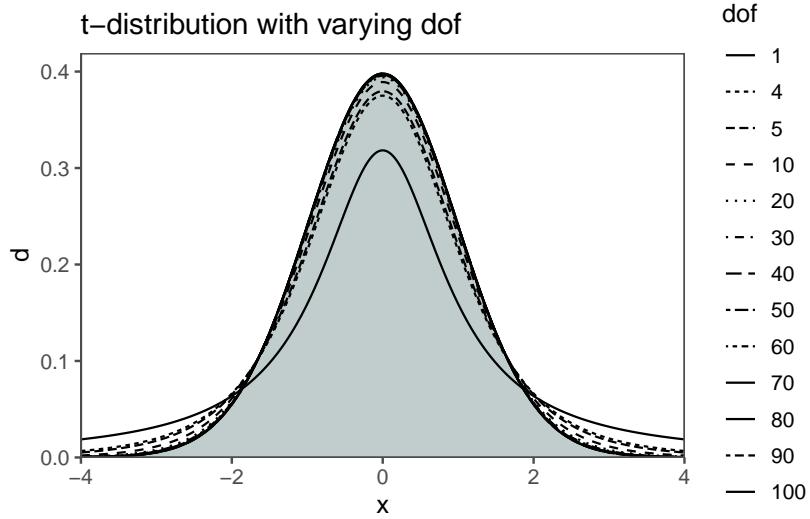


Figure 2.19: PDF of t-distribution with varying *dof*

the normal distribution. When df is small, the tails of the t-distribution are fatter, allowing for greater uncertainty in estimates.

Statisticians found that if they took samples of a constant size from a normal population, computed a statistic called a *t-score* for each sample, and put those into a relative frequency distribution, the distribution would be the same for samples of the same size drawn from any normal population. The shape of this sampling distribution of t's varies somewhat as sample size varies, but for any n , it is always the same. For example, for samples of 5, 90% of the samples have t-scores between -1.943 and $+1.943$, while for samples of 15, 90% have t-scores between ± 1.761 . The bigger the samples, the narrower the range of scores that covers any particular proportion of the samples (2.9) (Note the similarity to (2.1)). Since the *t-score* is computed for every x_i the resulting sampling distribution is called the *t-distribution*.

$$t_i = \frac{x_i - \mu_o}{sd/\sqrt{n}} \quad (2.6)$$

In Figure 2.19 it is shown, that with increasing *dof* (in this case *sample size*), the *t-distribution* approximates a normal distribution (gray area). Figure 2.19 also shows an example of the *t-distribution* in action. Of all possible samples with 9 *dof* 0.025 ($2\frac{1}{2}\%$) of those samples would have t-scores greater than 2.262, and .975 (97.5%) would have t-scores less than 2.262. The advantage of the *t-score* and *t-distribution* is clearly visible. All these values can be computed from sampled data, the population can remain *estimated* (2.9).

2.8.1 The drive shaft exercise - t-Distribution

The t-score computation and the z-standardization look very familiar. While the z-score calculation needs some population parameters, the t-score calculation does not need such. It therefore allows us, to estimate population parameters based on a sample - a very frequent use case in statistics.

Suppose we have some data (maybe the drive shaft exercise?) with which calculations can be done. First, the mean \bar{x} and sd is calculated according to (1.3) and (1.4). After this, the confidence level (we will get to this later in more detail) is specified. A value of 95% is a common choice of cl.

$$ci = 0.95 \quad (\text{for a } 95\% \text{ confidence level}) \quad (2.7)$$

Then the Standard Error (SE) is calculated using (2.8), which takes the sd and n of a sample into account (notice, how we did not use any population estimation?).

$$SE = \frac{sd}{\sqrt{n}} \quad (2.8)$$

In the next step, the critical *t-score* is calculated using the cl as shown in (2.9). *qt* in this case returns the value of the inverse cumulative function of the t-distribution given a certain random variable (or datapoint x_i) and $n - 1$ dof. Think of it as an automated look up in long statistical tables.

$$t_{score} = qt\left(\frac{1 - ci}{2}, df = n - 1\right) \quad (2.9)$$

With this, the *margin of error* can be calculated using the SE and the *t-score* as shown in (2.10).

$$\text{margin of error} = t_{score} \times SE \quad (2.10)$$

In the last step the Confidence Interval is calculated for the **lower** and the **upper** bound with (2.11) and (2.12).

$$lo = \bar{x} - \text{margin of error} \quad (2.11)$$

$$hi = \bar{x} + \text{margin of error} \quad (2.12)$$

2 Statistical Distributions

It all looks and feels very similar to using the normal distribution. Why this is the case, is shown in Figure 2.20. In Figure 2.20a the raw dataset is shown with the underlaid specification limits for the manufacturing of the drive shaft. For some groups the judgement if the drive shaft is within specification is quite clear (group 1, group 2 and group 5). For the other groups, this can not be done so easily. For the drive shaft data, we of course now some population data, therefore the *normal distribution* can be compared to the *t-distribution*. This is done in Figure 2.20b. On the x-axis the diameter is shown, the y-axis depicts the groups (as before). The distribution on top of the estimated parameters is the population (normal distribution), the distribution on the bottom follow a *t-distribution*. With $n > 30$ (as for this dataset), the difference between distribution is very small, further showcasing the use of the *t-distribution* (also see Figure 2.19 for comparison).

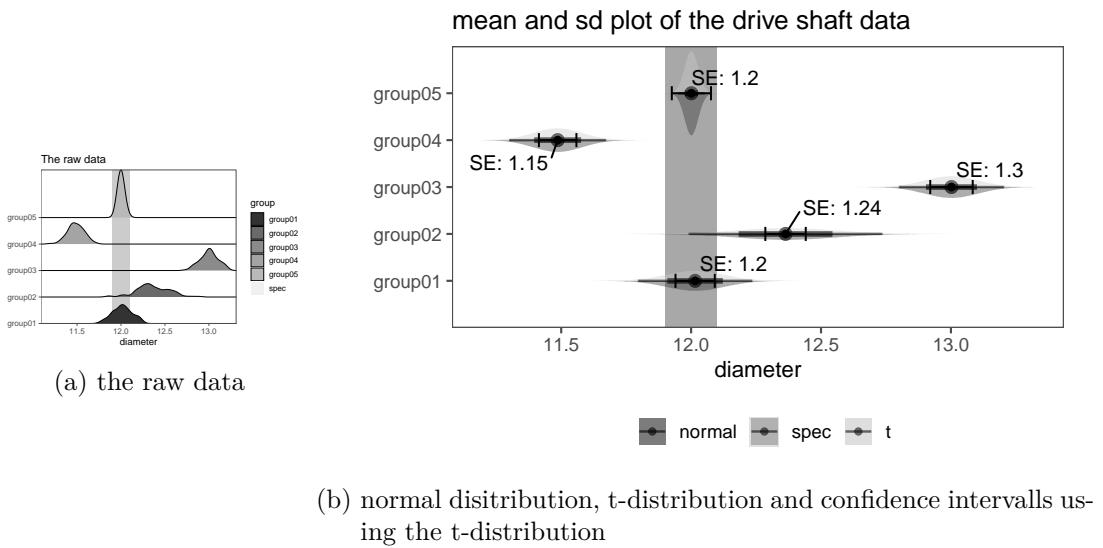
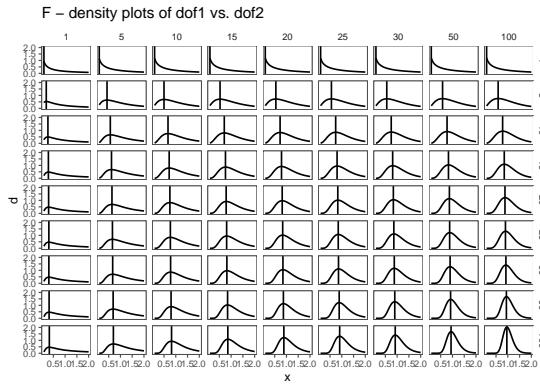
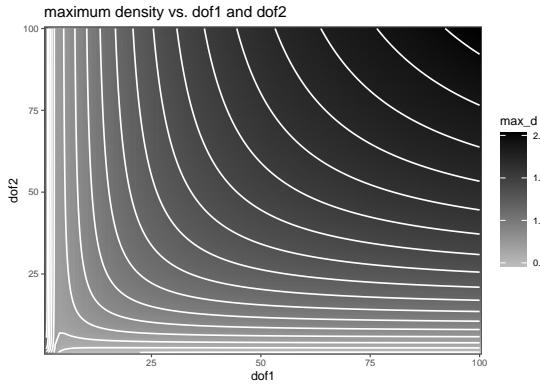


Figure 2.20: The drive shaft data and the application of the t-Distribution

2.9 F - Statistics

F-statistics, also known as the *F-test* or *F-ratio*, is a statistical measure used in analysis of variance and regression analysis (Taboga 2017). It assesses the ratio of two variances, indicating the extent to which the variability between groups or models is greater than the variability within those groups or models. The *F-statistic* plays a crucial role in hypothesis testing and model comparison.

Significance of F-statistics: The significance of the F-statistic lies in its ability to help researchers determine whether the differences between group means or the goodness-of-fit of a regression model are statistically significant. In ANOVA, a high F-statistic

(a) F-distribution for dof_1 on the horizontal and dof_2 on the vertical axis(b) the maximum density as a function of dof_1 and dof_2 in a continuous parameter spaceFigure 2.21: The influence of dof_1 and dof_2 on the density in the F-disitribution

suggests that at least one group mean differs significantly from the others, while in regression analysis, it indicates whether the regression model as a whole is a good fit for the data.

Applications of F-statistics:

- 1. Analysis of Variance (ANOVA):** F-statistics are extensively used in ANOVA to compare means across two or more groups. It helps determine whether there are significant differences among the means of these groups. For example, an ANOVA might be used to compare the mean test scores of students taught using different teaching methods.

- 2. Regression Analysis:** F-statistics are used in regression analysis to assess the overall significance of a regression model. Specifically, in multiple linear regression, it helps determine whether the model, which includes multiple predictor variables, is better at explaining the variance in the response variable compared to a model with no predictors. It tests the null hypothesis that all coefficients of the model are equal to zero.

2 Statistical Distributions

The degrees of freedom in an *F-distribution* refer to the two sets of numbers that determine the shape and properties of the distribution (Figure 2.21).

Numerator Degrees of Freedom (dof_1): The numerator degrees of freedom, often denoted as dof_1 , is associated with the variability between groups or models in statistical analyses (Figure 2.21a - horizontal axis). In the context of ANOVA, it represents the dof associated with the differences among group means. In regression analysis, it is related to the number of predictors or coefficients being tested simultaneously.

Denominator Degrees of Freedom (dof_2): The denominator degrees of freedom, often denoted as dof_2 , is associated with the variability within groups or models (Figure 2.21b - vertical axis). In ANOVA, it represents the degrees of freedom associated with the variability within each group. In regression analysis, it is related to the error or residual degrees of freedom, indicating the remaining variability not explained by the model.

The F-distribution is used to compare two variances: one from the numerator and the other from the denominator. The F-statistic, calculated as the ratio of these variances, follows an F-distribution (2.13).

$$f(x; dof_1, dof_2) = \frac{\Gamma\left(\frac{dof_1+dof_2}{2}\right)}{\Gamma\left(\frac{dof_1}{2}\right)\Gamma\left(\frac{dof_2}{2}\right)} \left(\frac{dof_1}{dof_2}\right)^{\frac{dof_1}{2}} \frac{x^{\frac{dof_1}{2}-1}}{\left(1 + \frac{dof_1}{dof_2}x\right)^{\frac{dof_1+dof_2}{2}}} \quad (2.13)$$

$$F_{m,n} = \frac{\chi_m^2/m}{\chi_n^2/n} \quad (2.14)$$

In practical terms: A higher numerator degrees of freedom (dof_1) suggests that there are more groups or predictors being compared, which may result in larger F-statistic values. A higher denominator degrees of freedom (dof_2) implies that there is more data within each group or model, which may lead to smaller F-statistic values. The F-distribution is right-skewed and always positive. It has different shapes depending on the values of dof_1 and dof_2 (Figure 2.21b). The exact shape is determined by these degrees of freedom and cannot be altered by changing sample sizes or data values (Figure 2.21b). Researchers use F-distributions to conduct hypothesis tests, such as F-tests in ANOVA and F-tests in regression, to determine if there are significant differences between groups or if a regression model is statistically significant.

In summary, degrees of freedom in the F-distribution are critical in hypothesis testing and model comparisons. They help quantify the variability between and within groups or models, allowing statisticians to assess the significance of observed differences and make informed statistical decisions.

2.10 Interconnections

1. Normal Distribution The **Normal Distribution** is characterized by its mean (μ) and standard deviation (σ), see Figure 2.22. It serves as the foundation for many statistical analyses.
2. Standardized Normal Distribution The **Standardized Normal Distribution**, denoted as $Z \sim N(0, 1)$, is a special case of the normal distribution. It has a mean (μ) of 0 and a standard deviation (σ) of 1. It is obtained by standardizing a normal distribution variable X : $Z = \frac{X-\mu}{\sigma}$ (Figure 2.22).
3. t Distribution The **t Distribution** is related to the normal distribution and depends on degrees of freedom. As dof increases, the t-distribution approaches the standard normal distribution (Figure 2.22).
4. Chi-Square Distribution The **Chi-Square Distribution** is indirectly connected to the normal distribution through the concept of “sum of squared standard normals.” When standard normal random variables (Z) are squared and summed, the resulting distribution follows a chi-square distribution.
5. F Distribution The **F Distribution** arises from the ratio of two independent chi-square distributed random variables. It is used for comparing variances between groups in statistical tests like ANOVA.

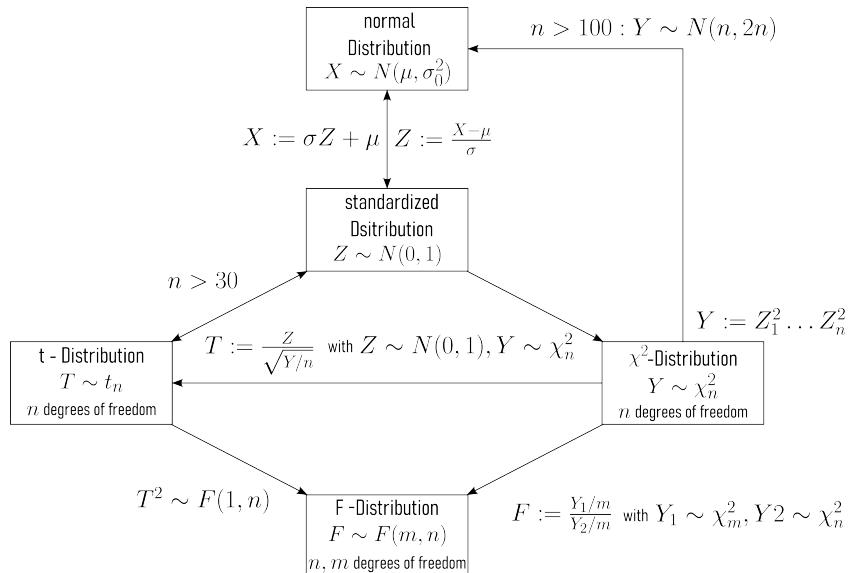


Figure 2.22: The distributions are interconnected in several different ways.

2.11 Binomial Distribution

The binomial distribution and the influence of different parameters.

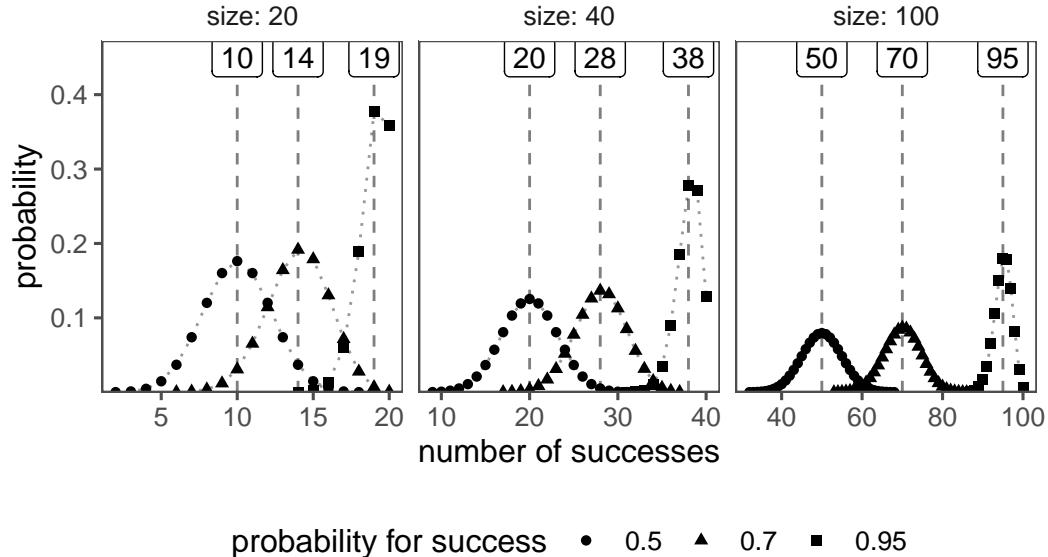


Figure 2.23: The binomial distribution

The binomial distribution is a **discrete** probability distribution that describes the number of successes in a fixed number of independent Bernoulli trials, each with the same probability of success. A Bernoulli trial, named after Swiss mathematician Jacob Bernoulli², is a random experiment or trial with two possible outcomes: success and failure. These outcomes are typically labeled as 1 for success and 0 for failure. The key characteristics of a Bernoulli trial are:

- Two Outcomes:** There are only two possible outcomes in each trial, and they are mutually exclusive. For example, in a coin toss, the outcomes could be heads (success, represented as 1) or tails (failure, represented as 0).
- Constant Probability:** The probability of success remains the same for each trial. This means that the likelihood of success and failure is consistent from one trial to the next.
- Independence:** Each trial is independent of others, meaning that the outcome of one trial does not influence the outcome of subsequent trials. For instance, the result of one coin toss doesn't affect the result of the next coin toss.

²Jacob Bernoulli (1654-1705): Notable Swiss mathematician, known for Bernoulli's principle and significant contributions to calculus and probability theory.

Examples of Bernoulli trials include:

- Flipping a coin (heads as success, tails as failure).
- Rolling a die and checking if a specific number appears (the number as success, others as failure).
- Testing whether a manufactured product is defective or non-defective (defective as success, non-defective as failure).

The Bernoulli trial is the fundamental building block for many other probability distributions, including the binomial distribution, which models the number of successes in a fixed number of Bernoulli trials.

2.11.1 Probability Mass Function (PMF)

The probability mass function (PMF), also known as the discrete probability density function, is a fundamental concept in probability and statistics.

- Definition: The PMF describes the probability distribution of a discrete random variable. It gives the probability that the random variable takes on a specific value. In other words, the PMF assigns probabilities to each possible outcome of the random variable.
- Formal Representation: For a discrete random variable X , the PMF is denoted as $P(X = x)$, where x represents a specific value. Mathematically, the PMF is defined as: $P(X = x) = \text{probability that } X \text{ takes the value } x$
- Properties: The probabilities associated with all hypothetical values must be non-negative and sum up to 1. Thinking of probability as “mass” helps avoid mistakes, as the total probability for all possible outcomes is conserved (similar to how physical mass is conserved).
- Comparison with Probability Density Function (PDF): A PMF is specific to *discrete* random variables, while a PDF is associated with continuous random variables. Unlike a PDF, which requires integration over an interval, the PMF **directly** provides probabilities for individual values.
- Mode: The value of the random variable with the largest probability mass is called the mode.
- Measure-Theoretic Formulation: The PMF can be seen as a special case of more general measure-theoretic constructions. It relates to the distribution of a random variable and the probability density function with respect to the counting measure.

2 Statistical Distributions

The PMF for the binomial distribution is given in (2.15)

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k} \quad (2.15)$$

2.11.2 The drive shaft exercise - Binomial Distribution

In the context of a drive shaft, you can think of it as a model for the number of defective drive shafts in a production batch. Each drive shaft is either good (success) or defective (failure).

Let's say you have a batch of 100 drive shafts, and the probability of any single drive shaft being defective is 0.05(5%). You want to find the probability of having a certain number of defective drive shafts in this batch.

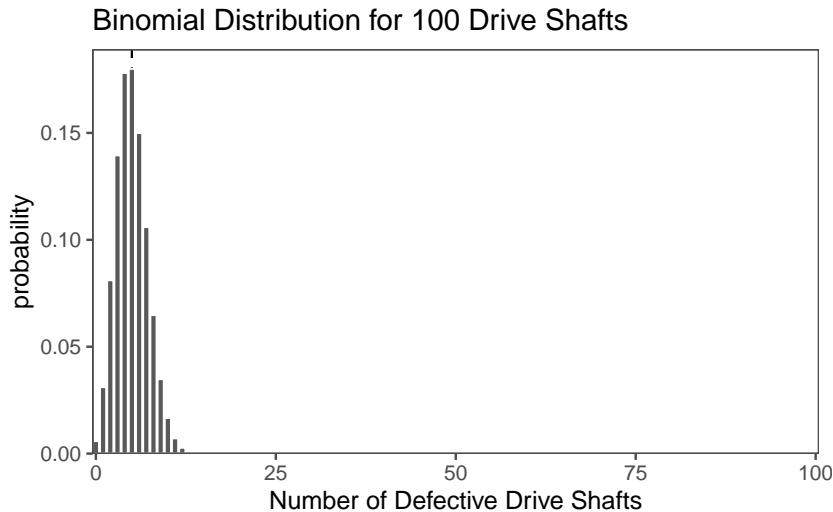


Figure 2.24: The binomial distribution and the drive shaft exercise.

2.12 Weibull - Distribution

The Weibull distribution is a probability distribution frequently used in statistics and reliability engineering to model the time until an event, particularly failures or lifetimes. It is named after Waloddi Weibull³, who developed it in the mid-20th century (Weibull 1951).

³Waloddi Weibull (1887–1979) was a Swedish engineer and statistician known for his work on the Weibull distribution, which is widely used in reliability engineering and other fields.

The weibull distribution with scale (λ) and shape (β) parameter

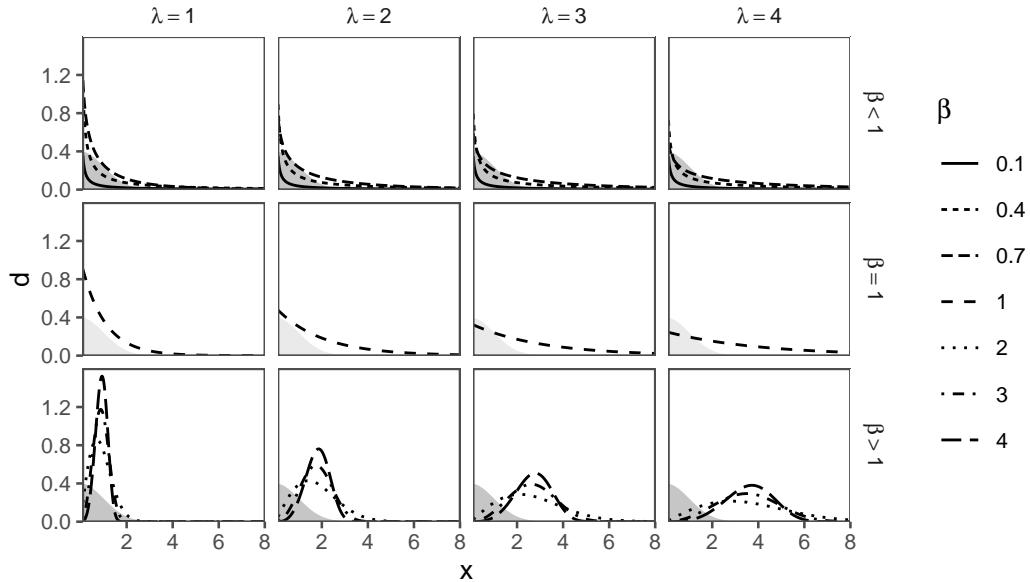


Figure 2.25: The weibull distribution and the influence of β and λ

The Weibull distribution is characterized by two parameters:

Shape Parameter (β): This parameter determines the shape of the distribution curve and can take on values greater than 0. Depending on the value of β , the Weibull distribution can exhibit different behaviors:

If $\beta < 1$, the distribution has a decreasing failure rate, indicating that the probability of an event occurring decreases over time. This is often associated with “infant mortality” or early-life failures. If $\beta = 1$, the distribution follows an exponential distribution with a constant failure rate over time. If $\beta > 1$, the distribution has an increasing failure rate, suggesting that the event becomes more likely as time progresses. This is often associated with “wear-out” failures.

Scale Parameter (λ): This parameter represents a characteristic scale or location on the time axis. It influences the position of the distribution on the time axis. A larger λ indicates that events are more likely to occur at later times.

Applications: - Reliability Engineering: The Weibull distribution is extensively used in reliability engineering to assess the lifetime and failure characteristics of components and systems. Engineers can estimate the distribution parameters from data to predict product reliability, set warranty periods, and plan maintenance schedules.

- Survival Analysis: In medical research and epidemiology, the Weibull distribution is employed to analyze survival data, such as time until the occurrence of a disease

2 Statistical Distributions

or death. It helps in modeling and understanding the progression of diseases and the effectiveness of treatments.

- Economics and Finance: The Weibull distribution is used in finance to model the time between financial events, like market crashes or loan defaults. It can provide insights into risk assessment and portfolio management.

2.12.1 The drive shaft exercise - Weibull distribution

The weibull distribution can be applied to estimate the probability of a part to fail after a given time. Suppose there have been $n = 100$ drive shafts produced. In order to assure that the assembled drive shaft would last during their service time, they have been tested in a test-stand that mimics the mission profile⁴ of the product. This process is called *qualification* and a big part of any product development (Meyna 2023). The measured hours are shown in Figure 2.26 in a histogram of the data. On the x-axis the Time to failure is shown, while the y-axis shows the number of parts that failed within the time. The histogram plot is overlayed with an empirical density plot as a solid line, as well as the theoretical distribution as a dotted line (Luckily, we know the distribution parameters).

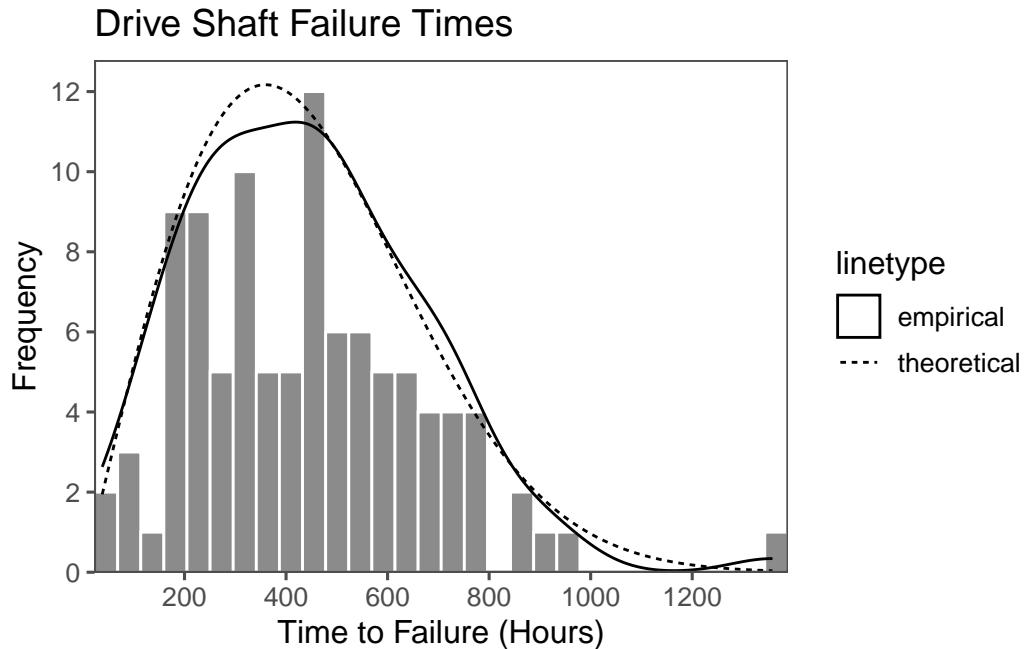


Figure 2.26: The measured hours how long the drive shafts lasted in the test stand.

⁴A mission profile for parts is a detailed plan specifying how specific components in a system should perform, considering factors like environment, performance, safety, and compliance.

2.13 Poisson - Distribution

The Poisson distribution is a probability distribution commonly used in statistics to model the number of events that occur within a fixed interval of time or space, given a known average rate of occurrence. It is named after the French mathematician Siméon Denis Poisson⁵.

The Poisson distribution is an applicable probability model in such situations under specific conditions:

- 1. Independence:** Events should occur independently of each other within the specified interval of time or space. This means that the occurrence of one event should not affect the likelihood of another event happening.
- 2. Constant Rate:** The average rate (*lambda*, denoted as λ) at which events occur should be constant over the entire interval. In other words, the probability of an event occurring should be the same at any point in the interval.
- 3. Discreteness:** The events being counted must be discrete in nature. This means that they should be countable and should not take on continuous values.
- 4. Rare Events:** The Poisson distribution is most appropriate when the events are rare, meaning that the probability of more than one event occurring in an infinitesimally small interval is negligible. This assumption helps ensure that the distribution models infrequent events.
- 5. Fixed Interval:** The interval of time or space in which events are counted should be fixed and well-defined. It should not vary or be open-ended.
- 6. Memorylessness:** The Poisson distribution assumes that the probability of an event occurring in the future is independent of past events. In other words, it does not take into account the history of events beyond the current interval.
- 7. Count Data:** The Poisson distribution is most suitable for count data, where you are interested in the number of events that occur in a given interval.

In the context of a Poisson distribution, the parameter lambda (λ) represents the average rate of events occurring in a fixed interval of time or space. It is a crucial parameter that helps define the shape and characteristics of the Poisson distribution.

Average Rate: λ is a positive real number that represents the average or expected number of events that occur in the specified interval. It tells you, on average, how many events you would expect to observe in that interval.

Rate of Occurrence: λ quantifies the rate at which events happen. A higher value of λ indicates a higher rate of occurrence, while a lower value of λ indicates a lower rate.

⁵Siméon Denis Poisson (1781-1840) was a notable French mathematician, renowned for his work in probability theory and mathematical physics.

2 Statistical Distributions

Shape of the Distribution: The value of λ determines the shape of the Poisson distribution. Specifically:

When λ is small, the distribution is skewed to the right and is more concentrated toward zero (Figure 2.27). When λ is moderate, the distribution approaches a symmetric bell shape (Figure 2.27). When λ is large, the distribution becomes increasingly similar to a normal distribution (Figure 2.27).

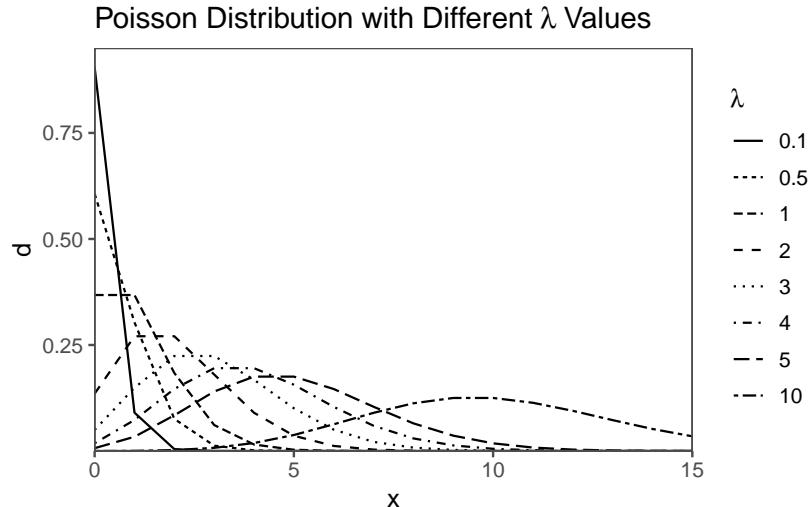


Figure 2.27: The poisson distribution with different λ values.

2.14 Gamma - Distribution

The gamma distribution is a probability distribution that is often used in statistics to model the waiting time until a Poisson process reaches a certain number of events. It is a continuous probability distribution with two parameters, typically denoted as α (shape parameter) and β (rate parameter).

Key points about the gamma distribution:

1. It is often used to model the waiting times for events that occur at a constant rate, such as the time between arrivals in a Poisson process.
2. The exponential distribution is a special case of the gamma distribution when $\alpha = 1$ (Figure 2.28).
3. The gamma distribution is right-skewed for $\alpha > 1$ and left-skewed for $0 < \alpha < 1$ (Figure 2.28).
4. The mean of the gamma distribution is $\frac{\alpha}{\beta}$, and its variance is $\frac{\alpha}{\beta^2}$ (Figure 2.28).

2.14 Gamma - Distribution

It is widely used in various fields, including reliability analysis, queuing theory, and finance.

The connection to other distributions:

Exponential Distribution: The exponential distribution is a special case of the gamma distribution with $\alpha = 1$.

χ^2 : When α is an integer, the gamma distribution with shape parameter α is equivalent to the chi-squared distribution with 2α degrees of freedom.

Erlang Distribution: The Erlang distribution is a specific case of the gamma distribution where α is an integer, representing the sum of α exponentially distributed random variables.

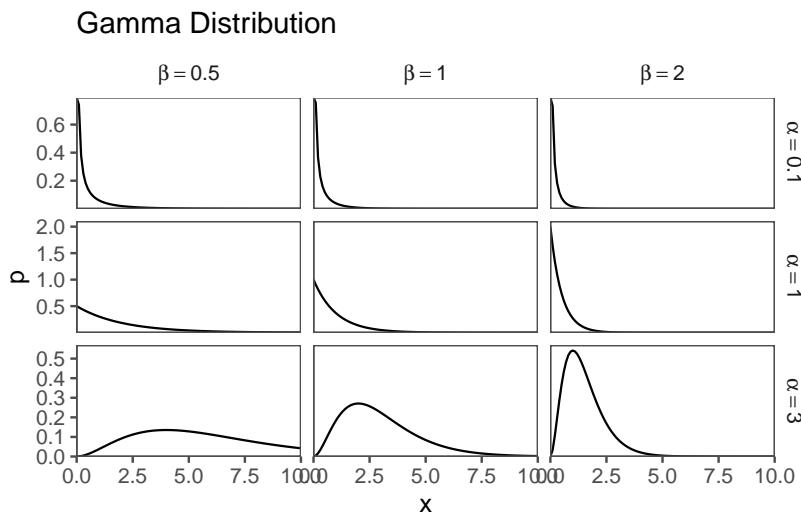


Figure 2.28: The Gamma distribution with varying α (shape) and β (scale)

3 Inferential Statistics

Inferential statistics involves making predictions, generalizations, or inferences about a population based on a sample of data. These techniques are used when researchers want to draw conclusions beyond the specific data they have collected. Inferential statistics help answer questions about relationships, differences, and associations within a population.

3.1 Hypothesis Testing - Basics



Figure 3.1: We are hypotheses.

Null Hypothesis (H_0): This is the default or status quo assumption. It represents the belief that there is no significant change, effect, or difference in the production process. It is often denoted as a statement of equality (e.g., the mean production rate is equal to a certain value).

Alternative Hypothesis (H_a): This is the claim or statement we want to test. It represents the opposite of the null hypothesis, suggesting that there is a significant change, effect, or difference in the production process (e.g., the mean production rate is not equal to a certain value).

3 Inferential Statistics

3.1.1 The drive shaft exercise - Hypotheses

During the QC of the drive shaft $n = 100$ samples are taken and the diameter is measured with an accuracy of $\pm 0.01mm$. Is the true mean of all produced drive shafts within the specification?

For this we can formulate the hypotheses.

H₀: The drive shaft diameter is within the specification.

H_a: The drive shaft diameter is not within the specification.

In the following we will explore, how to test for these hypotheses.

3.2 Standard Error

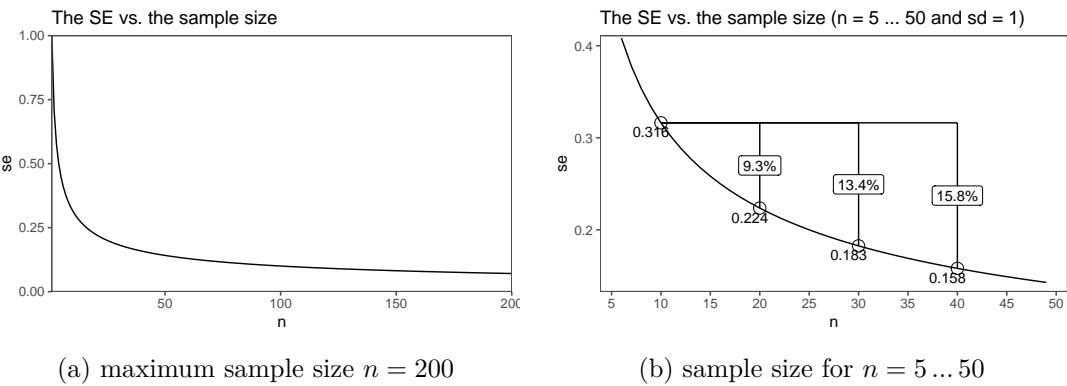


Figure 3.2: The SE for varying sample sizes n

Standard error is a statistical measure that quantifies the variation or uncertainty in sample statistics, particularly the mean (average). It is a valuable tool in inferential statistics and provides an estimate of how much the sample mean is expected to vary from the true population mean.

$$SE = \frac{sd}{\sqrt{n}} \quad (3.1)$$

A smaller standard error indicates that the sample mean is likely very close to the population mean, while a larger standard error suggests greater variability and less precision in estimating the population mean. Standard error is crucial when constructing confidence intervals and performing hypothesis tests, as it helps in assessing the reliability of sample statistics as estimates of population parameters.

3.3 Confidence Intervals

Variance vs. Standard Deviation: The standard error formula is based on the standard deviation of the sample, not the variance. The standard deviation is the square root of the variance.

Scaling of Variability: The purpose of the standard error is to measure the variability or spread of sample means. The square root of the sample size reflects how that variability decreases as the sample size increases. When the sample size is larger, the sample mean is expected to be closer to the population mean, and the standard error becomes smaller to reflect this reduced variability.

Central Limit Theorem: The inclusion of \sqrt{n} in the standard error formula is closely tied to the Central Limit Theorem, which states that the distribution of sample means approaches a normal distribution as the sample size increases. \sqrt{n} helps in this context to ensure that the standard error appropriately reflects the distribution's properties.

3.3 Confidence Intervals

A Confidence Interval is a statistical concept used to estimate a range of values within which a population parameter, such as a population mean or proportion, is likely to fall. It provides a way to express the uncertainty or variability in our sample data when making inferences about the population. In other words, it quantifies the level of confidence we have in our estimate of a population parameter.

Confidence intervals are typically expressed as a range with an associated confidence level. The confidence level, often denoted as $1 - \alpha$, represents the probability that the calculated interval contains the true population parameter. Common confidence levels include 90%, 95%, and 99%.

There are different ways of calculating CI.

1. For the population mean μ_0 when the population standard deviation σ_0^2 is known ((3.2)).

$$CI = \bar{X} \pm t \frac{\sigma_0}{\sqrt{n}} \quad (3.2)$$

- \bar{X} is the sample mean.
- Z is the critical value from the standard normal distribution corresponding to the desired confidence level (e.g., 1.96 for a 95% confidence interval).
- σ_0 is the populations standard deviation
- n is the sample size

3 Inferential Statistics

2. For the population mean μ_0 when the population standard deviation σ_0 is Unknown (t-confidence interval), see (3.3).

$$CI = \bar{X} \pm t \frac{sd}{\sqrt{n}} \quad (3.3)$$

- \bar{X} is the sample mean.
 - t is the critical value from the t-distribution with $n - 1$ degrees of freedom corresponding to the desired confidence level
 - sd is the sample standard deviation
 - n is the sample size
3. For a population proportion p , see (3.4).

$$CI = \hat{p} \pm Z \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \quad (3.4)$$

- \hat{p} is the sample proportion
 - Z is the critical value from the standard normal distribution corresponding to the desired confidence level
 - n is the sample size
4. The method for calculating confidence intervals may vary depending on the estimated parameter. Estimating a population median or the differences between two population means, other statistical techniques may be used.

3.3.1 The drive shaft exercise - Confidence Intervals

The 95% CI for the drive shaft data is shown in Figure 3.3. For comparison the histogram with an overlayed density curve is plotted. The highlighted area shows the minimum and maximum CI, the calculated mean is shown as a dashed line.

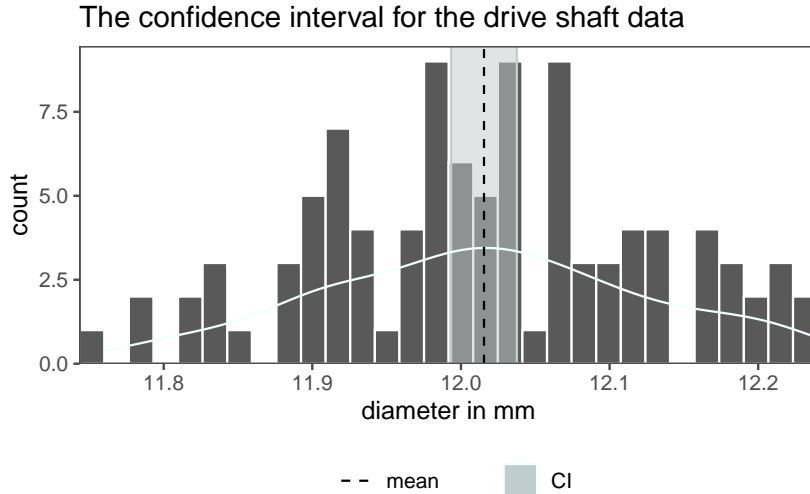


Figure 3.3: The 95% CI for the drive shaft data.

3.4 Significance Level

The significance level α is a critical component of hypothesis testing in statistics. It represents the maximum acceptable probability of making a Type I error, which is the error of rejecting a null hypothesis when it is actually true. In other words, α is the probability of concluding that there is an effect or relationship when there isn't one. Commonly used significance levels include 0.05(5%), 0.01(1%), and 0.10(10%). The choice of α depends on the context of the study and the desired balance between making correct decisions and minimizing the risk of Type I errors.

3.5 False negative - risk

The risk for a false negative outcome is called β - risk. It is calculated using statistical power analysis. Statistical power is the probability of correctly rejecting a null hypothesis when it is false, which is essentially the complement of beta (β).

$$\beta = 1 - \text{Power} \quad (3.5)$$

3.6 Power Analysis

Statistical power is calculated using software, statistical tables, or calculators specifically designed for this purpose. Generally speaking: The greater the statistical power, the

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greater is the evidence to accept or reject the H_0 based on the study. Power analysis is also very useful in determining the sample size before the actual experiments are conducted. Below is an example for a power calculation for a two-sample t-test.

$$\text{Power} = 1 - \beta = P \left(\frac{|\bar{X}_1 - \bar{X}_2|}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}} > Z_{\frac{\alpha}{2}} - \frac{\delta}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}} \right)$$

1. Effect Size: This represents the magnitude of the effect you want to detect. Larger effects are easier to detect than smaller ones.
2. Significance Level (α): This is the predetermined level of significance that defines how confident you want to be in rejecting the null hypothesis (e.g., typically set at 0.05).
3. Sample Size (n): The number of observations or participants in your study. Increasing the sample size generally increases the power of the test.
4. Power ($1 - \beta$): This is the probability of correctly rejecting the null hypothesis when it is false. Higher power is desirable, as it minimizes the chances of a Type II error (failing to detect a true effect).
5. Type I Error (α): The probability of incorrectly rejecting the null hypothesis when it is true. This is typically set at 0.05 or 5% in most studies.
6. Type II Error (β): The probability of failing to reject the null hypothesis when it is false. Power is the complement of β ($\text{Power} = 1 - \beta$).

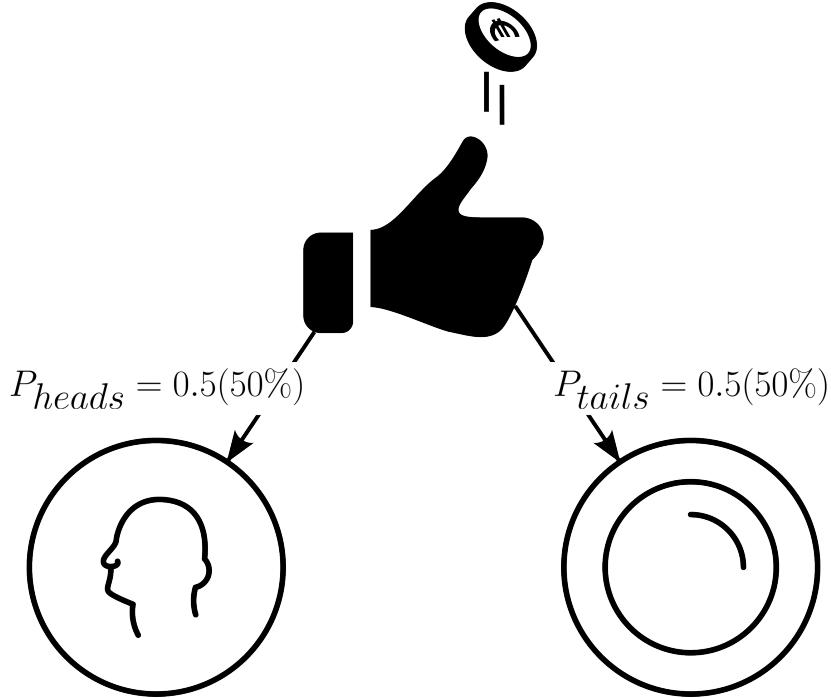


Figure 3.4: The coin toss with the respective probabilities (Champely 2020).

H₀: The coin is fair and lands heads 50% of the time.

H_a: The coin is loaded and lands heads more than 50% of the time.

```
pwr.p.test(h = ES.h(p1 = 0.75, p2 = 0.50),
            sig.level = 0.05,
            power = 0.80,
            alternative = "greater")
```

proportion power calculation for binomial distribution (arcsine transformation)

```
h = 0.5235988
n = 22.55126
sig.level = 0.05
power = 0.8
alternative = greater
```

The sample size $n = 23$, meaning 23 coin flips means that the statistical power is 80% at a $\alpha = 0.05$ significance level ($\beta = 1 - \text{power} = 0.2 \approx 20\%$). But what if the sample size varies? This is the subject of Figure 3.5. On the x-axis the power is shown (or

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the β -risk on the upper x-axis), whereas the sample size n is depicted on the y-axis. To increase the power by 10% to be 90% the sample sized must be increased by 11. A further power increase of 5% would in turn mean an increase in sample size to be $n = 40$. This highlights the non-linear nature of power calculations and why they are important for experimental planning.

Power and β risk for the example

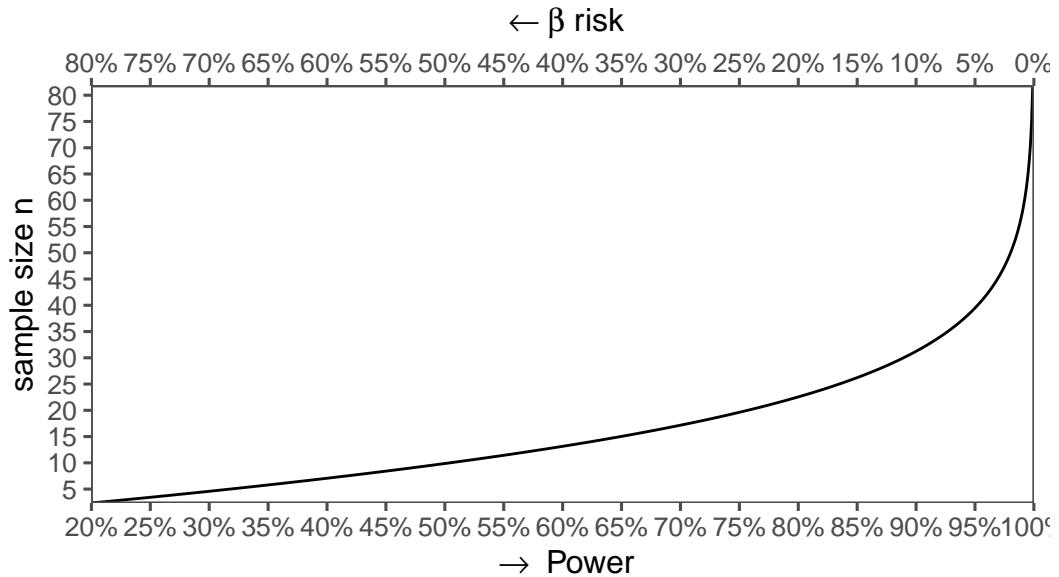


Figure 3.5: The power vs. the sample size

3.6.1 A word on Effect Size

Cohen (Cohen 2013) describes effect size as “the degree to which the null hypothesis is false.” In the coin flipping example, this is the difference between 75% and 50%. We could say the effect was 25% but recall we had to transform the absolute difference in proportions to another quantity using the ES.h function. This is a crucial part of doing power analysis correctly: An effect size must be provided on the expected scale. Doing otherwise will produce wrong sample size and power calculations.

When in doubt, Conventional Effect Sizes can be used. These are pre-determined effect sizes for “small”, “medium”, and “large” effects, see Cohen (2013).

Power and β risk for the example

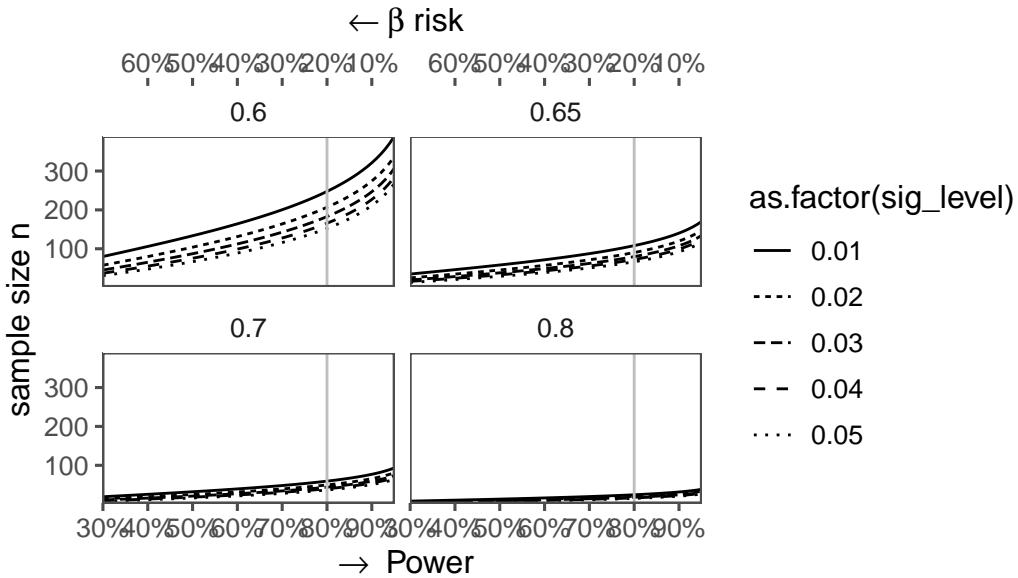


Figure 3.6: The power vs. the sample size for different effect sizes

3.7 p-value

The p-value is a statistical measure that quantifies the evidence against a null hypothesis. It represents the probability of obtaining test results as extreme or more extreme than the ones observed, assuming the null hypothesis is true. In hypothesis testing, a smaller p-value indicates stronger evidence against the null hypothesis. If the p-value is less than or equal to α ($p \leq \alpha$), you reject the null hypothesis. If the p-value is greater than α ($p > \alpha$), you fail to reject the null hypothesis. A common threshold for determining statistical significance is to reject the null hypothesis when $p \leq \alpha$.

The p-value however does not give an assumption about the effect size, which can be quite insignificant (Nuzzo 2014). While the p-value therefore is the probability of accepting H_a as true, it is not a measure of magnitude or relative importance of an effect. Therefore the CI and the effect size should always be reported with a p-value. Some Researchers even claim that most of the research today is false (Ioannidis 2005). In practice, especially in the manufacturing industry, the p-value and its use is still popular. Before implementing any measures in a series production, those questions will be asked. The confident and reliable engineer asks them beforehand and is always his own greatest critique.

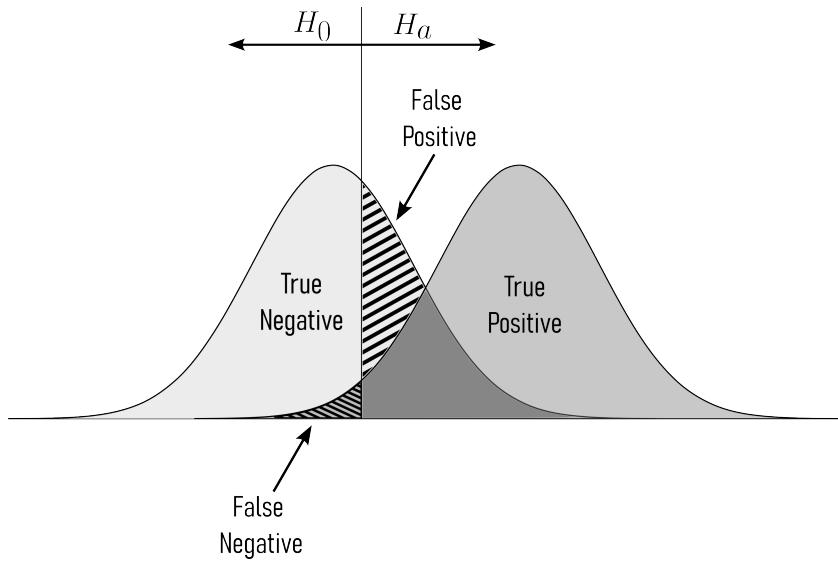


Figure 3.7: Type I and Type II error in the context of inferential statistics.

3.8 Statistical errors

- Type I Error (False Positive, see Figure 3.8):

A Type I error occurs when a null hypothesis that is actually true is rejected. In other words, it's a false alarm. It is concluded that there is a significant effect or difference when there is none. The probability of committing a Type I error is denoted by the significance level α . *Example:* Imagine a drug trial where the null hypothesis is that the drug has no effect (it's ineffective), but due to random chance, the data appears to show a significant effect, and you incorrectly conclude that the drug is effective (Type I error).

- Type II Error (False Negative, see Figure 3.8):

A Type II error occurs when a null hypothesis that is actually false is not rejected. It means failing to detect a significant effect or difference when one actually exists. The probability of committing a Type II error is denoted by the symbol β . *Example:* In a criminal trial, the null hypothesis might be that the defendant is innocent, but they are actually guilty. If the jury fails to find enough evidence to convict the guilty person, it is a Type II error.

Type I Error is falsely concluding, that there is an effect or difference when there is none (false positive). Type II Error failing to conclude that there is an effect or difference when there actually is one (false negative).

table of error types

		Null Hypothesis (H_0) is	
		TRUE	FALSE
Decision about Null Hypothesis (H_0)	Fail to reject	Correct inference (true negative) $p = 1 - \alpha$	Type II error (false negative) $p = \beta$
	Reject	Type I error (false positive) $p = \alpha$	Correct inference (true positive) $p = 1 - \beta$

Figure 3.8: The statistical Errors (Type I and Type II).

The relationship between *Type I* and *Type II* errors is often described as a trade-off. As the risk of Type I errors is reduced by lowering the significance level (α), the risk of Type II errors (β) is typically increased (Figure 3.7). This trade-off is inherent in hypothesis testing, and the choice of significance level depends on the specific goals and context of the study. Researchers often aim to strike a balance between these two types of errors based on the consequences and costs associated with each. This balance is a critical aspect of the design and interpretation of statistical tests.

3.9 Parametric and Non-parametric Tests

Parametric and non-parametric tests in statistics are methods used for analyzing data. The primary difference between them lies in the assumptions they make about the underlying data distribution:

1. Parametric Tests:

- These tests assume that the data follows a specific probability distribution, often the normal distribution.
- Parametric tests make assumptions about population parameters like means and variances.
- They are more powerful when the data truly follows the assumed distribution.
- Examples of parametric tests include t-tests, ANOVA, regression analysis, and parametric correlation tests.

2. Non-Parametric Tests:

- Non-parametric tests make minimal or no assumptions about the shape of the population distribution.
- They are more robust and can be used when data deviates from a normal distribution or when dealing with ordinal or nominal data.
- Non-parametric tests are generally less powerful compared to parametric tests but can be more reliable in certain situations.
- Examples of non-parametric tests include the Mann-Whitney U test, Wilcoxon signed-rank test, Kruskal-Wallis test, and Spearman's rank correlation.

The choice between parametric and non-parametric tests depends on the nature of the data and the assumptions. Parametric tests are appropriate when data follows the assumed distribution, while non-parametric tests are suitable when dealing with non-normally distributed data or ordinal data. Some examples for parametric and non-parametric tests are given in Table 3.1.

Table 3.1: Some parametric and non-parametric statistical tests.

Parametric Tests	Non-Parametric Tests
One-sample t-test	Wilcoxon signed rankk test
Paired t-test	Mann-Whitney U test
Two-sample t-test	Kruskal Wallis test
One-Way ANOVA	Welch Test

3.10 Paired and Independent Tests

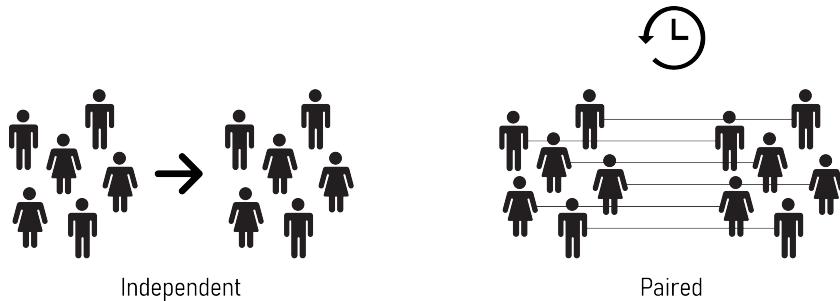


Figure 3.9: The difference between paired and independent Tests.

1. Paired Statistical Test:

- Paired tests are used when there is a natural pairing or connection between two sets of data points. This pairing is often due to repeated measurements on the same subjects or entities.
- They are designed to assess the difference between two related samples, such as before and after measurements on the same group of individuals.
- The key idea is to reduce variability by considering the differences within each pair, which can increase the test sensitivity.

2. Independent Statistical Test:

- Independent tests, also known as unpaired or two-sample tests, are used when there is no inherent pairing between the two sets of data.
- These tests are typically applied to compare two separate and unrelated groups or samples.
- They assume that the data in each group is independent of the other, meaning that the value in one group doesn't affect the value in the other group.

An example for a paired test is, if two groups of data are to be compared in two different points in time (see Figure 3.9).

3.11 Distribution Tests

The importance of testing for normality (or other distributions) lies in the fact that various statistical techniques, such as parametric tests (e.g., t-tests, ANOVA), are based on the assumption of for example normality. When data deviates significantly from a normal distribution, using these parametric methods can lead to incorrect conclusions and biased results. Therefore, it is essential to determine how a dataset is approximately distributed before applying such techniques.

Several tests for normality are available, with the most common ones being the Kolmogorov-Smirnov test, the Shapiro-Wilk test, and the Anderson-Darling test. These tests provide a quantitative measure of how well the data conforms to a normal distribution.

In practice, it is important to interpret the results of these tests cautiously. Sometimes, a minor departure from normality may not affect the validity of parametric tests, especially when the sample size is large. In such cases, using non-parametric methods may be an alternative. However, in cases where normality assumptions are crucial, transformations of the data or choosing appropriate non-parametric tests may be necessary to ensure the reliability of statistical analyses.

Tests for normality do not free you from the burden of thinking for yourself.

3.11.1 Quantile-Quantile plots

Quantile-Quantile plots are a graphical tool used in statistics to assess whether a dataset follows a particular theoretical distribution, typically the normal distribution. They provide a visual comparison between the observed quantiles¹ of the data and the quantiles expected from the chosen theoretical distribution.

A neutral explanation of how QQ plots work:

3.11.1.1 Sample data

In Table 3.2 $n = 10$ datapoints are shown as a sample dataset.

Table 3.2: 10 randomly sampled datapoints for the creation of the QQ-plot

x	smpl_no
-0.56047565	1
-0.23017749	2
1.55870831	3

¹A quantile is a statistical concept used to divide a dataset into equal-sized subsets or intervals.

0.07050839	4
0.12928774	5
1.71506499	6
0.46091621	7
-1.26506123	8
-0.68685285	9
-0.44566197	10

3.11.1.2 Data Sorting

To create a QQ plot, the data must be sorted in ascending order.

Table 3.3: The sorted data points.

x	smpl_no
-1.26506123	8
-0.68685285	9
-0.56047565	1
-0.44566197	10
-0.23017749	2
0.07050839	4
0.12928774	5
0.46091621	7
1.55870831	3
1.71506499	6

3.11.1.3 Theoretical Quantiles

Theoretical quantiles are calculated based on the chosen distribution (e.g., the normal distribution). These quantiles represent the expected values if the data perfectly follows that distribution.

Table 3.4: The calculated theoretical quantiles

x	smpl_no	x_norm	x_thrtcl
-1.26506123	8	-1.404601888	0.08006985
-0.68685285	9	-0.798376211	0.21232610
-0.56047565	1	-0.665875352	0.25274539
-0.44566197	10	-0.545498338	0.29270541
-0.23017749	2	-0.319572479	0.37464622

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0.07050839	4	-0.004316756	0.49827787
0.12928774	5	0.057310762	0.52285118
0.46091621	7	0.405008410	0.65726434
1.55870831	3	1.555994430	0.94014529
1.71506499	6	1.719927421	0.95727718

3.11.1.4 Plotting Points

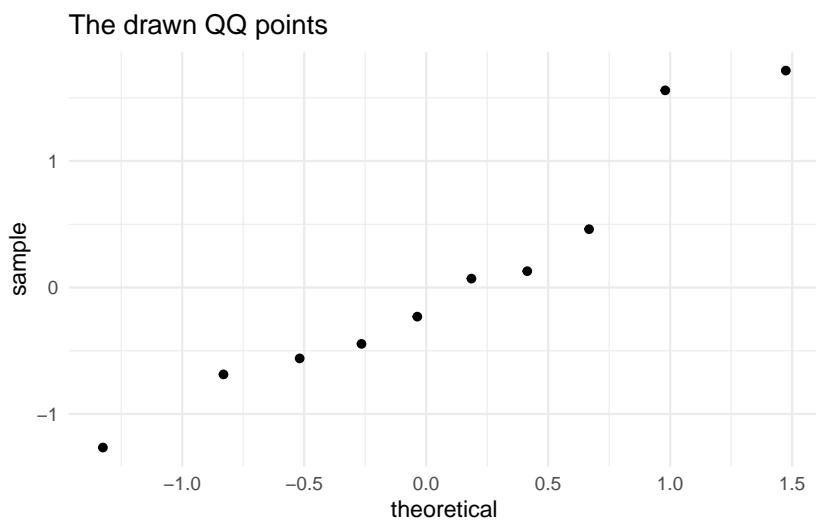


Figure 3.10: The QQ points as calculated before.

For each data point, a point is plotted in the QQ plot. The x-coordinate of the point corresponds to the theoretical quantile, and the y-coordinate corresponds to the observed quantile from the data, see Figure 3.10.

3.11.1.5 Perfect Normal Distribution

A perfect normal distribution line.

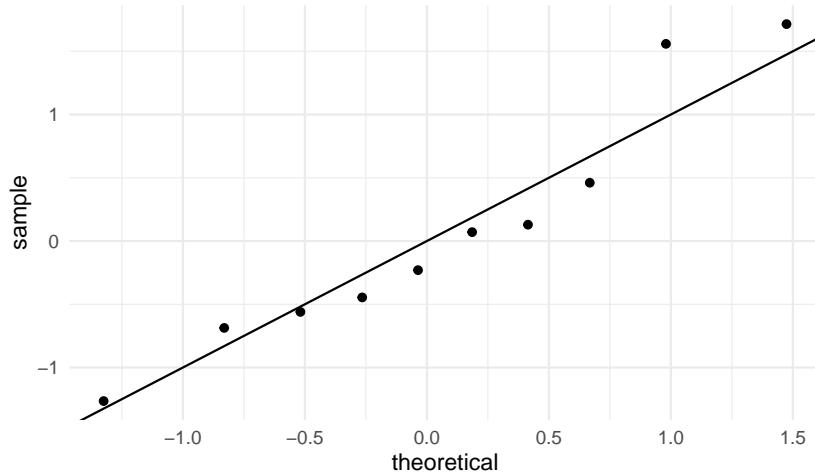


Figure 3.11: A perfect normal distribution would be indicated if all points would fall on this straight line.

In the case of a perfect normal distribution, all the points would fall along a straight line at a 45-degree angle. If the data deviates from normality, the points may deviate from this line in specific ways, see Figure 3.11.

3.11.1.6 Interpretation

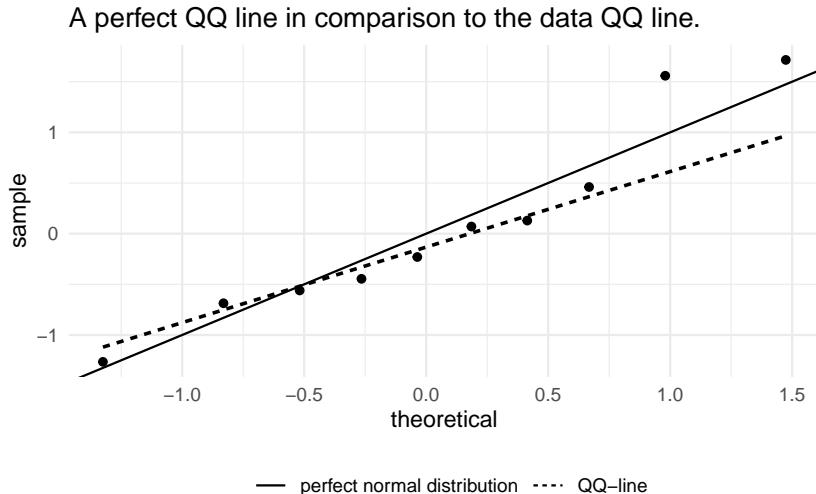


Figure 3.12: The QQ line as plotted using the theoretical and sample quantiles.

Deviations from the straight line suggest departures from the assumed distribution. For example, if points curve upward, it indicates that the data has heavier tails than a normal distribution. If points curve downward, it suggests lighter tails. S-shaped curves or other patterns can reveal additional information about the data's distribution. In Figure 3.12 the QQ-points are shown together with the respective QQ-line and a line of perfectly normal distributed points. Some deviations can be seen, but it is hard to judge, if the data is normally distributed or not.

3.11.1.7 Confidence Interval

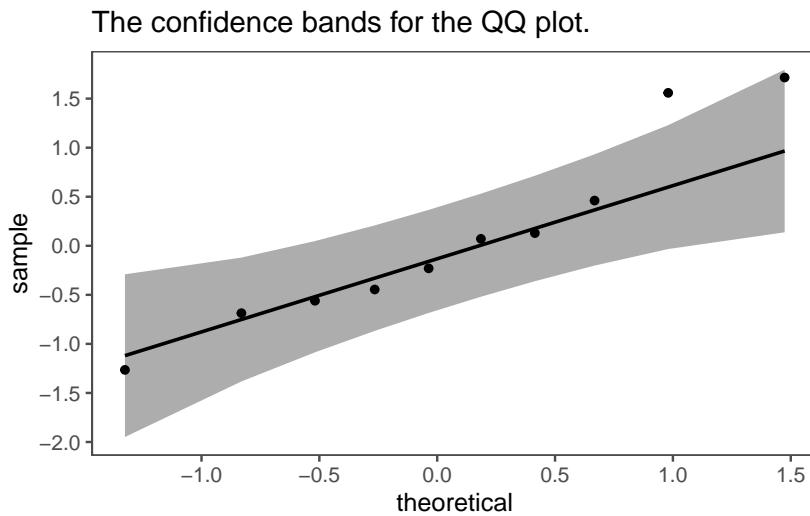


Figure 3.13: The QQ plot with confidence bands.

Because it is hard to judge from Figure 3.12 if the points are normally distributed, it makes sense to get limits for normally distributed points. This is shown in Figure 3.13. The gray area depicts the (95%) confidence bands for a normal distribution. All the points fall into the area, as well as the line. This shows, that the points are likely to be normally distributed.

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3.11.1.8 The drive shaft exercise

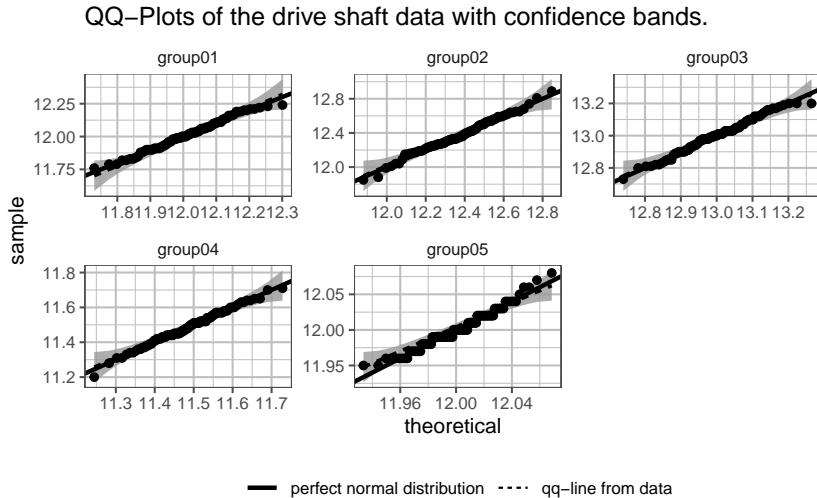


Figure 3.14: The QQ plots for each drive shaft group shown in subplots.

The QQ plot method is extended to the drive shaft exercise in Figure 3.14. In each subplot the plot for the respective group is shown together with the QQ-points, the QQ-line and the respective confidence bands. The scaling for each plot is different to enhance visibility of every subplot. A line for the perfect normal distribution is also shown in solid linestyle. From group 1 ... 4 all points fall into the QQ confidence bands. Group05 differs however. The points from visible categories, which is a strong indicator, that the measurement system may be to inaccurate.

3.11.2 Quantitative Methods

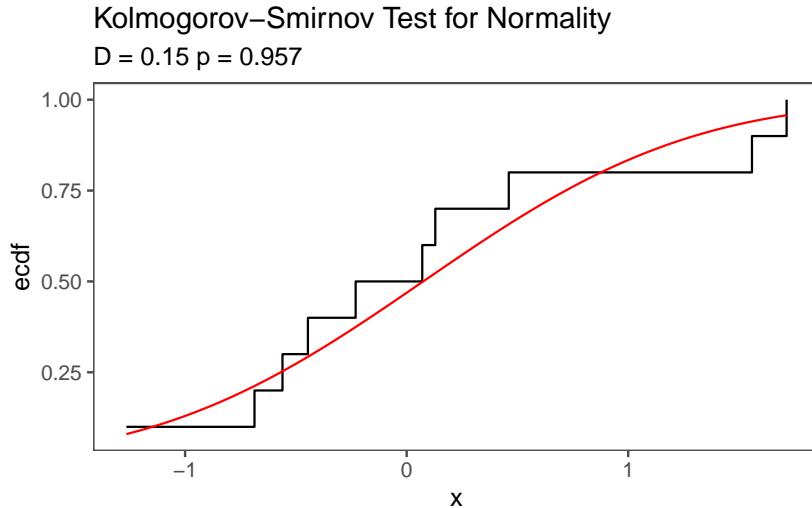


Figure 3.15: A visualisation of the KS test using the 10 datapoints from before

The Kolmogorov-Smirnov test for normality, often referred to as the KS test, is a statistical test used to assess whether a dataset follows a normal distribution. It evaluates how closely the cumulative distribution function of the dataset matches the expected CDF of a normal distribution.

1. **Null Hypothesis (H₀):** The null hypothesis in the KS test states that the sample data follows a normal distribution.
2. **Alternative Hypothesis (H_a):** The alternative hypothesis suggests that the sample data significantly deviates from a normal distribution.
3. **Test Statistic (D):** The KS test calculates a test statistic, denoted as D which measures the maximum vertical difference between the empirical CDF of the data and the theoretical CDF of a normal distribution. It quantifies how far the observed data diverges from the expected normal distribution. A visualization of the KS-test is shown in Figure 3.15. The red line denotes a perfect normal distribution, whereas the step function shows the empirical CDF of the data itself.
4. **Critical Value:** To assess the significance of D , a critical value is determined based on the sample size and the chosen significance level (α). If D exceeds the critical value, it indicates that the dataset deviates significantly from a normal distribution.
5. **Decision:** If D is greater than the critical value, the null hypothesis is rejected, and it is concluded that the data is not normally distributed. If D is less than or equal

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to the critical value, there is not enough evidence to reject the null hypothesis, suggesting that the data may follow a normal distribution.

It is important to note that the KS test is sensitive to departures from normality in both tails of the distribution. There are other normality tests, like the *Shapiro-Wilk test* and *Anderson-Darling test*, which may be more suitable in certain situations. Researchers typically choose the most appropriate test based on the characteristics of their data and the assumptions they want to test.

3.11.3 Expanding to non-normal distributions

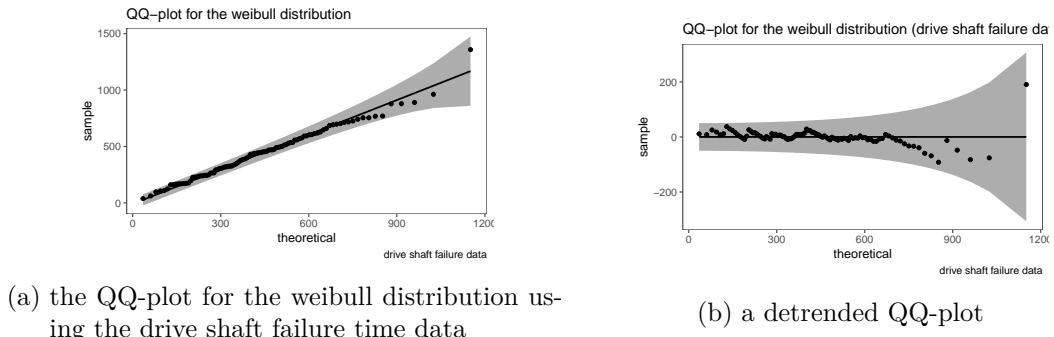


Figure 3.16: The QQ-plot can easily be extended to non-normal distributions.

The QQ-plot can easily be extended to non-normal distributions as well. This is shown in Figure 3.16. In Figure 3.16a a classic QQ-plot for Figure 2.26 is shown. The same rules as before still apply, they are *only* extended to the weibull distribution. In Figure 3.16b a *detrended* QQ-plot is shown in order to account for visual bias. It is of course known, that the data follows a *weibull* distribution with a shape parameter $\beta = 2$ and a scale parameter $\lambda = 500$, but such distributional parameters can also be estimated (Delignette-Muller and Dutang 2015).

3.12 Test 1 Variable

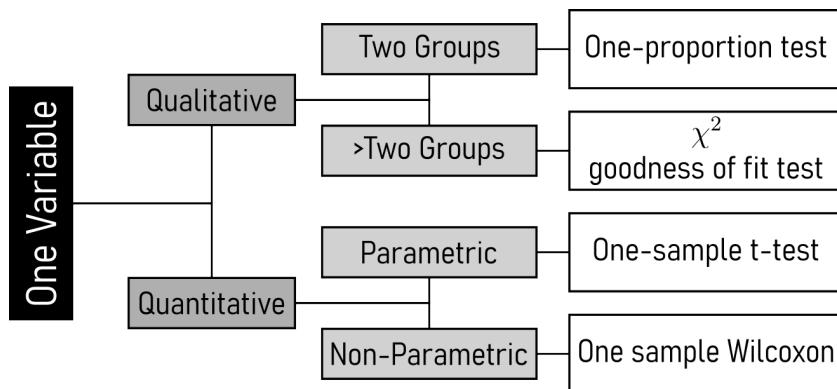


Figure 3.17: Statistical tests for one variable.

3.12.1 One Proportion Test

Table 3.5: The raw data for the proportion test.

Category	Count	Total	plt_lbl
A	35	100	35 counts 100 trials
B	20	100	20 counts 100 trials

The one proportion test is used on categorical data with a binary outcome, such as success or failure. Its prerequisite is having a known or hypothesized population proportion that the sample proportion shall be compared to. This test helps determine if the sample proportion significantly differs from the population proportion, making it valuable for studies involving proportions and percentages.

Table 3.6: The test results for the proportion test.

estimate1	estimate2	statistic	p.value	parameter	conf.low	conf.high	alternative
0.350	0.200	4.915	0.027	1.000	0.018	0.282	two.sided

3.12.2 Chi² goodness of fit test

Table 3.7: The raw data for the gof χ^2 test.

group	count_n_observed
group01	100.000
group02	100.000
group03	100.000
group04	100.000
group05	100.000

Table 3.8: The test results for the gof χ^2 test.

statistic	p.value	parameter
0.000	1.000	4.000

The χ^2 goodness of Fit Test (gof) is applied on categorical data with expected frequencies. It is suitable for analyzing nominal or ordinal data. This test assesses whether there is a significant difference between the observed and expected frequencies in your dataset, making it useful for determining if the data fits an expected distribution.

3.12.3 One-sample t-test

The one-sample t-test is designed for continuous data when you have a known or hypothesized population mean that you want to compare your sample mean to. It relies on the assumption of normal distribution, making it applicable when assessing whether a sample's mean differs significantly from a specified population mean.

The test can be applied in various settings. One is, to test if measured data comes from a population with a certain mean (for example a test against a specification). To show the application, the *drive shaft data* is employed. In Table 3.9 the *per group* summarised data of the drive shaft data is shown.

Table 3.9: The raw data for the one sample t-test.

group	mean_diameter	sd_diameter
group01	12.015	0.111
group02	12.364	0.189
group03	13.002	0.102
group04	11.486	0.094
group05	12.001	0.026

3.12 Test 1 Variable

One important prerequisite for the One sample t-test normally distributed data. For this, graphical and numerical methods have been introduced in previous chapters. First, a classic QQ-plot is created for every group (see Figure 3.18). From a first glance, the data appears to be normally distributed.

The graphical check for normality

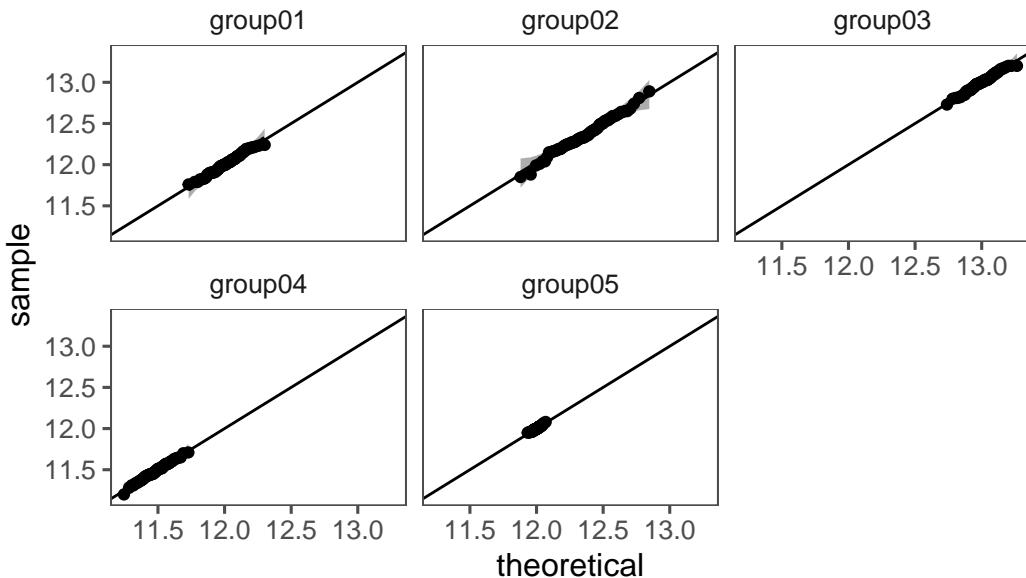


Figure 3.18: The qq-plot for the drive shaft data

A more quantitative approach to tests for normality is shown in Table 3.10. Here, each group is tested with the KS-test for normality. H_0 is accepted (the data is normal distributed) because the computed p-value is larger than the significance level ($\alpha = 0.05$).

Table 3.10: The results for the one KS normality test for each group.

group	statistic	p.value	method	alternative
group01	0.048	0.975	Asymptoticone-sampleKolmogorov-Smirnovtest	two-sided
group02	0.067	0.754	Asymptoticone-sampleKolmogorov-Smirnovtest	two-sided
group03	0.075	0.633	Asymptoticone-sampleKolmogorov-Smirnovtest	two-sided

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Table 3.10: The results for the one KS normality test for each group.

group	statistic	p.value	method	alternative
group04	0.060	0.862	Asympoticone-sampleKolmogorov-Smirnovtest	two-sided
group05	0.127	0.081	Asympoticone-sampleKolmogorov-Smirnovtest	two-sided

There is sufficient evidence to assume normal distributed data within each group. The next step is, to test if the data comes from a certain population mean (μ_0). In this case, the population mean is the specification of the drive shaft at a diameter = 12mm.

Table 3.11: The results for the one sample t-test (against mean = 12mm).

group	estimate	statistic	p.value	parameter	conf.low	conf.high	method	alternative
group01	12.015	1.391	0.167	99.000	11.993	12.038	OneSample	two.sided
group02	12.364	19.274	0.000	99.000	12.326	12.401	OneSample	two.sided
group03	13.002	97.769	0.000	99.000	12.982	13.022	OneSample	two.sided
group04	11.486	-54.441	0.000	99.000	11.468	11.505	OneSample	two.sided
group05	12.001	0.418	0.677	99.000	11.996	12.006	OneSample	two.sided

3.12.4 One sample Wilcoxon test

For situations where your data may not follow a normal distribution or when dealing with ordinal data, the one-sample Wilcoxon test is a non-parametric alternative to the t-test. It is used to evaluate whether a sample's median significantly differs from a specified population median.

The wear and tear of drive shafts can occur due to various factors related to the vehicle's operation and maintenance. Some common causes include:

1. **Normal Usage:** Over time, the drive shaft undergoes stress and strain during regular driving. This can lead to gradual wear on components, especially if the vehicle is frequently used.
2. **Misalignment:** Improper alignment of the drive shaft can result in uneven distribution of forces, causing accelerated wear. This misalignment may stem from issues with the suspension system or other related components.

3.12 Test 1 Variable

3. **Lack of Lubrication:** Inadequate lubrication of the drive shaft joints and bearings can lead to increased friction, accelerating wear. Regular maintenance, including proper lubrication, is essential to mitigate this factor.
4. **Contamination:** Exposure to dirt, debris, and water can contribute to the degradation of drive shaft components. Contaminants can infiltrate joints and bearings, causing abrasive damage over time.
5. **Vibration and Imbalance:** Excessive vibration or imbalance in the drive shaft can lead to increased stress on its components. This may result from issues with the balance of the rotating parts or damage to the shaft itself.
6. **Extreme Operating Conditions:** Harsh driving conditions, such as off-road terrain or constant heavy loads, can accelerate wear on the drive shaft. The components may be subjected to higher levels of stress than they were designed for, leading to premature wear and tear.

The wear and tear because of the reasons above can be rated on a scale with discrete values from 1 ... 5 with 2 being the reference value. It is therefore interesting, if the wear and tear rating of $n = 100$ drive shafts per group differs *significantly* from the reference value 2. Because we are dealing with discrete data, the one sample t-test can not be used.

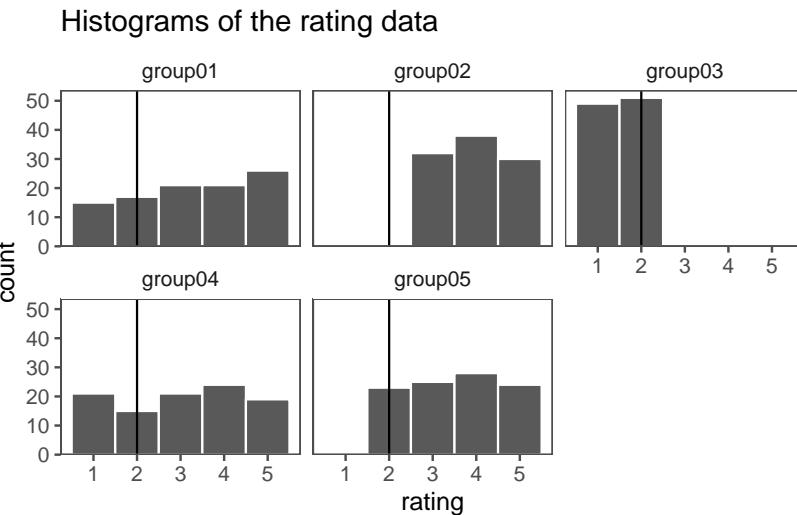


Figure 3.19: The wear and tear rating data histograms.

3 Inferential Statistics

Table 3.12: The results for the one sample Wilcoxon test for every group against the reference value.

group	statistic	p.value	alternative
group01	3,208.500	0.000	greater
group02	5,050.000	0.000	greater
group03	0.000	1.000	greater
group04	3,203.500	0.000	greater
group05	3,003.000	0.000	greater

Table 3.13: The results for the one sample t-test compared to the results of a one sample Wilcoxon test.

group	t_tidy_p.value	wilcox_tidy_p.value
group01	0.167	0.182
group02	0.000	0.000
group03	0.000	0.000
group04	0.000	0.000
group05	0.677	0.803

3.13 Test 2 Variable (Qualitative or Quantitative)

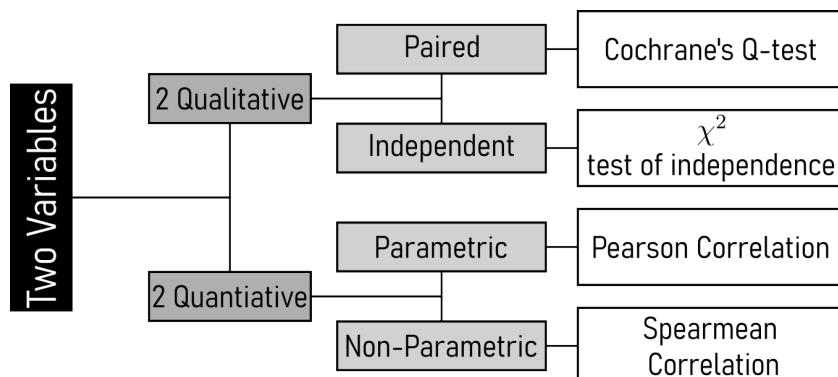


Figure 3.20: Statistical tests for two variables.

3.13.1 Cochrane's Q-test

Cochran's Q test is employed when you have categorical data with three or more related groups, often collected over time or with repeated measurements. It assesses if there is

3.13 Test 2 Variable (Qualitative or Quantitative)

a significant difference in proportions between the related groups.

3.13.2 Chi² test of independence

This test is appropriate when you have two categorical variables, and you want to determine if there is an association between them. It is useful for assessing whether the two variables are dependent or independent of each other.

In the context of the drive shaft production the example assumes a dataset with categorical variables like “Defects” (Yes/No) and “Operator” (Operator A/B).

3.13.2.1 Contingency tables

A contingency table, also known as a cross-tabulation or crosstab, is a statistical table that displays the frequency distribution of variables. It organizes data into rows and columns to show the frequency or relationship between two or more categorical variables. Each cell in the table represents the count or frequency of occurrences that fall into a specific combination of categories for the variables being analyzed. It is commonly used in statistics to examine the association between categorical variables and to understand patterns within data sets.

Table 3.14: The contingency table for this example.

Defects	Operator A	Operator B
No	2	3
Yes	3	2

3.13.2.2 test results

With $p \approx 1 > 0.05$ the p -value is greater than the significance level of $\alpha = 0.05$. The H_0 is therefore proven, there is no difference between the operators. The test results are depicted below-

```
Pearson's Chi-squared test with Yates' continuity correction
```

```
data: contingency_table
X-squared = 0, df = 1, p-value = 1
```

3 Inferential Statistics

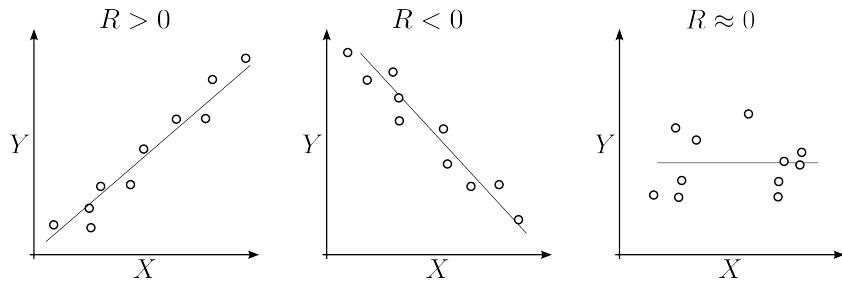


Figure 3.21: Correlation between two variables and the quantification thereof.

3.13.3 Correlation

Correlation refers to a statistical measure that describes the relationship between two variables. It indicates the extent to which changes in one variable are associated with changes in another.

Correlation is measured on a scale from -1 to 1:

- A correlation of 1 implies a perfect positive relationship, where an increase in one variable corresponds to a proportional increase in the other.
- A correlation of -1 implies a perfect negative relationship, where an increase in one variable corresponds to a proportional decrease in the other.
- A correlation close to 0 suggests a weak or no relationship between the variables.

Correlation doesn't imply causation; it only indicates that two variables change together but doesn't determine if one causes the change in the other.

3.13.3.1 Pearson Correlation

Pearson's product-moment correlation

```
data: drive_shaft_rpm_dia$rpm and drive_shaft_rpm_dia$diameter
t = 67.895, df = 498, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.9406732 0.9578924
sample estimates:
cor
0.95
```

3.13 Test 2 Variable (Qualitative or Quantitative)

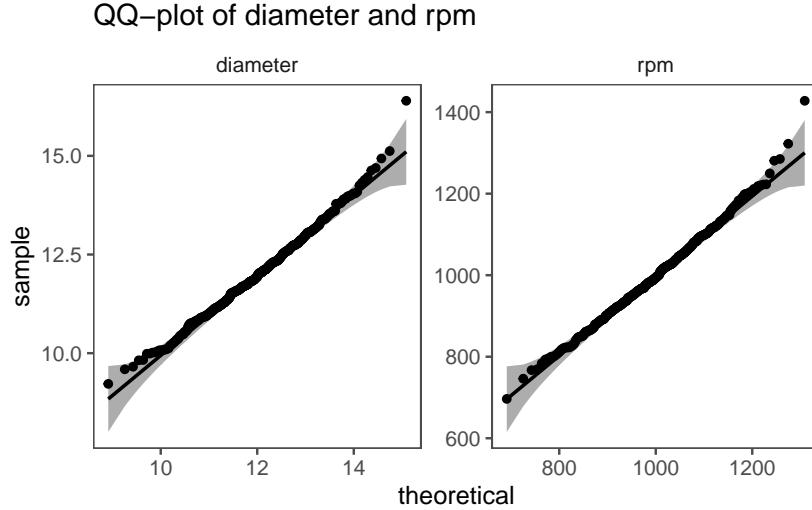


Figure 3.22: The QQ-plot of both variables. There is strong evidence that they are normally distributed.

When you have two continuous variables and want to measure the strength and direction of their linear relationship, Pearson correlation is the go-to choice (Pearson 1895). It assumes normally distributed data and is particularly valuable for exploring linear associations between variables and is calculated via (3.6).

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x}) \times (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \times \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (3.6)$$

The Pearson Correlation Coefficient works best with normal distributed data. The normal distribution of the data is verified in Figure 3.22.

3.13.3.2 Spearman Correlation

Spearman (Spearman 1904) correlation is a non-parametric alternative to Pearson correlation. It is used when the data is not normally distributed or when the relationship between variables is monotonic but not necessarily linear.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (3.7)$$

3 Inferential Statistics

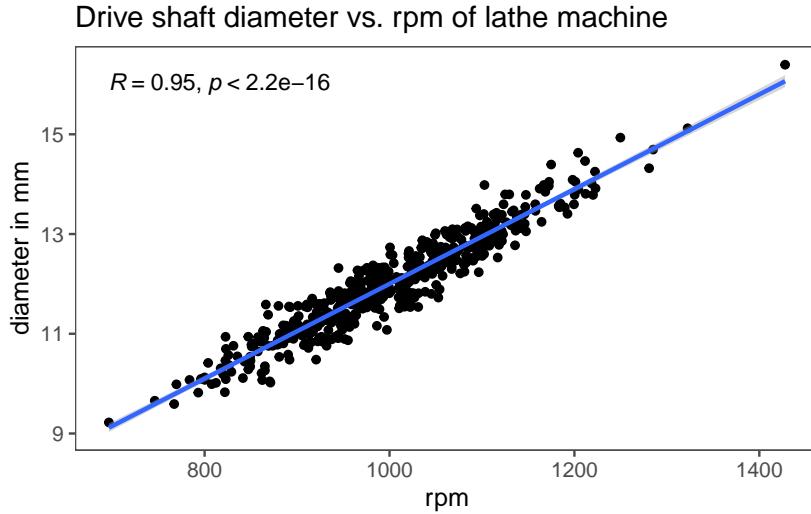


Figure 3.23: Correlation between rpm of lathe machine and the diameter of the drive shaft.

In Figure 3.24 the example data for a drive shaft production is shown. The `Production_Time` and the `Defects` seem to form a relationship, but the data does not appear to be normally distributed. This can also be seen in the QQ-plots of both variables in Figure 3.25.

Spearman's rank correlation rho

```
data: drive_shaft_time_defect$Production_Time and drive_shaft_time_defect$Defects
S = 15990, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.9040529
```

Pearson's product-moment correlation

```
data: drive_shaft_time_defect$Production_Time and drive_shaft_time_defect$Defects
t = 17.731, df = 98, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
0.8167872 0.9129728
sample estimates:
```

3.13 Test 2 Variable (Qualitative or Quantitative)

Production Time vs. Number of Defects.

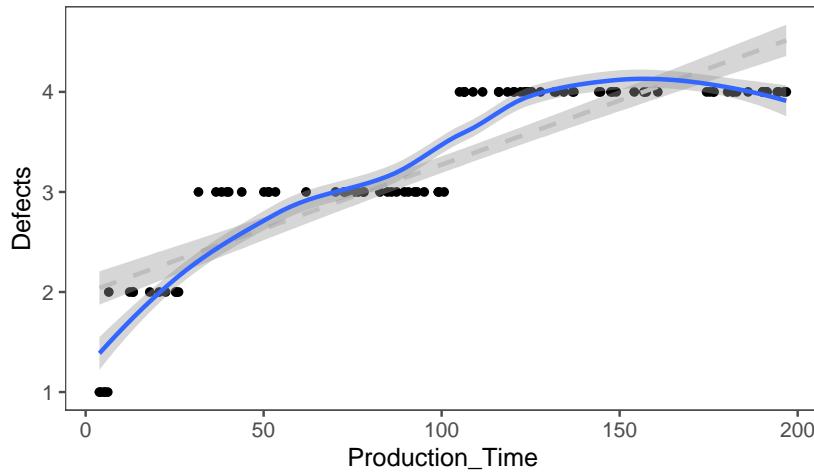


Figure 3.24: The relationship between the production time and the number of defects.
The data seems to have a relationship, but it is clearly not linear.

```
cor
0.8731278
```

3.13.3.3 Correlation - methodological limits

While correlation analysis and summary statistics are certainly useful, one must always consider the raw data. The data taken from Davies, Locke, and D'Agostino McGowan (2022) showcases this. The summary statistics in Table 3.15 are practically the same, one would not suspect different underlying data. When the raw data is plotted though (Figure 3.26), it can be seen that the data appears to be highly non linear, forming different shapes as well as different categories etc.

Always check the raw data.

Table 3.15: The datasauRus data and the respective summary statistics.

dataset	mean_x	mean_y	std_dev_x	std_dev_y	corr_x_y
away	54.266	47.835	16.770	26.940	-0.064
bullseye	54.269	47.831	16.769	26.936	-0.069
circle	54.267	47.838	16.760	26.930	-0.068
dino	54.263	47.832	16.765	26.935	-0.064
dots	54.260	47.840	16.768	26.930	-0.060
h_lines	54.261	47.830	16.766	26.940	-0.062
high_lines	54.269	47.835	16.767	26.940	-0.069

Table 3.15: The datasauRus data and the respective summary statistics.

dataset	mean_x	mean_y	std_dev_x	std_dev_y	corr_x_y
slant_down	54.268	47.836	16.767	26.936	-0.069
slant_up	54.266	47.831	16.769	26.939	-0.069
star	54.267	47.840	16.769	26.930	-0.063
v_lines	54.270	47.837	16.770	26.938	-0.069
wide_lines	54.267	47.832	16.770	26.938	-0.067
x_shape	54.260	47.840	16.770	26.930	-0.066

3.14 Test 2 Variables (2 Groups)

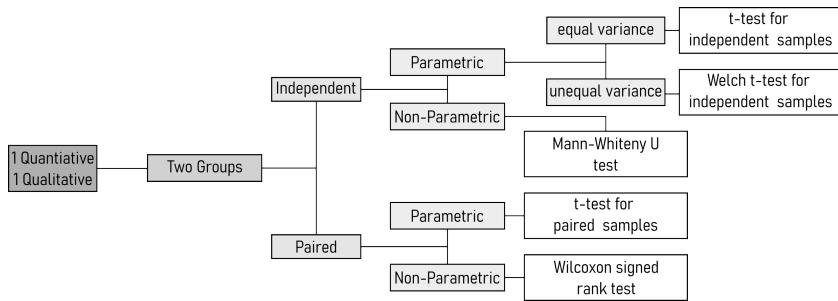


Figure 3.27: Statistical tests for two variables.

3.14.1 Test for equal variance (homoscedasticity)

Tests for equal variances, also known as tests for homoscedasticity, are used to determine if the variances of two or more groups or samples are equal. Equal variances are an assumption in various statistical tests, such as the t-test and analysis of variance (ANOVA). When the variances are not equal, it can affect the validity of these tests. Two common tests for equal variances are:

Certainly, here are bullet points outlining the null hypothesis, prerequisites, and decisions for each of the three tests:

3.14.1.1 F-Test (Hahs-Vaughn and Lomax 2013)

- **Null Hypothesis:** The variances of the different groups or samples are equal.
- **Prerequisites:**
 - Independence

3.14 Test 2 Variables (2 Groups)

The QQ-plots for the variables. There is strong evidence that the variables are not normally distributed.

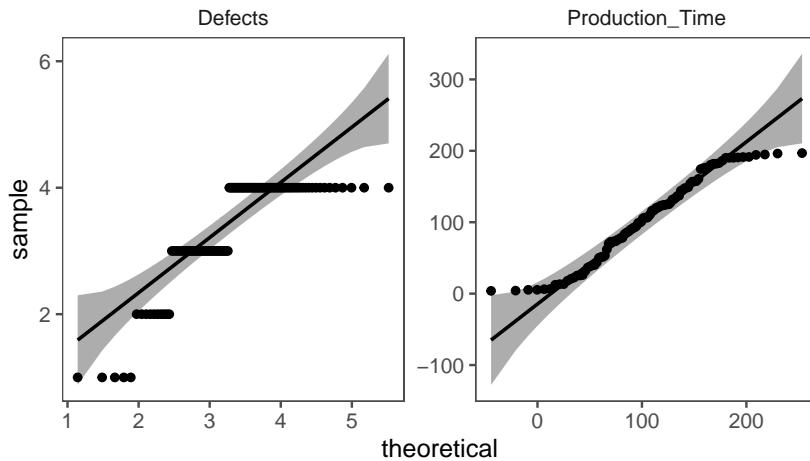


Figure 3.25: The QQ-plots of both variables.

- Normality
- Number of groups = 2

- **Decisions:**

- $p > \alpha \rightarrow$ fail to reject H_0
- $p < \alpha \rightarrow$ reject H_0

F test to compare two variances

```
data: ds_wide$group01 and ds_wide$group03
F = 1.1817, num df = 99, denom df = 99, p-value = 0.4076
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.7951211 1.7563357
sample estimates:
ratio of variances
 1.181736
```

3.14.1.2 Bartlett Test (Bartlett 1937)

- **Null Hypothesis:** The variances of the different groups or samples are equal.
- **Prerequisites:**
 - Independence

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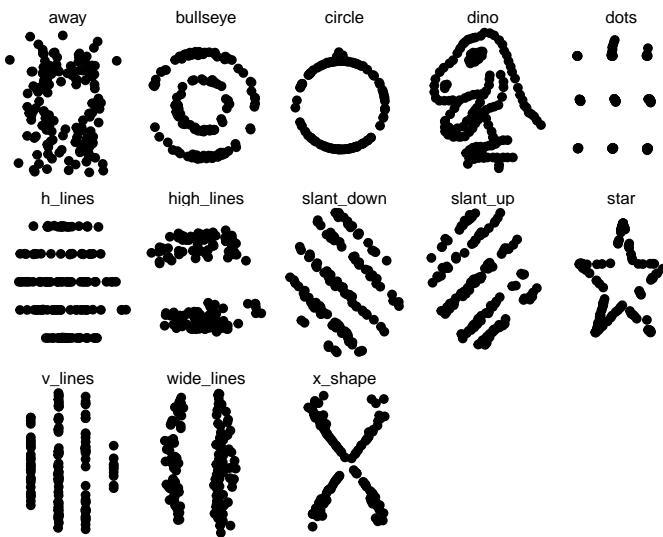


Figure 3.26: The raw data from the datasauRus packages shows, that summary statistics may be misleading.

- Normality
- Number of groups > 2

- **Decisions:**

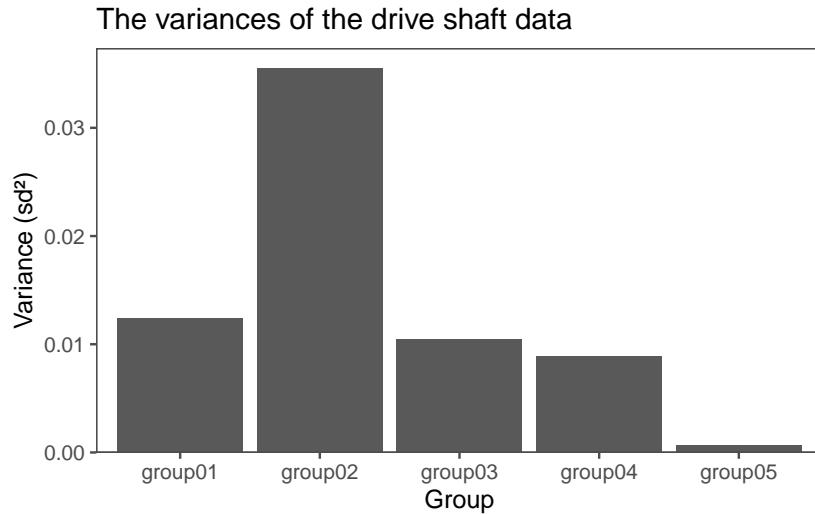
- $p > \alpha \rightarrow$ fail to reject H_0
- $p < \alpha \rightarrow$ reject H_0

Bartlett test of homogeneity of variances

```
data: diameter by group
Bartlett's K-squared = 275.61, df = 4, p-value < 2.2e-16
```

3.14.1.3 Levene Test (Olkin June)

- **Null Hypothesis:** The variances of the different groups or samples are equal.
- **Prerequisites:**
 - Independence
 - Number of groups > 2
- **Decisions:**
 - $p > \alpha \rightarrow$ fail to reject H_0

Figure 3.28: The variances (sd^2) for the drive shaft data.

- $p < \alpha \rightarrow \text{reject H0}$

```
Levene's Test for Homogeneity of Variance (center = median)
Df F value    Pr(>F)
group   4 38.893 < 2.2e-16 ***
495
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3.14.2 t-test for independent samples

The independent samples t-test is applied when you have continuous data from two independent groups. It evaluates whether there is a significant difference in means between these groups, assuming a normal distribution of the data.

- **Null Hypothesis:** The means of the two samples are equal.
- **Prerequisites:**
 - Independence
 - Normal Distribution
 - Number of groups = 2
 - equal Variances of the groups

First, the variances are compared in order to check if they are equal using the F-Test (as described in Section 3.14.1.1).

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F test to compare two variances

```
data: group01 %>% pull("diameter") and group03 %>% pull("diameter")
F = 1.1817, num df = 99, denom df = 99, p-value = 0.4076
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.7951211 1.7563357
sample estimates:
ratio of variances
 1.181736
```

With $p > \alpha = 0.05$ the H_0 is accepted, the variances are equal.

The next step is to check the data for normality using the KS-test (as described in Section 3.11.2).

Asymptotic one-sample Kolmogorov-Smirnov test

```
data: group01 %>% pull("diameter")
D = 0.048142, p-value = 0.9746
alternative hypothesis: two-sided
```

Asymptotic one-sample Kolmogorov-Smirnov test

```
data: group03 %>% pull("diameter")
D = 0.074644, p-value = 0.6332
alternative hypothesis: two-sided
```

With $p > \alpha = 0.05$ the H_0 is accepted, the data seems to be normally distributed.

3.14 Test 2 Variables (2 Groups)

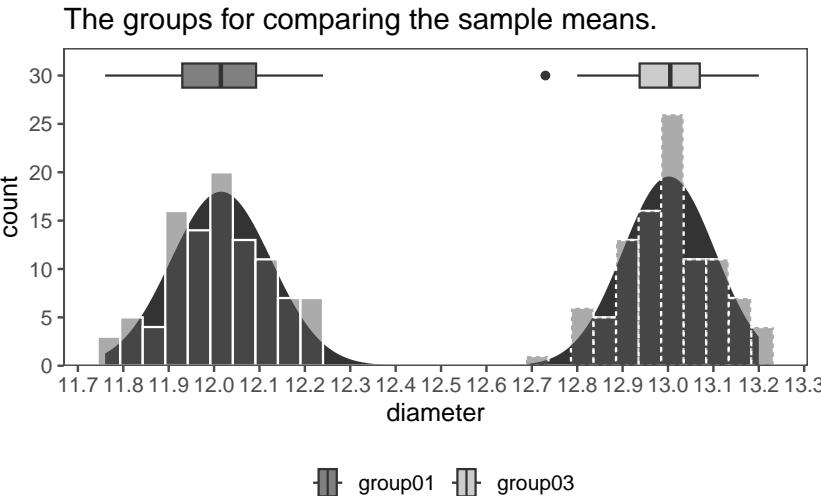


Figure 3.29: The data within the two groups for comparing the sample means using the t-test for independent samples.

The formal test is then carried out. With $p < \alpha = 0.05$ H_0 is rejected, the data comes from populations with different means.

Two Sample t-test

```
data: group01 %>% pull(diameter) and group03 %>% pull(diameter)
t = -65.167, df = 198, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.0164554 -0.9567446
sample estimates:
mean of x mean of y
12.0155 13.0021
```

3.14.3 Welch t-test for independent samples

Similar to the independent samples t-test, the Welch t-test is used for continuous data with two independent groups (WELCH 1947). However, it is employed when there are unequal variances between the groups, relaxing the assumption of equal variances in the standard t-test.

- **Null Hypothesis:** The means of the two samples are equal.
- **Prerequisites:**

3 Inferential Statistics

- Independence
- Normal Distribution
- Number of groups = 2

First, the variances are compared in order to check if they are equal using the F-Test (as described in Section 3.14.1.1).

F test to compare two variances

```
data: group01 %>% pull("diameter") and group02 %>% pull("diameter")
F = 0.34904, num df = 99, denom df = 99, p-value = 3.223e-07
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.2348504 0.5187589
sample estimates:
ratio of variances
 0.3490426
```

With $p < \alpha = 0.05$ H_0 is rejected and H_a is accepted. The variances are different.

Using the KS-test (see Section 3.11.2) the data is checked for normality.

Asymptotic one-sample Kolmogorov-Smirnov test

```
data: group01 %>% pull("diameter")
D = 0.048142, p-value = 0.9746
alternative hypothesis: two-sided
```

Asymptotic one-sample Kolmogorov-Smirnov test

```
data: group02 %>% pull("diameter")
D = 0.067403, p-value = 0.7539
alternative hypothesis: two-sided
```

With $p > \alpha = 0.05$ H_0 is accepted, the data seems to be normally distributed.

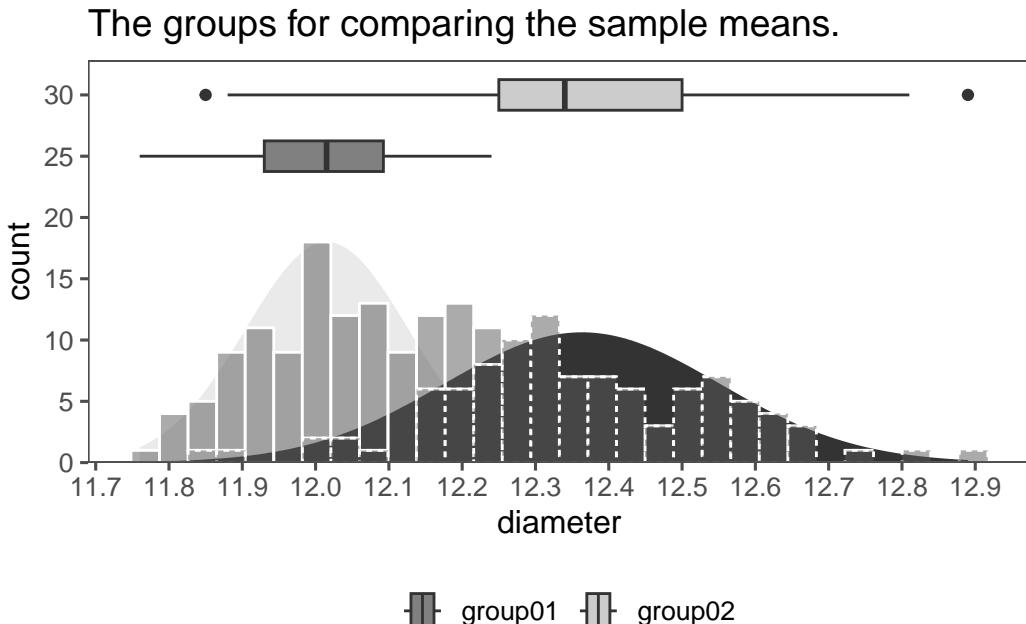


Figure 3.30: The data within the two groups for comparing the sample means using the Welch-test for independent samples.

Then, the formal test is carried out.

Welch Two Sample t-test

```
data: group01 %>% pull(diameter) and group02 %>% pull(diameter)
t = -15.887, df = 160.61, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.3912592 -0.3047408
sample estimates:
mean of x mean of y
12.0155 12.3635
```

With $p < \alpha = 0.05$ we reject H_0 , the data seems to be coming from different population means, even though the variances are overlapping (and different).

3.14.4 Mann-Whitney U test

For non-normally distributed data or small sample sizes, the Mann-Whitney U test serves as a non-parametric alternative to the independent samples t-test (Mann and Whitney 1947). It assesses whether there is a significant difference in medians between two independent groups.

- **Null Hypothesis:** The medians of the two samples are equal.
- **Prerequisites:**

- Independence
- no specific distribution (non-parametric)
- Number of groups = 2

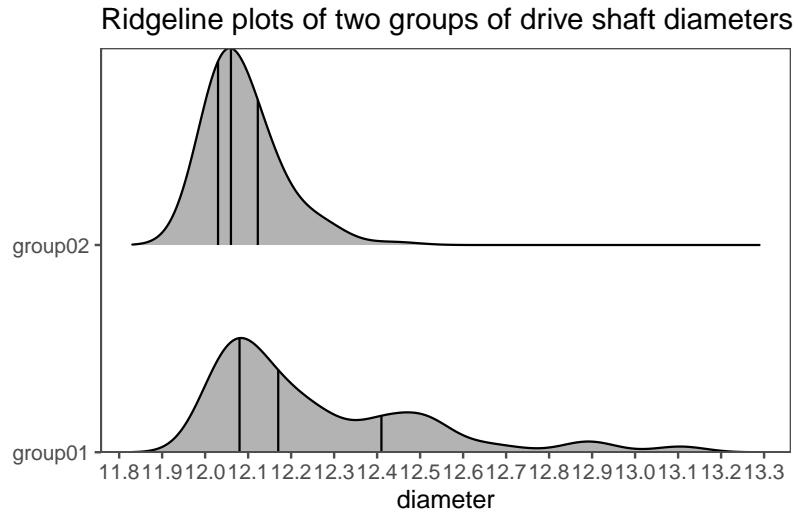


Figure 3.31: The data within the two groups for comparing the sample medians using the Mann-Whitney-U Test.

This time a graphical method to check for normality is employed (QQ-plot, see Section 3.11.1). From the Figure 3.32 it is pretty clear, that the data is not normally distributed. Furthermore, the variances seem to be unequal as well.

3.14 Test 2 Variables (2 Groups)

The QQ-plots for the data to check for normality.

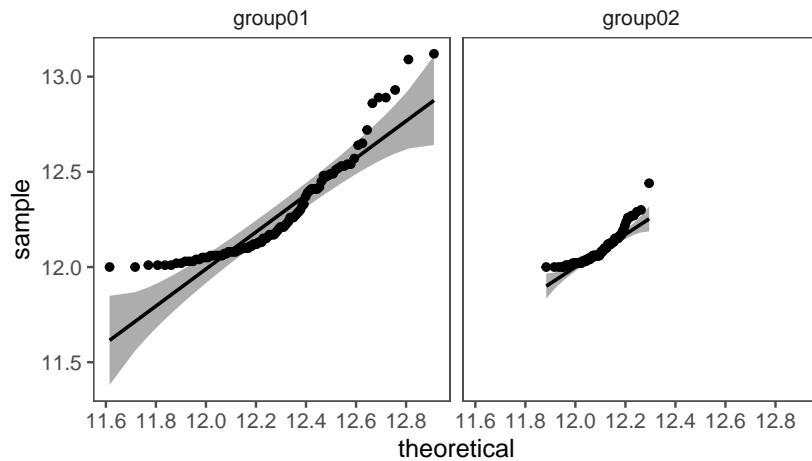


Figure 3.32: The data within the two groups for comparing the sample medians using the Mann-Whitney-U Test.

Then, the formal test is carried out. With $p < \alpha = 0.05$ H_0 is rejected, the true location shift is not equal to 0.

Wilcoxon rank sum test with continuity correction

```
data: diameter by group
W = 7396, p-value = 4.642e-09
alternative hypothesis: true location shift is not equal to 0
```

3.14.5 t-test for paired samples

The paired samples t-test is suitable when you have continuous data from two related groups or repeated measures. It helps determine if there is a significant difference in means between the related groups, assuming normally distributed data.

- **Null Hypothesis:** True mean difference is not equal to 0.
- **Prerequisites:**

- Paired Data
- Normal Distribution
- equal variances
- Number of groups = 2

Using the F-Test, the variances are compared.

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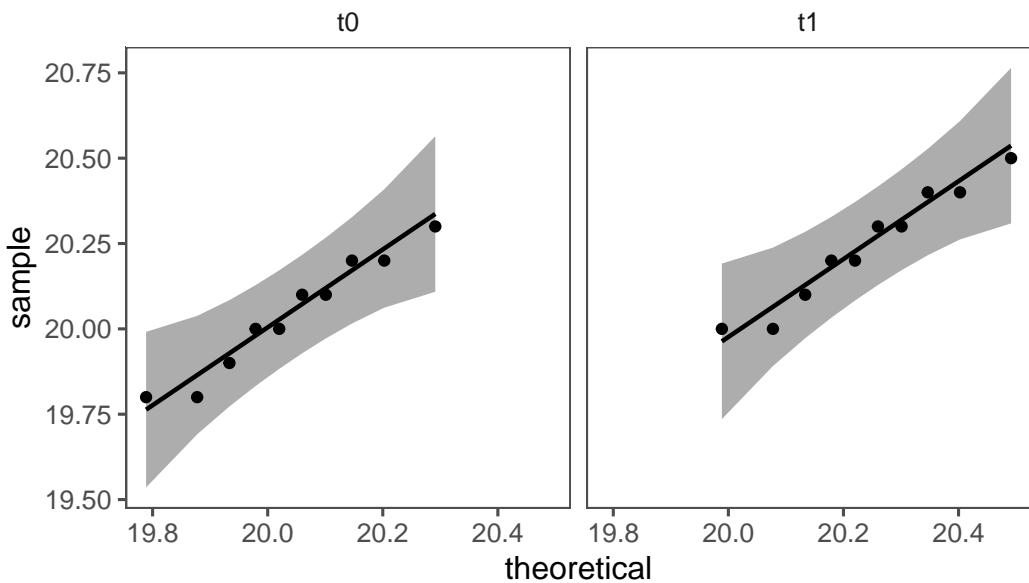
F test to compare two variances

```
data: diameter by timepoint
F = 1, num df = 9, denom df = 9, p-value = 1
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
0.2483859 4.0259942
sample estimates:
ratio of variances
1
```

With $p > \alpha = 0.05$ H_0 is accepted, the variances are equal.

Using a QQ-plot the data is checked for normality.

QQ-plots of the treatment data at the different timepoints



Without a formal test, the data is assumed to be normally distributed.

3.14 Test 2 Variables (2 Groups)

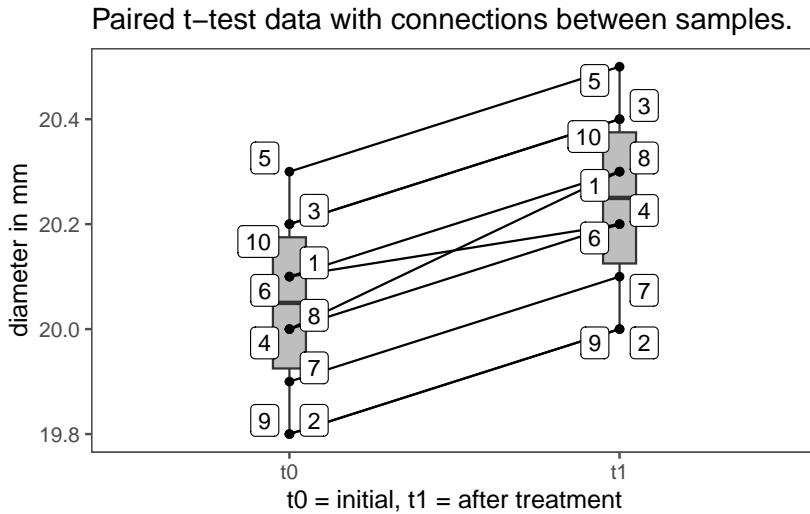


Figure 3.33: A boxplot of the data, showing the connections between the datapoints.

The formal test is then carried out.

```
# A tibble: 1 x 8
  .y.     group1 group2   n1   n2 statistic    df      p
* <chr>   <chr>  <chr> <int> <int>    <dbl> <dbl>    <dbl>
1 diameter t0     t1       10    10     -13.4     9 0.000000296
```

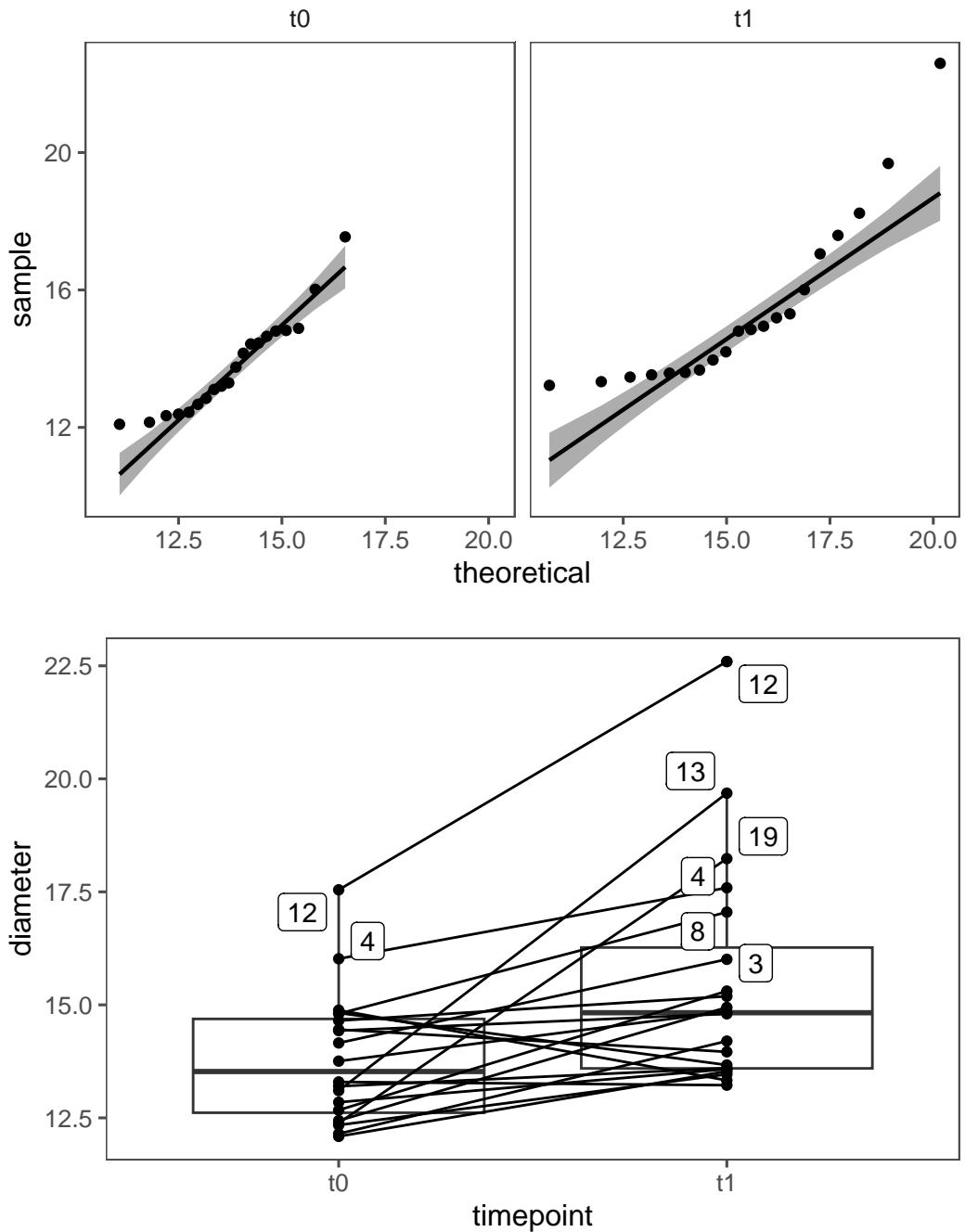
With $p < \alpha = 0.05$ H_0 is rejected, the treatment changed the properties of the product.

3.14.6 Wilcoxon signed rank test

For non-normally distributed data or situations involving paired samples, the Wilcoxon signed rank test is a non-parametric alternative to the paired samples t-test. It evaluates whether there is a significant difference in medians between the related groups.

- **Null Hypothesis:** True mean difference is not equal to 0.
- **Prerequisites:**
 - Paired Data
 - Number of groups = 2

3 Inferential Statistics



```
# A tibble: 1 x 7
  .y.     group1 group2    n1    n2 statistic      p
* <chr>   <chr>  <chr>  <int> <int>    <dbl>    <dbl>
1 diameter t0      t1        20    20       25 0.00169
```

3.15 Test 2 Variables (> 2 Groups)

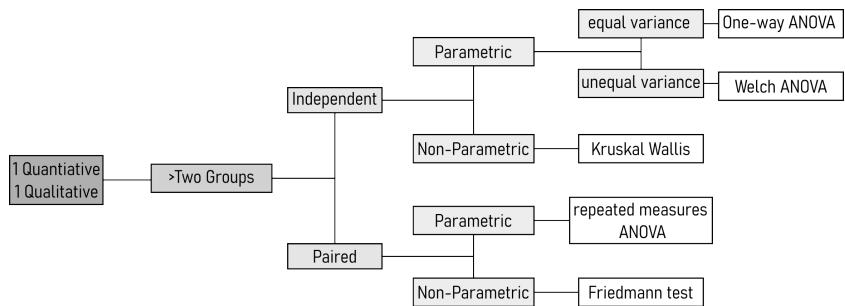


Figure 3.34: Statistical tests for one variable.

3.15.1 Analysis of Variance (ANOVA) - Basic Idea

ANOVA's ability to compare multiple groups or factors makes it widely applicable across diverse fields for analyzing variance and understanding relationships within data. In the context of engineering sciences the application of ANOVA include:

- 1. Experimental Design and Analysis:** Engineers often conduct experiments to optimize processes, test materials, or evaluate designs. ANOVA aids in analyzing these experiments by assessing the effects of various factors (like temperature, pressure, or material composition) on the performance of systems or products. It helps identify significant factors and their interactions to improve engineering processes.
- 2. Product Testing and Reliability:** Engineers use ANOVA to compare the performance of products manufactured under different conditions or using different materials. This analysis helps ensure product reliability by identifying which factors significantly impact product quality, durability, or functionality.
- 3. Process Control and Improvement:** ANOVA plays a crucial role in quality control and process improvement within engineering. It helps identify variations in manufacturing processes, such as assessing the impact of machine settings or production methods on product quality. By understanding these variations, engineers can make informed decisions to optimize processes and minimize defects.
- 4. Supply Chain and Logistics:** In engineering logistics and supply chain management, ANOVA aids in analyzing the performance of different suppliers or transportation methods. It helps assess variations in delivery times, costs, or product quality across various suppliers or logistical approaches.
- 5. Simulation and Modeling:** In computational engineering, ANOVA is used to analyze the outputs of simulations or models. It helps understand the significance

3 Inferential Statistics

of different input variables on the output, enabling engineers to refine models and simulations for more accurate predictions.

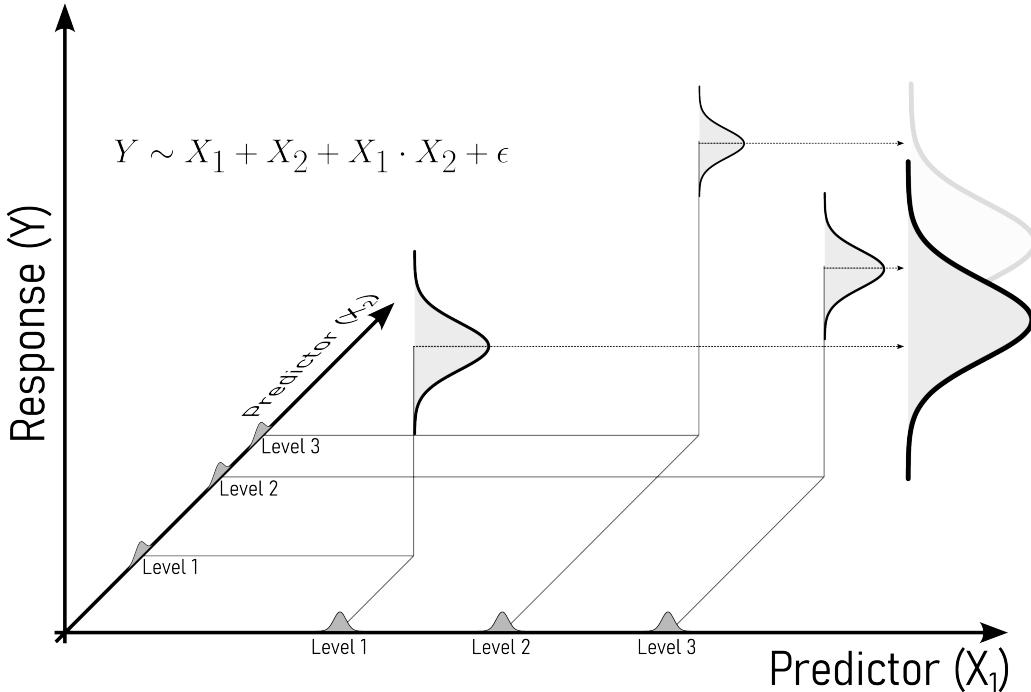


Figure 3.35: The basic idea of an ANOVA.

Across such fields ANOVA is often used to:

Comparing Means: ANOVA is employed when comparing means between three or more groups. It assesses whether there are statistically significant differences among the means of these groups. For instance, in an experiment testing the effect of different fertilizers on plant growth, ANOVA can determine if there's a significant difference in growth rates among the groups treated with various fertilizers.

Modeling Dependencies: ANOVA can be extended to model dependencies among variables in more complex designs. For instance, in factorial ANOVA, it's used to study the interaction effects among multiple independent variables on a dependent variable. This allows researchers to understand how different factors might interact to influence an outcome.

Measurement System Analysis (MSA): ANOVA is integral in MSA to evaluate the variation contributed by different components of a measurement system. In assessing the reliability and consistency of measurement instruments or processes, ANOVA helps in dissecting the total variance into components attributed to equipment variation, operator variability, and measurement error.

3.15 Test 2 Variables (> 2 Groups)

As with statistical tests before, the applicability of the ANOVA depends on various factors.

3.15.1.1 Sum of squared error (SSE)

The sum of squared errors is a statistical measure used to assess the goodness of fit of a model to its data. It is calculated by squaring the differences between the observed values and the values predicted by the model for each data point, then summing up these squared differences. The SSE indicates the total variability or dispersion of the observed data points around the fitted regression line or model. Lower SSE values generally indicate a better fit of the model to the data.

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3.8)$$

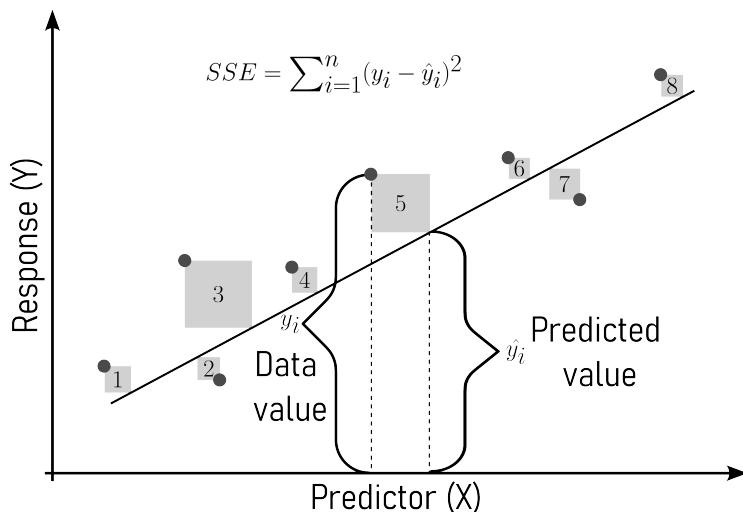


Figure 3.36: A graphical depiction of the SSE.

3.15.1.2 Mean squared error (MSE)

The mean squared error is a measure used to assess the average squared difference between the predicted and actual values in a dataset. It is frequently employed in regression analysis to evaluate the accuracy of a predictive model. The MSE is calculated by taking the average of the squared differences between predicted values and observed values. A lower MSE indicates that the model's predictions are closer to the actual values, reflecting better accuracy.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3.9)$$

3.15.2 One-way ANOVA

The one-way analysis of variance (ANOVA) is used for continuous data with three or more independent groups. It assesses whether there are significant differences in means among these groups, assuming a normal distribution.

- **Null Hypothesis:** True mean difference is equal to 0.
- **Prerequisites:**
 - equal variances
 - Number of groups > 2
 - One response, one predictor variable

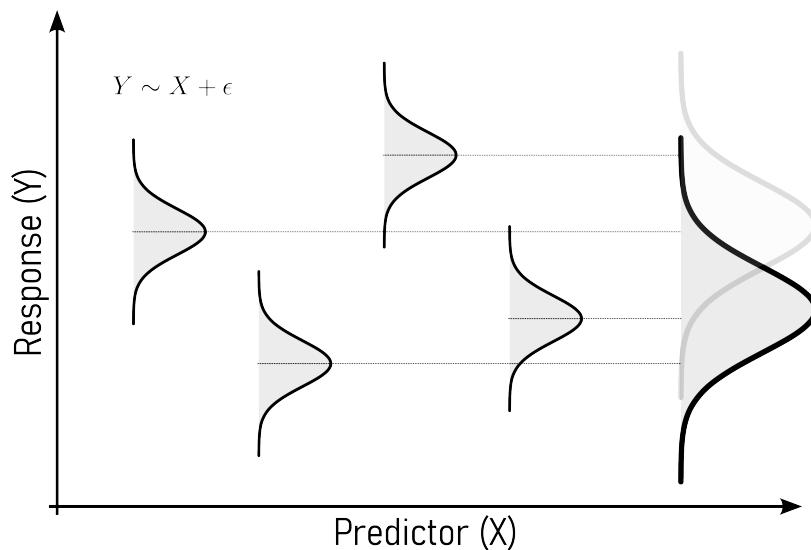


Figure 3.37: The basic idea of a One-way ANOVA.

The most important prerequisite for a One-way ANOVA are equal variances. Because there are more than two groups, the Bartlett test (as introduced in Section 3.14.1.2) is chosen (data is normally distributed).

Bartlett test of homogeneity of variances

3.15 Test 2 Variables (> 2 Groups)

```
data: diameter by group
Bartlett's K-squared = 275.61, df = 4, p-value < 2.2e-16
```

Because $p < \alpha = 0.05$ the variances are different.

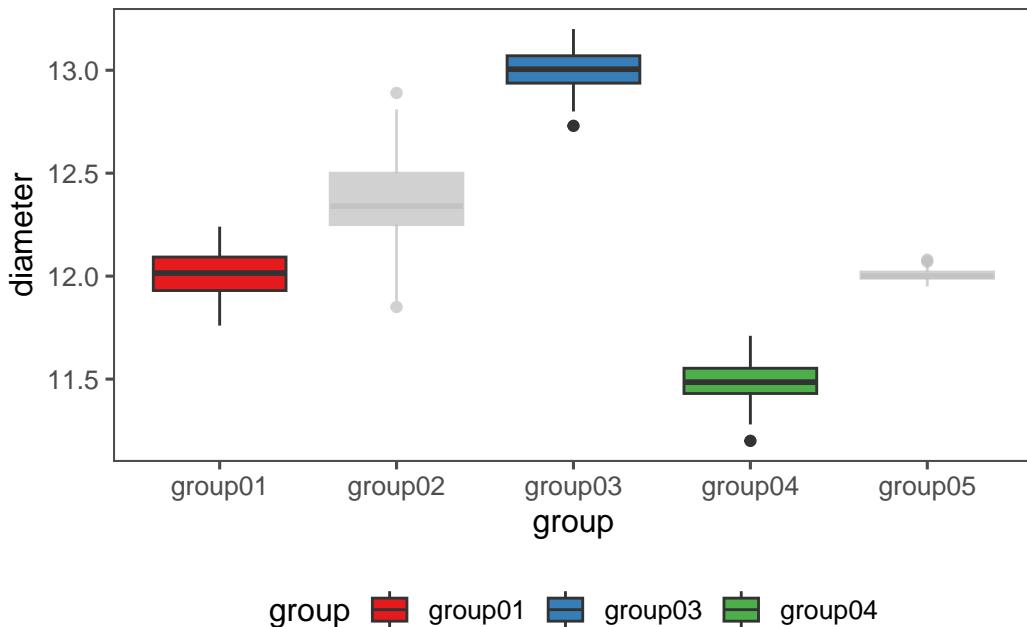


Figure 3.38: The groups with equal variance are highlighted.

Bartlett test of homogeneity of variances

```
data: diameter by group
Bartlett's K-squared = 2.7239, df = 2, p-value = 0.2562
```

With $p > \alpha = 0.05$ H_0 is accepted, the variances of group01, group02 and group03 are equal.

Of course, many software package provide an automated way of performing a One-way ANOVA, but the first will be explained in detail. The general model for a One-way ANOVA is shown in (3.10).

$$Y \sim X + \epsilon \quad (3.10)$$

- H_0 : All population means are equal.

3 Inferential Statistics

- H_a : Not all population means are equal.

For a One-way ANOVA the predictor variable X is the mean (\bar{x}) of all datapoints x_i .

First the SSE and the MSE is calculated for the complete model (H_a is true), see Table 3.16. The complete model means, that every mean, for every group is calculated and the SSE according to (3.8) is calculated.

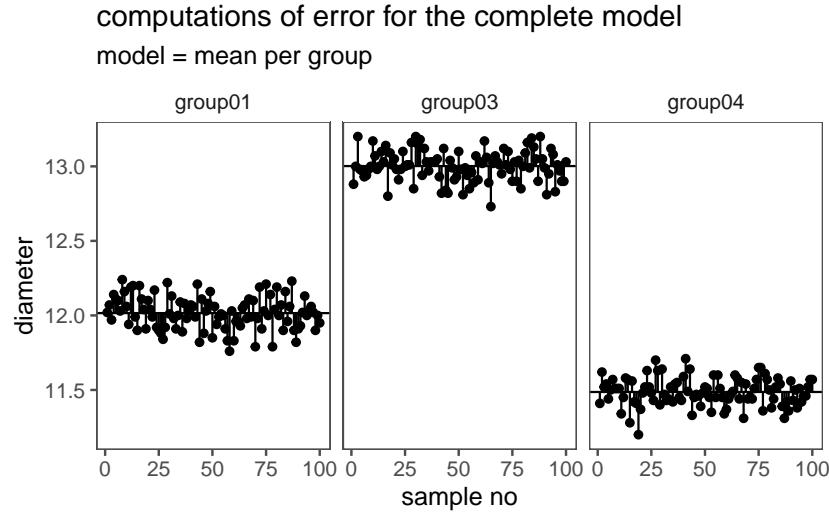


Figure 3.39: Computation of error for the complete model (mean per group as model)

Table 3.16: The SSE and MSE for the complete model.

sse	df	n	p	mse
3.150	297.000	300.000	3.000	0.011

Then, the SSE and the MSE is calculated for the reduced model (H_0 is true). In the reduced model, the mean is not calculated per group, the overall mean is calculated (results in Table 3.17).

Table 3.17: The SSE and MSE from the reduced model.

sse	df	n	p	mse
121.506	299.000	300.000	1.000	0.406

The SSE , df and MSE explained by the complete model are calculated:

3.15 Test 2 Variables (> 2 Groups)

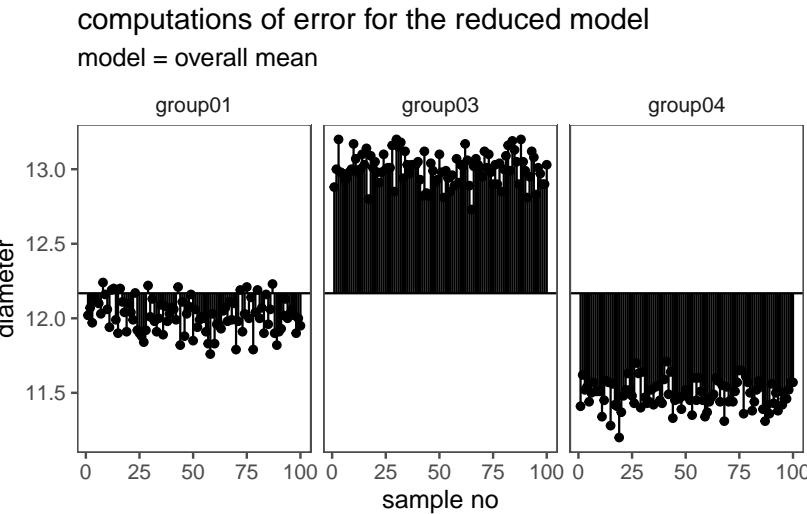


Figure 3.40: Computation of error for the reduced model (overall mean as model)

$$SSE_{explained} = SSE_{reduced} - SSE_{complete} = 118.36 \quad (3.11)$$

$$df_{explained} = df_{reduced} - df_{complete} = 2 \quad (3.12)$$

$$MSE_{explained} = \frac{SSE_{explained}}{df_{explained}} = 59.18 \quad (3.13)$$

The ratio of the variance (MSE) as explained by the complete model to the reduced model is then calculated. The probability of this statistic is afterwards calculated (if H_0 is true).

[1] 2.762026e-236

The probability of a F-statistic with $pf = 5579.207$ is 0.

A crosscheck with a automated solution (`aov`-function) yields the results shown in Table 3.18.

Table 3.18: The ANOVA results from the `aov` function.

term	df	sumsq	meansq	statistic	p.value
group	2.000	118.356	59.178	5,579.207	0.000
Residuals	297.000	3.150	0.011	NA	NA

3 Inferential Statistics

Some sanity checks are of course required to ensure the validity of the results. First, the variance of the residuals must be equal along the groups (see Figure 3.41).

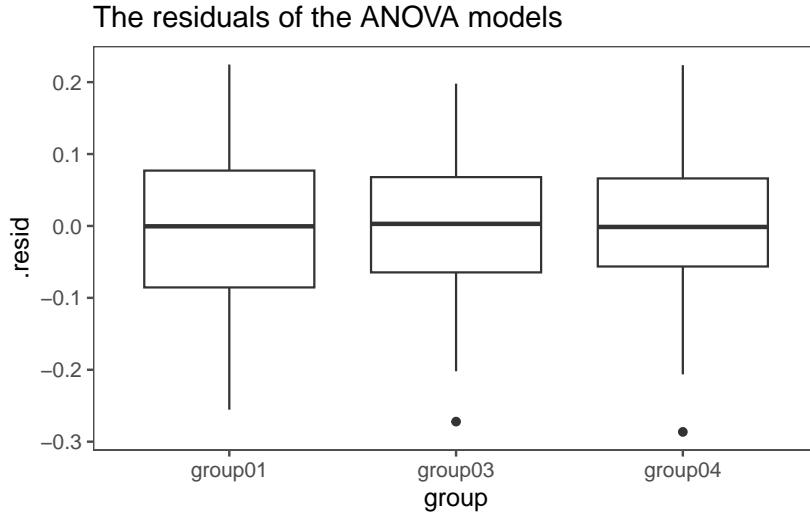


Figure 3.41: The variances of the residuals.

Also, the residuals from the model must be normally distributed (see Figure 3.42).

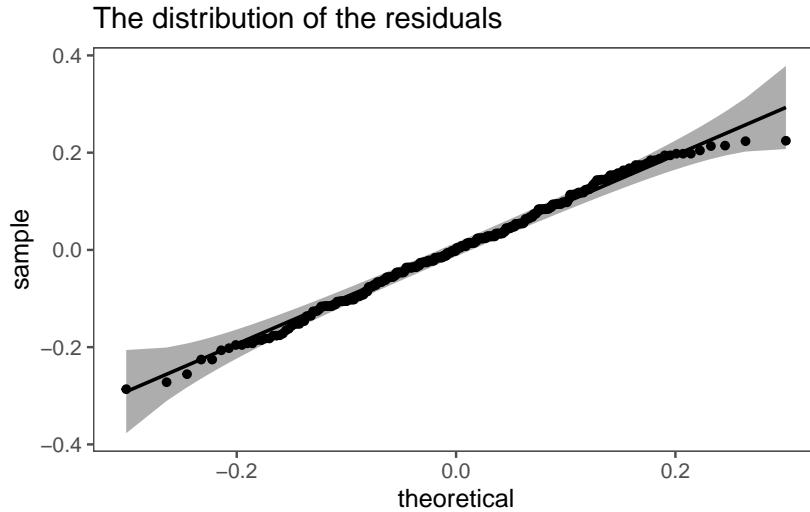


Figure 3.42: The distribution of the residuals.

The model seems to be valid (equal variances of residuals, normal distributed residuals).

3.15 Test 2 Variables (> 2 Groups)

With $p < \alpha = 0.05$ H_0 can be rejected, the means come from different populations.

3.15.3 Welch ANOVA

Welch ANOVA: Similar to one-way ANOVA, the Welch ANOVA is employed when there are unequal variances between the groups being compared. It relaxes the assumption of equal variances, making it suitable for situations where variance heterogeneity exists.

- **Null Hypothesis:** True mean difference is not equal to 0.
- **Prerequisites:**
 - Number of groups > 2
 - One response, one predictor variable

The Welch ANOVA drops the prerequisite of equal variances in groups. Because there are more than two groups, the Bartlett test (as introduced in Section 3.14.1.2) is chosen (data is normally distributed).

```
Bartlett test of homogeneity of variances
```

```
data: diameter by group
Bartlett's K-squared = 275.61, df = 4, p-value < 2.2e-16
```

With $p < \alpha = 0.05$ H_0 can be rejected, the variances are not equal.

The ANOVA table for the Welch ANOVA is shown in Table 3.19.

Table 3.19: The ANOVA results from the ANOVA Welch Test (not assuming equal variances).

num.df	den.df	statistic	p.value	method
4.000	215.085	3,158.109	0.000	One-way analysis ofmeans (not assuming equalvariances)

3.15.4 Kruskal Wallis

Kruskal-Wallis Test: When dealing with non-normally distributed data, the Kruskal-Wallis test is a non-parametric alternative to one-way ANOVA. It is used to evaluate whether there are significant differences in medians among three or more independent groups.

In this example the drive strength is measured using three-point bending. Three different methods are employed to increase the strength of the drive shaft.

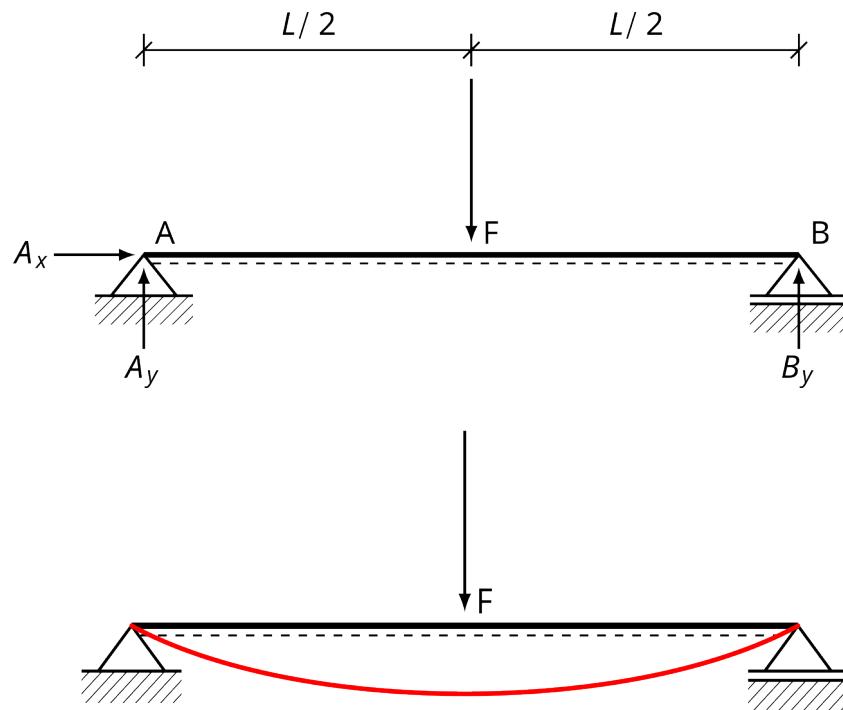


Figure 3.43: The mechanical Background for a three-point bending test

- Method A: baseline material
- Method B: different geometry
- Method C: different material

In Figure 3.44 the raw drive shaft strength data for Method A, B and C is shown. At first glance, the data does not appear to be normally distributed.

3.15 Test 2 Variables (> 2 Groups)

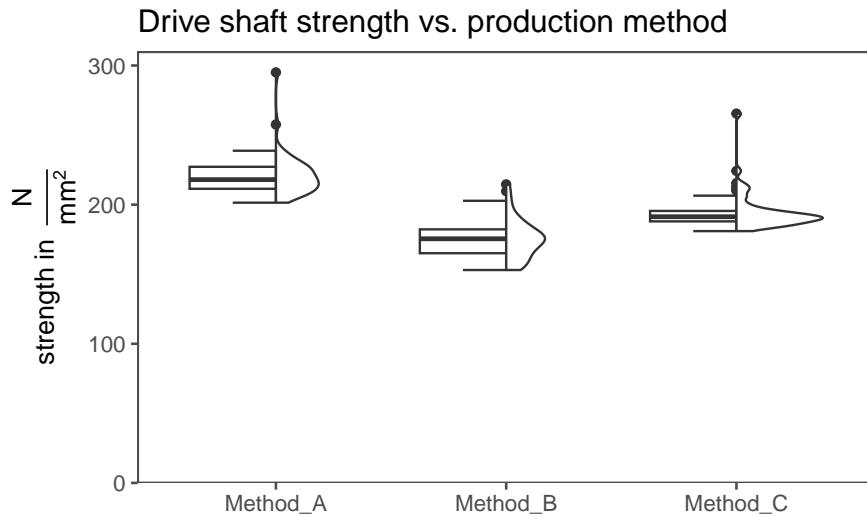


Figure 3.44: The raw data from the drive shaft strength testing.

In Figure 3.45 the visual test for normal distribution is performed. The data does not appear to be normally distributed.

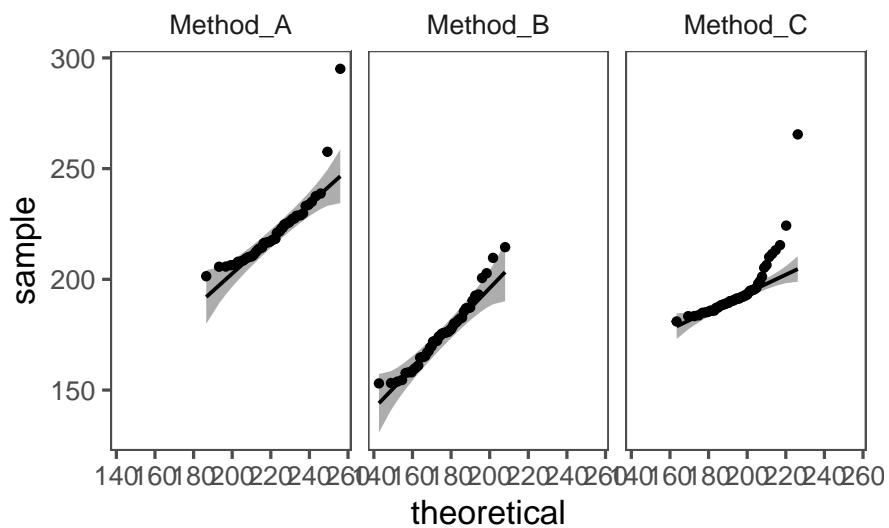


Figure 3.45: The qq-plot for the drive shaft strength testing data.

The Kruskal-Wallis test is then carried out. With $p < \alpha = 0.05$ it is shown, that the groups come from populations with different means. The next step is to find which of the groups are different using a post-hoc analysis.

3 Inferential Statistics

Kruskal-Wallis rank sum test

```
data: strength by group
Kruskal-Wallis chi-squared = 107.65, df = 2, p-value < 2.2e-16
```

The Kruskal-Wallis Test (as the ANOVA) can only tell you, if there is a significant difference between the groups, not what groups are different. Post-hoc tests are able to determine such, but must be used with a correction for multiple testing (see (Tamhane 1977))

Pairwise comparisons using Wilcoxon rank sum test with continuity correction

```
data: kw_shaft_data$strength and kw_shaft_data$group

Method_A Method_B
Method_B < 2e-16  -
Method_C 6.8e-14  2.0e-10

P value adjustment method: bonferroni
```

Because $p < \alpha = 0.05$ it can be concluded, that all means are different from each other.

3.15.5 repeated measures ANOVA

Repeated Measures ANOVA: The repeated measures ANOVA is applicable when you have continuous data with multiple measurements within the same subjects or units over time. It is used to assess whether there are significant differences in means over the repeated measurements, under the assumptions of sphericity and normal distribution.

In this example, the diameter of $n = 20$ drive shafts is measured after three different steps.

- Before Machining
- After Machining
- After Inspection

3.15 Test 2 Variables (> 2 Groups)

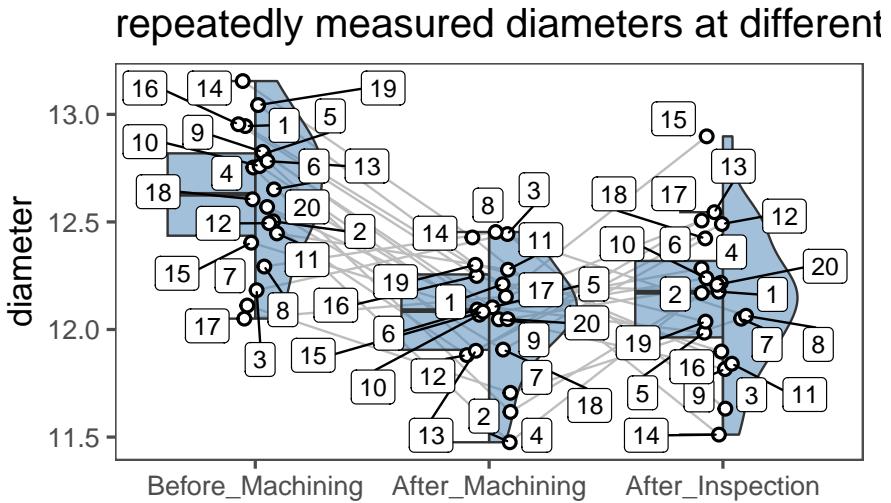


Figure 3.46: The raw data for the repeated measures ANOVA.

First, outliers are identified. There is no strict rule to identify outliers, in this case a classical measure is applied according to (3.14)

$$\text{outlier} = \begin{cases} x_i & > Q3 + 1.5 \cdot IQR \\ x_i & < Q1 - 1.5 \cdot IQR \end{cases} \quad (3.14)$$

```
# A tibble: 1 x 5
  timepoint      Subject_ID diameter is.outlier is.extreme
  <chr>           <fct>     <dbl>    <lgl>      <lgl>
1 After_Inspection 15        12.9     TRUE       FALSE
```

A check for normality is done employing the Shapiro-Wilk test (Shapiro and Wilk 1965).

timepoint	variable	statistic	p
After_Inspection	diameter	0.968	0.727
After_Machining	diameter	0.954	0.456
Before_Machining	diameter	0.968	0.741

The next step is to check the dataset for sphericity, meaning to compare the variance of the groups among each other in order to determine the equality thereof. For this the Mauchly Test for sphericity is employed (Mauchly 1940).

3 Inferential Statistics

```
Effect      W      p p<.05
1 timepoint 0.927 0.524
```

With $p > \alpha = 0.05$ H_0 is accepted, the variances are equal. Otherwise sphericity corrections must be applied (Greenhouse and Geisser 1959).

The next step is to perform the repeated measures ANOVA, which yields the following results.

Effect	DFn	DFd	F	p	p<.05	ges
timepoint	2.000	36.000	18.081	0.000	*	0.444

With $p < \alpha = 0.05$ H_0 is rejected, the different timepoints yield different diameters. Which groups are different is then determined using a post-hoc test, including a correction for the significance level (Bonferroni 1936).

In this case, the assumptions for a t-test are met, the pairwise t-test can be used.

group1	group2	n1	n2	statistic	df	p	p.adj	signif
After_Inspection	After_Machining	19	19	0.342	18	0.736	1.000	ns
After_Inspection	Before_Machining	19	19	-4.803	18	0.000	0.000	***
After_Machining	Before_Machining	19	19	-6.283	18	0.000	0.000	****

with $p < \alpha = 0.05$ H_0 is rejected for the comparison `Before_Machining - After_Machining` and `After_Inspection - Before_Machining`. It can therefore be concluded that the machining has a significant influence on the diameter, whereas the inspection has none.

3.15.6 Friedman test

The Friedman test is a non-parametric alternative to repeated measures ANOVA (Friedman 1937). It is utilized when dealing with non-normally distributed data and multiple measurements within the same subjects. This test helps determine if there are significant differences in medians over the repeated measurements.

The same data as for the repeated measures ANOVA will be used.

.y.	n	statistic	df	p	method
diameter	20.000	16.900	2.000	0.000	Friedman test

With $p < \alpha = 0.05$ H_0 is rejected, the timepoints play a vital role for the drive shaft parameter.

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