Chapter 4
Choosing Between Parametric and Non-parametric Tests in Statistical Data Analysis

4.1 Introduction

Statistical data analysis and hypothesis testing in any type of research or data analysis usually fall under two likely categories: *parametric* and *non-parametric* tests. In scientific research, statistical methods are mainly used to conduct quantitative research or analysis. Thus, the *hypothesis* testing (be it parametric or non-parametric) is primarily designed and used to describe and interpret the "assumptions" that underlie the adopted statistical methods. In Chap. 6, the authors will expand on the different types of Statistical Methods and Analysis the researchers can perform particularly taking into account the parametric and non-parametric tests discussed in this current chapter.

The decision to conduct parametric or non-parametric analysis largely depends on the type of data (see Chap. 5) the researchers intend to investigate or analyze (Stojanović et al., 2018). The different statistical approaches or procedures are followed based on the type of the available dataset (nominal, ordinal, continuous, discrete, number of independent versus dependent variables, etc.). Hopkins et al. (2018) note that when researchers collect data for hypotheses testing and the investigations to follow; they often refer to the underlying proportions, means, medians, or standard deviations, etc. as "parameters" to describe the general population in question. As a result, the researchers tend to predetermine those "parameters" from the collected sample (i.e., drawn from the population) by calculating the sample estimates or quantification, otherwise referred to as "statistics". Thus, statistical methods or analysis are applied to estimate the parameters (Hopkins et al., 2018). Likewise, Stojanović et al. (2018) note that making the right choice as to which statistical method or test to apply for the research strongly influences the extent and level of the data interpretation and impact.

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4.2 Parametric Versus Non-parametric Tests

In this section, the authors focus on describing in detail what parametric and non-parametric tests are, and when to choose between the two types of test in research experiments or hypothesis testing.

4.2.1 Parametric Test

Parametric tests are fundamentally used to make assumptions based on the *distributions* that underlie the available data the researchers or analysts want to analyze (Hopkins et al., 2018; Turner et al., 2020). With the parametric tests, it is assumed that several conditions which are used to measure the validity and reliability of the test and results must be met. According to Turner et al. (2020), the term "parametric" refers to parameters of the resultant data (distribution) which assumes that the sample (mean, standard deviations, etc.) is normally distributed as illustrated in Fig. 4.1a.

In the other setting (non-parametric), which the authors discuss in detail in the next section of this chapter (Sect. 4.2.2)—the data samples or population can appear to be not normally distributed (see: Fig. 4.1b and c), which in turn, implies the

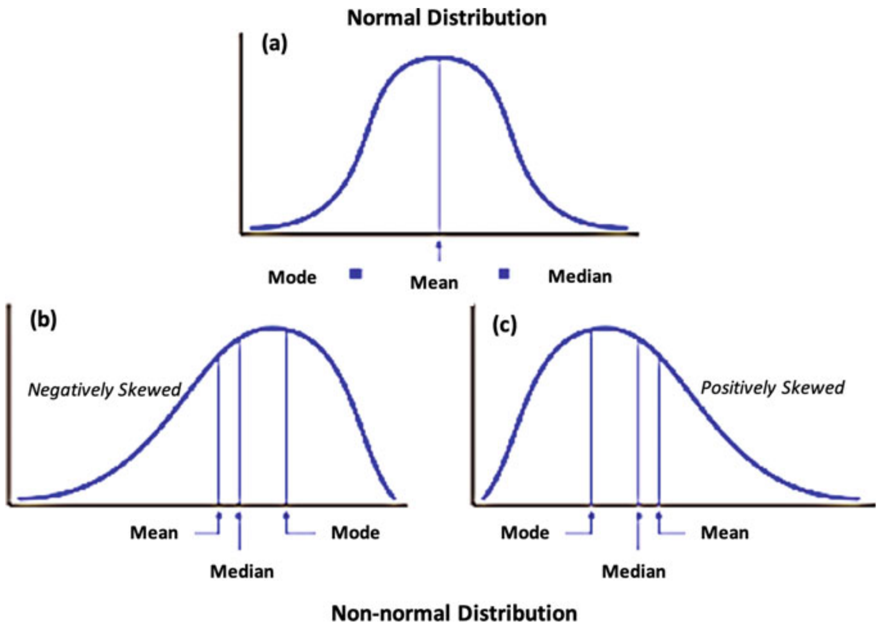

Fig. 4.1 Normal versus non-normal data distribution, adapted from Antonopoulos and Kakisis (2019)

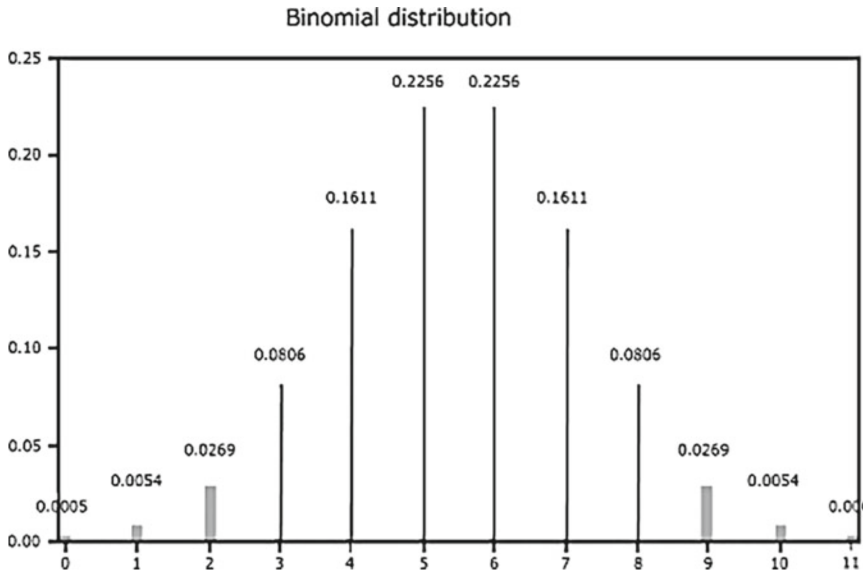

Fig. 4.2 Binomial distribution sample example, adapted from ScienceDirect (2019)

application of statistical methods that support those types of data (otherwise referred to as non-parametric procedures).

By definition, the term parametric can be referred to methods or procedures that assume specific types of distributions such as: the Binomial or Poisson distributions (Turner et al., 2020), as shown in Figs. 4.1a and 4.2.

In theory, as gathered in Figs. 4.1a and 4.2; *parametric tests* are based on the presupposition that the analyzed or investigated datasets follow a normal "bell-shaped curve" distribution of values (Antonopoulos & Kakisis, 2019; ScienceDirect, 2019) often allied to the *central limit theorem* (Stojanović et al., 2018). According to the ScienceDirect (2019) source or topic on the parametric tests, a graphical representation of data drawn from a particular group of population (i.e., studied phenomenon) that appears to be closely or normally distributed will always come out as a typical bell-shaped curve (referred to as Gaussian distribution) in contrast to the *non-parametric* datasets that tend to be skewed, lumpy, with gaps scattered about, or having a few warts and outliers.

In a nutshell, the standard conditions (or assumptions) that underlie the parametric tests are outlined as follows (Rana et al., 2016):

- The observations must be independent. The sampled data should not be associated to any factor that can potentially affect the outcome of the analysis.
- The observations should (necessarily) be drawn from a normally distributed population.
- The sample data is better represented by the *mean* or standard deviation.

- The captured datasets should essentially be measured or represented on an interval or ratio scale.

4.2.2 Non-parametric Tests

Non-parametric tests are referred to as “distribution-free” statistical tests given the fact that the supporting methods assume that the readily available datasets follow a certain but not specified distribution (De Canditiis, 2019; Minitab, 2015; Rana et al., 2016; Turner et al., 2020). The non-parametric tests are mostly applied to samples which are represented as nominal or ordinal data (Rana et al., 2016). Although, the test can also be conducted on interval and ratio datasets provided the data sample(s) in question do not follow a normal distribution. Therefore, a majority of the non-parametric tests or methods can handle ordinal data, ranked data, etc., without being utterly affected by outliers (Derrick et al., 2020; Winthrop, 2019). The tests (non-parametric) are applied with the emphasis that it does not require or demand for any given (specified) condition(s) to be met particularly with regards to the parameters of the population from which the sample is drawn.

As illustrated earlier in Figs. 4.1b and c part, unlike the parametric tests (that are better represented in mean or standard deviations—see Fig. 4.1a), the non-parametric tests are most adequate or suitable when the said datasets in question are better represented by median (see: Fig. 4.1b and c).

Furthermore, as gathered in Figs. 4.1b and c, non-parametric tests are grounded on the presupposition that the investigated or scrutinized datasets show a non-normal “skewed or uneven curve” distribution of values (Antonopoulos & Kakisis, 2019; ScienceDirect, 2019).

In short definition, the authors outline the various common conditions (assumptions) that constitute the non-parametric tests as follows:

- When the analysis does not require any rigorous (stringent) assumptions to be met for the test or hypothesis testing process to follow.
- The observations should necessarily be drawn from a *non-normally distributed population*.
- The sampled data is better represented by the *median.*
- The captured datasets should essentially be measured on a *nominal* or *ordinal* scale. Although, in some settings, the methods (non-parametric) support the interval and ratio data provided they are non-normally distributed.

In summary, the *non-parametric* tests are alternative to the *parametric* tests, especially for small sample sizes, whereby there is the presence of extreme asymmetries, skewness, and/or multimodality (Stojanović et al., 2018; Woodrow, 2014).

4.3 Choosing Between Parametric and Non-parametric Test

> "…the type of dataset one has ready for the research or hypothesis testing will essentially determine the type of statistical method or data analysis that is applicable or fitting for the research…" (see Fig. 4.3).

When statistically comparing the causes (based on the input variables) and effects (output variables) between different groups (sample composition) in a dataset, researchers have to choose whether to use the parametric or non-parametric statistical methods (le Cessie et al., 2020). For example, the suitability of a particular statistical method when investigating the difference(s) between variables (e.g., nominal, ordinal, continuous, discrete, etc.) among different groups (e.g., independent or dependent) would necessarily depend on the distribution of the variables (e.g., normal versus non-normal) (see: Table 4.1).

In summary, when choosing the type of statistical method to apply for the research investigation (parametric versus non-parametric), one should consider among the many factors the following elements (Rana et al., 2016):

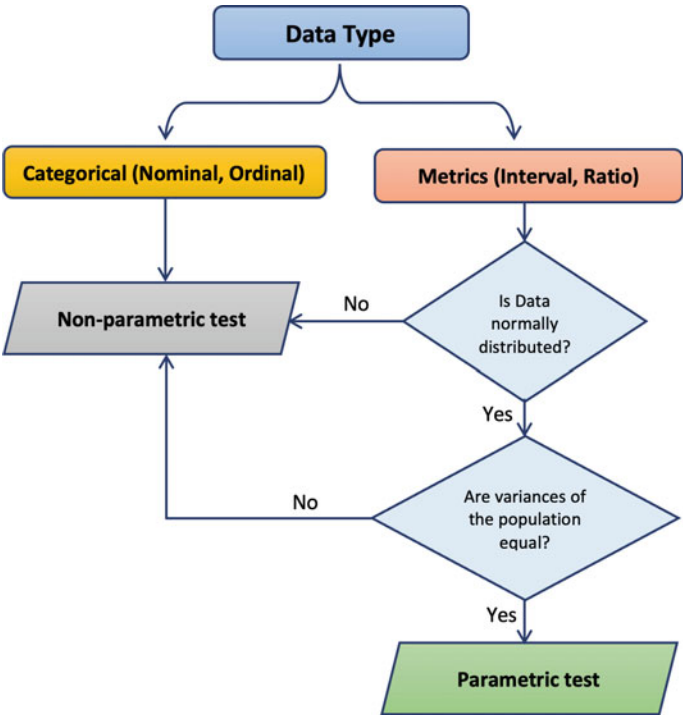

Fig. 4.3 Choosing between parametric and non-parametric tests

Table 4.1 Parametric tests versus the non-parametric equivalents table based on the data distribution, type of variable and correlation, number of groups, and independent versus dependent variables

Statistical test	Data distribution	Level of measurement	Correlation	Sample composition (groups and independence between groups)				
				1 group	2 groups		K groups (>2)	
					Independent	Dependent	Independent	Dependent
Parametric	Normal	Interval or ratio	Pearson's cor test	*t*-test or Z-test	Independent sample *t*-test	Paired sample *t*-test	One-way ANOVA	Repeated measure ANOVA
Non-parametric	Non-normal	Nominal (categorical)		Chi-squared test (X^2)	Chi-squared test (X^2)	McNemar´s test	Chi-squared test (X^2)	Cochran´s Q test
		Ordinal or rank	Kendall's tau or Spearman´s rho test	Chi-squared test (X^2)	Mann–Whitney Utest	Wilcoxon signed-rank test	Kruskal–Wallis H test	Friedman´s ANOVA

- Scale of measurement of the data, e.g., nominal, ordinal, interval, ratio, continuous, discrete, etc.
- Distribution of the population, e.g., normal versus non-normal
- Homogeneity of variances, e.g., equal versus unequal variances
- Independence versus dependency of the drawn samples considering the variables.

4.3.1 Types of Parametric Versus Non-parametric Tests in Statistical Analysis

It is paramount to decide between the *parametric* and *non-parametric* tests, including all the assumptions associated with the different methods (as outlined in the previous section–Sect. 4.2 and Table 4.1) when choosing one above the other.

Here in this section of the chapter, the authors outline and illustrate some of the most commonly used parametric tests in the available or current literature and their non-parametric equivalents (Table 4.1), with some examples of use case scenarios of each test presented in Sect. 4.3.2.

In Table 4.1, the authors provided a list of the different parametric and non-parametric tests, and the necessary conditions under which one should perform each test.

4.3.2 Examples and Use Case Scenarios: Parametric Versus Non-parametric Tests

Following the guideline listed in Table 4.1, the authors explain the different types of statistical tests using examples of some typical research scenarios:

Parametric test (for Normally distributed data, Interval or Ratio, Large data sample size)**:**

- **Pearson's Cor test** (*Correlation*): determine if student's grades (dependent variable) are increased or tend to increase in proportion to their study time (independent variable).
- ***t*-test** (*One sample group*): determine the *Mean* of the age of all students within a particular school or department.
- **Independent sample *t*-test** (*Two groups of Independent variables):* determine the *Mean* of all students within a particular school or department who are undergoing a specific teaching methodology (e.g., Hybrid model versus Traditional model of teaching).
- **Paired sample *t*-test** (*Two groups of Dependent variables*): determine the difference in the grades of students *before* (pre) versus *after* (post) undergoing the hybrid model of teaching.

- **One-way ANOVA** (*More than 2 groups (i.e., K > 2) of Independent variables*): determine the *Mean* of all students within a particular school or department who are undergoing either the Hybrid model versus Traditional model versus Both (Hybrid and Traditional).
- **Repeated measure ANOVA** (*More than 2 groups (i.e., K > 2) of Dependent variables*): determine the Difference in the grades of students before versus after 1st semester versus after 2nd semester of undergoing the Hybrid model of teaching.

Non-parametric test (for Non-normally or distribution-free data, Nominal or Ordinal data, Small data sample size):

- **Kendall´s tau or Spearman´s rho test** (*Correlation*): determine if student's grades (dependent variable) are increased in proportion to the teaching methodology adopted by the teachers.
- **Chi-squared test (X^2)** (*One sample group, 2 groups, and K groups (>2) of Independent variables*): determine the Differences between the observed and expected values or scores in male versus female students´ grade undergoing either the Hybrid model versus Traditional teaching model.
- **Mann–Whitney U test** (*Two groups of Independent variables, ordinal data*): determine the *Median* of all students within a particular school or department who are either undergoing the Hybrid model versus Traditional model of teaching.
- **Wilcoxon signed-rank test** (*Two groups of Dependent ranked variables*): determine the Difference in the grades of students before versus after undergoing the Hybrid model of teaching.
- **Mc-Nemar´s test** (*Two groups of Dependent nominal or categorical variables*): determine the Difference in number of students with good grades versus poor grades after 1st semester versus after 2nd semester of undergoing the hybrid model of teaching.
- **Kruskal–Wallis H test** (*More than 2 groups (i.e., K > 2) of Independent ordinal variables*): determine the *Median* of all students within a particular school or department who are undergoing the hybrid model versus Traditional model versus Both (Hybrid and Traditional).
- **Friedman´s ANOVA** (*K groups i.e., > 2 of Dependent variables*): determine the Difference in the grades of students before versus after 1st semester versus after 2nd semester of undergoing the Hybrid model of teaching.

***Note: the authors have provided a detailed/in-depth description of the different types of statistical data analysis and methods in Chap. 6 "Understanding the Different Types of Statistical Data Analyzes and Methods" (see Chap. 6).

Table 4.2 Difference between parametric versus non-parametric test

Parametric	Non-parametric
Existence of specific assumption(s) being made about the population in question	There is no specific assumption(s) with regard to the population in question
Information about the studied population is known	There is no available information about the studied population
Null hypotheses are developed based on the parameters or distribution of the population	The Null hypotheses are developed independent of the parameters or distribution of the population
The tests (parametric) apply to measuring just the variables and not their attributes	The tests (non-parametric) are applicable to both the variables and their attributes, e.g., gender, marital status, etc
The outcomes of the tests are more powerful and convincing when applicable	The outcomes of the test are less powerful than the parametric tests
The statistical tests and methods are grounded on the distribution of the available datasets	The statistical tests and methods are arbitrary
Cannot be applied for nominal data types, only interval or ratio	Can be applied for nominal and ordinal data types
Mostly used to measure Mean and Standard deviations	Mostly used to measure MEDIANS
Sampled datasets show a "bell-shaped" curve when graphically represented	Sampled datasets show a "skewed or lumpy" curve when graphically represented

4.4 Differences Between Parametric Versus Non-parametric Tests

In this section, the authors outline some of the main differences between the Parametric and Non-parametric tests (Table 4.2):

4.5 Advantages and Disadvantages of Parametric Versus Non-parametric Tests

Some advantages and disadvantages of adopting or applying each of the tests (parametric versus non-parametric) are provided in Table 4.3 below.

4.6 Summary

As a general rule of thumb in statistics, in situations whereby the *variables* are represented or measured on a continuous (or metric) scale, the "parametric tests" should be applied or conducted.

Table 4.3 Advantages and disadvantages of using the parametric versus non-parametric tests

	Advantages (pro)	Disadvantages (cons)
Parametric	Ensures that all components (population, parameters, assumptions) are compatible with one another Most useful when determining variations between groups of variables Can be easily applied and less complicated than the non-parametric methods Given that real information regarding the population is known, the confidence intervals are guaranteed Has more statistical power than other tests such as the non-parametric	Mostly used only for quantitative datasets Data has to follow an approximate interval (normal) for the test to be applied Results may not be valid when it comes to small datasets or sample size They are not effective for ranked data or samples with outliers Since parametric tests are conducted based on pre-defined assumptions, it consequentially, allows one to make generalizations from a sample to the studied population
Non-parametric	Simple and easy to understand Methods are applicable for datasets with attributes, e.g., gender, marital status, etc Complicated sampling theory is not a problem No assumptions are made about the population Supports nominal data scales	In statistical settings where parametric alternative is applicable, the non-parametric tests are less powerful Supported methods are less effective than the parametric tests in drawing reliable conclusions No current method for analyzing the association of variances in the underlying models

On the other hand, if the variable(s) are represented in nominal or ordinal (categorical) scale of measurement, the "non-parametric tests" should be considered or applied.

Furthermore, the parametric tests assume that the analyzed data or sample distribution is normally distributed (i.e., bell-shaped) and consists of related parameters in the population distribution by *mean* or *standard deviations*.

On the other hand, the non-parametric tests make no assumption(s) about the shape (which are often skewed) or parameters of the population distribution by the *median* (Hopkins et al., 2018).

Statistically, the parametric tests are generally more powerful than the non-parametric methods.

Different methods can be used to determine if the sampled datasets for the research are derivative from a normally distributed population. The most frequently used methods in the current literature are the Kolmogorov–Smirnov test, the Anderson–Darling test, and the Shapiro–Wilk test (Antonopoulos & Kakisis, 2019; LaMorte, 2017; Stojanović et al., 2018), as discussed earlier by the authors in Chap. 3. According to LaMorte (2017), each test for normality of a data or sample is essentially a goodness of fit test and consequentially compares the said dataset to quantiles of the normal and/or specified distribution. Thus, the default (null) hypothesis for each test is represented as H_0; whereby the data is assumed to follow a normal distribution in comparison to the alternative hypothesis (H_1) in which the data are assumed or may in reality not follow a normal distribution. In return, if the test turns out to be statistically significant, i.e., $p < 0.05$; with the value (statistics) of the normality test less than 0.5, then the readily available data is said to not follow a normal distribution (and as described earlier in this chapter, a non-parametric test would be best decided) (LaMorte, 2017; Stojanović et al., 2018). Thus, with the normality results (test statistics):

- When $p < 0.5$, then non-parametric test is best conducted.
- When $p > 0.5$, then parametric test is best conducted.

Technically, there are many existing statistical tools that can be used to determine if the researchers' datasets or samples are normally distributed, and consequently, perform either the parametric or the non-parametric procedures. Among the many existing tools includes statistical packages such as: R (Rstudio, 2023), SPSS Statistics (IBM, 2023), STATA (Stata.com ©, 2023), SAS (Sas.com ©, 2023), Minitab (Minitab.com ©, 2023), MATLAB (MATLAB, 2023), Python (Python, 2023), etc.

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