An Overview of Parametric and Non-Parametric Tests used in Economic Studies

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Abstract:

Selecting the appropriate statistical test is a fundamental step in research, particularly when analyzing relationships and differences between variables. Many students and researchers face difficulties in deciding whether to use parametric or non-parametric tests, leading to potential errors in data interpretation. This paper provides a guide to understanding the key differences between parametric and non-parametric tests and their underlying assumptions. Parametric tests assume normality, homogeneity of variance, and interval/ratio data, whereas non-parametric alternatives are used when these assumptions are violated, particularly with ordinal or non-normally distributed data.

Keywords: parametric, non-parametric, tests, assumptions, hypothesis testing

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1. Introduction:

In statistical analysis, choosing the appropriate test to examine relationships and differences between variables is a critical yet challenging task for students and researchers. The decision between parametric and non-parametric tests often depends on factors such as data distribution, sample size, and measurement scale. Misapplication of these tests can lead to incorrect conclusions, undermining the validity of research findings. Despite the availability of various statistical tests, many students and researchers struggle with selecting the right method for their data, leading to confusion and potential errors in their analyses.

This paper aims to clarify the distinctions between parametric and non-parametric tests, providing a structured guide to help researchers make informed decisions. Parametric tests, such as the t-test and ANOVA, rely on assumptions about population parameters and normal distribution, whereas non-parametric tests, like the Mann-Whitney test and Kruskal-Wallis test, are distribution-free and suitable for ordinal or non-normally distributed data. Through practical examples, this paper illustrates how to apply these tests correctly, ensuring accurate and reliable results. As a result, the paper will enhance understanding of statistical test selection, ultimately improving the robustness of research across various disciplines.

To select the appropriate statistical test, several key considerations must be addressed. First, it is essential to define the research objective: is it to examine the relationship between two variables, or to evaluate the influence of multiple variables on a single outcome. Next, one should determine whether the analysis seeks to compare group differences or assess correlations. Equally important is identifying the nature of the data—whether it is discrete, continuous, nominal, or ordinal. Additionally, it is necessary to establish whether the data sets are paired (dependent) or unpaired (independent), and whether the comparison involves two groups or more than two. The following sections provide a detailed explanation of when and how to appropriately apply parametric and non-parametric tests based on these considerations.

2. Parametric tests:

Parametric tests are used when the data meet specific assumptions. These include having quantitative data measured on an interval or ratio scale, a population that follows a normal distribution, and equal variances across comparison groups (homogeneity of variance). Additionally, the observations must be independent of one another. When these conditions are satisfied, parametric tests can be applied directly to the raw data to obtain valid and reliable results. In the following, we present the common parametric tests.

2.1. The one-sample t-Test:

The one-sample *t*-test determines whether the mean of a single sample significantly differs from a known or hypothesized population mean.

For example: assessing the average students mean against a standard

– **Assumptions of the one-sample t-Test:**

- The dependent variable must be continuous
- Observations must be independent of each other
- The variable should be approximately normally distributed in the population.

– **Hypotheses:**

- ***H*0:** the sample mean is equal to the population mean ($\mu = \mu_0$)
- ***H*1:** the sample mean is not equal to the population mean ($\mu \neq \mu_0$)

– **Decision rule:**

- Reject the null hypothesis if: P-value < 0.05
- **Example:** assume that the average mathematics score for all first-year students at a university is 11.95 over 20 (population mean). A random sample of 100 students was selected, yielding a sample mean of 10.81 over 20. In this case, we can use the one-sample t-test to determine whether the sample mean is significantly different from the population mean.

2.2. The Independent samples t-Test:

The independent samples t-test is a widely used statistical method designed to compare the means of a continuous variable between two distinct and unrelated groups. This test is particularly useful when researchers want to determine whether a significant difference exists between the average outcomes of two independent populations or categories.

– **Assumptions of the independent samples t-Test:**

- The dependent variable must be continuous
- Observations must be independent between and within groups.
- The dependent variable should be approximately normally distributed in each group.
- There should be homogeneity of variances between the two groups (Levene's test).

– **Hypotheses:**

- **H_0:** $\mu_1 = \mu_2$ (no mean difference)
- **H_1:** $\mu_1 \neq \mu_2$ (there is a mean difference)

– **Decision rule:**

- Reject the null hypothesis if: P-value < 0.05
- **Example:** suppose we want to compare the average mathematics scores between male and female students to determine if there is a significant difference in performance between the two groups.

  In this case, the independent samples t-test would be the appropriate statistical test, not the one-sample t-test, since we are comparing the means of two independent groups.

2.3. The Paired Samples t-Test:

The paired samples t-test, also known as the dependent samples t-test, is a statistical technique used to compare the means of a continuous variable measured at two different times or under two different conditions within the same group of subjects. This test is particularly useful when the data points are naturally paired or matched, such as pre-test and post-test scores of the same students, or when comparing measurements taken before and after an intervention. The primary goal is to determine whether the average difference between the two sets of paired observations is statistically significant.

- **Assumptions of the paired samples t-Test:**
- The dependent variable must be continuous
- Observations must consist of paired values (e.g., before and after measurements).
- The differences between the paired values should be approximately normally distributed.
- **Hypotheses:**
- ***H_0*:** $\mu_1 = \mu_2$ (no mean difference)
- ***H_1*:** $\mu_1 \neq \mu_2$ (there is a mean difference)
- **Decision rule:**
- Reject the null hypothesis if: P-value < 0.05
- **Example:** for a sample of 30 students, we want to determine whether there is a significant difference between the mid-term and final exam scores in Mathematics**.** To do this, we compare the mean scores of the two exams for the same students using the paired samples t-test, since the data consists of two related measurements taken from the same group of students.

2.4. The One-Way ANOVA:

The One-Way Analysis of Variance (ANOVA) is a statistical method used to compare the means of three or more independent groups to determine whether there are statistically significant differences among them. This test is particularly valuable when researchers want to assess the effect of a single independent categorical variable, often called a "factor," on a continuous dependent variable.

- **Assumptions of the One-Way ANOVA:**
- The dependent variable must be continuous
- Observations must be independent between and within groups.
- The dependent variable should be approximately normally distributed within each group.
- There should be homogeneity of variances across groups (Levene's test).
- **Hypotheses:**
- ***H_0*:** all group means are equal ($\mu_1 = \mu_2 = \mu_3 = ...$)
- ***H_1*:** at least two means differ significantly
- **Decision rule:**

- Reject the null hypothesis if: P-value < 0.05 (follow up with post-hoc tests).
- **Example:** we want to examine whether there is a significant difference in Mathematics scores based on the type of Baccalaureate: Mathematics Baccalaureate, Science Baccalaureate, or Management Baccalaureate.
  Since we are comparing the means across three independent groups, the appropriate test to use is the One-Way ANOVA.

2.5. Pearson's Correlation:

The objective of Pearson's Correlation (r) is to measure the strength and direction of the linear relationship between two continuous variables.

Strength Guidelines for Pearson's Correlation are:

- Very strong correlation if: $0.80 \leq |r| < 1.00$
- Strong correlation if: $0.60 \leq |r| < 0.79$
- Moderate correlation if: $0.40 \leq |r| < 0.59$
- Weak correlation if: $0.20 \leq |r| < 0.39$
- Very weak correlation if: $0.00 \leq |r| < 0.19$

– **Assumptions of Pearson's correlation Test:**

- The two variables are continuous and measured in pairs.
- Observations are independent of each other.
- Both variables should be approximately normally distributed.
- There is a linear relationship between the two variables.

– **Hypotheses:**

- ***H*0:** there is no correlation between the two continuous variables (r = 0).
- ***H*1:** there is significant correlation between the two continuous variables (r ≠ 0)

– **Decision rule:**

- Reject the null hypothesis if: P-value < 0.05
- **Example:** suppose we want to determine whether there is a significant correlation between Mathematics scores and Statistics scores in a sample of 100 students. Since both variables are continuous, the appropriate test to measure the strength and direction of their relationship is Pearson's correlation coefficient.

In table1, we present a summary table of common parametric tests.

Table N°1: Summary table of the common parametric tests

Test	Purpose	Assumptions	Hypotheses	Decision Rule
One-Sample t-Test	Test if the sample	- Continuous dependent variable	$H_0: \mu = \mu_0$ $H_1: \mu \neq \mu_0$	Reject H_0 if $p <$

	mean differs from a known population mean	- Independent observations - Approx. normal distribution		0.05
Independent Samples t-Test	Compare means between two independent groups	- Continuous dependent variable - Independent observations between/within groups - Normality in each group - Homogeneity of variances (Levene's test)	H_0: $\mu_1 = \mu_2$ H_1: $\mu_1 \neq \mu_2$	Reject H_0 if $p < 0.05$
Paired Samples t-Test	Compare means of two related groups (e.g. pre-post)	- Continuous dependent variable - Paired observations - Normal distribution of differences	H_0: $\mu_1 = \mu_2$ H_1: $\mu_1 \neq \mu_2$	Reject H_0 if $p < 0.05$
One-Way ANOVA	Compare means across ≥ 3 independent groups	- Continuous dependent variable - Independent observations - Normality within each group - Homogeneity of variances (Levene's test)	H_0: $\mu_1 = \mu_2 = \mu_3 = ...$ H_1: At least two means differ	Reject H_0 if $p < 0.05$ (follow up with post-hoc test)
Pearson's Correlation	Measure strength and direction of linear relation between 2 variables	- Both variables are continuous and paired - Independent observations - Normality - Linearity between variables	H_0: $r = 0$ H_1: $r \neq 0$	Reject H_0 if $p < 0.05$

Source: by the author based on the parametric tests section

3. Non-parametric tests:

Non-parametric tests are statistical methods used when the assumptions of parametric tests (normality, homogeneity of variance, etc.) are violated. They are particularly suitable for:

- Ordinal or nominal data;
- Non-normally distributed datasets;
- Small sample sizes.

Since these tests do not assume a specific data distribution, they offer greater flexibility and robustness in analyzing ranked, categorical, or skewed data.

3.1. Wilcoxon Signed-Rank Test

The Wilcoxon Signed-Rank Test is used to compare the median differences between two related samples. It is suitable for paired or matched data when the assumptions of the paired t-test (such as normality) are not met.

- **Key Features of Wilcoxon Signed-Rank Test:**
- The test is a non-parametric alternative to the paired samples t-test
- The test is suitable for ordinal or non-normally distributed continuous data.
- **Hypotheses :**
- ***H₀***: $M_1=M_2$ (there is no median difference between paired observations)
- ***H₁***: $M_1 \neq M_2$ (there is median difference between paired observations)
- **Decision rule:**
- Reject the null hypothesis if: P-value < 0.05
- **Example:** in a sample of 100 clients, we aim to compare their satisfaction levels with airport services between Year 1 and Year 2. Since the satisfaction level is an ordinal variable (1.not satisfied, 2. averagely satisfied, 3. satisfied), and the data are paired (same clients evaluated across two years), the appropriate test to use is the Wilcoxon Signed-Rank Test.

3.2. Mann-Whitney U Test

The Mann-Whitney U Test is a non-parametric statistical test used to compare the medians of two independent groups. It is particularly useful when the assumptions required for the independent samples t-test, such as normality of data distribution and homogeneity of variances, are not met.

- **Key Features of Mann-Whitney U Test:**
- The test is a non-parametric alternative to the independent samples t-test when data are not normally distributed.
- The test is suitable for ordinal data.
- **Hypotheses:**
- ***H₀***: $M_1=M_2$ (there is no median difference between the two independent groups)
- ***H₁***: $M_1 \neq M_2$ (there is median difference between the two independent groups)
- **Decision rule:**
- Reject the null hypothesis if: P-value < 0.05
- **Example:**

  In a sample of 100 clients (50 males and 50 females), we aim to compare satisfaction levels with airport services between males and females.

  The satisfaction level is an ordinal variable with three categories:

  - 1. Not satisfied,
  - 2. Averagely satisfied,
  - 3. Very satisfied.

  Since the data are independent between the two groups, the appropriate test is the Mann-Whitney U Test, which assesses whether there is a significant difference in satisfaction levels between males and females.

3.3. Kruskal-Wallis Test

The Kruskal-Wallis Test is a non-parametric statistical test used to compare the medians of three or more independent groups. It serves as the non-parametric alternative to the one-way ANOVA when the assumptions of normality and homogeneity of variances are not satisfied. This test is particularly useful when dealing with ordinal data or continuous data that are not normally distributed.

– **Key Features of Kruskal-Wallis Test:**
- Kruskal-Wallis Test is a non-parametric alternative to the one-way ANOVA.
- The test does not assume normality or equality of variances.

– **Hypotheses :**
- H_0: $M_1 = M_2 = M_3$…(all group medians are equal)
- H_1: at least one group median differs from the other medians.

– **Decision rule:**
- Reject the null hypothesis if: P-value < 0.05
- **Example:**

In a sample of 100 clients**,** we aim to compare the satisfaction levels with airport services across three age groups:

- Teenagers (13–19 years old),
- Adults (20–59 years old)**,**
- Elderly people (60 years and above).

The satisfaction level is an ordinal variable with three categories: 1.not satisfied, 2. averagely satisfied, and 3. very satisfied.

Since we are comparing more than two independent groups on an ordinal variable, the appropriate test is the Kruskal-Wallis Test**,** which evaluates whether there is a significant difference in satisfaction levels among the three age groups.

3.4. Spearman's Correlation Test:

Spearman's correlation coefficient (r) is the alternative of Pearson's correlation coefficient in case of the violation of the assumptions of this latter. The test can also be used to measure the correlation between a continuous variable and an ordinal variable, or to measure the correlation between two ordinal variables.

Strength Guidelines for Spearman's Correlation are:

- Very strong correlation if: $0.80 \leq |r| < 1.00$
- Strong correlation if: $0.60 \leq |r| < 0.79$
- Moderate correlation if: $0.40 \leq |r| < 0.59$
- Weak correlation if: $0.20 \leq |r| < 0.39$
- Very weak correlation if: $0.00 \leq |r| < 0.19$

– **Hypotheses :**
- $H0$: there is no correlation between the two continuous variables (r = 0).
- $H1$: there is significant correlation between the two continuous variables ($r \neq 0$)

– **Decision rule:**
- Reject the null hypothesis if: P-value < 0.05

- **Example:**
  Suppose we want to determine whether there is a significant correlation between clients' satisfaction levels and their ages in a sample of 100 clients.
  - The satisfaction level is an ordinal variable with three categories: 1.not satisfied, 2. averagely satisfied, and 3.very satisfied, and the age of clients is a continuous variable.

  Since we are examining the relationship between an ordinal variable and a continuous variable, the appropriate test is Spearman's correlation coefficient. This test assesses whether there is a significant relationship between the satisfaction levels of clients and their ages.

3.5. Chi-square Test of independence:

Chi-square test is used to test for the association between two categorical variables.

– **Assumptions of the test:**
  - The two variables must be categorical.
  - Observations should be independent.
  - A sufficiently large sample size is required.

– **Hypotheses:**
- ***H*0:** there is no association between the two variables (they are independent).
- ***H*1:** there is significant association between the two variables (they are dependent)

– **Decision rule:**
- Reject the null hypothesis if: P-value < 0.05

- **Example:**
  Suppose we want to examine whether there is a significant association between clients' satisfaction levels with airport services and their gender in a sample of 100 clients (50 males and 50 females).
  - Satisfaction level is a categorical variable with three categories: 1.not satisfied, 2.averagely satisfied, and 3.very satisfied.
  - Gender is also a categorical variable with two categories: male and female.

  Since both variables are categorical, the appropriate test is the Chi-square test of independence**.** This test helps us determine whether satisfaction levels are independent of gender, or if there is a statistically significant association between gender and satisfaction level**.**

In table2, we present a summary table of common non-parametric tests.

Table N°2: Summary table of the common non-parametric tests

Test	Purpose	Data Type	Hypotheses	Decision Rule
Wilcoxon Signed-Rank Test	Compare medians of two related samples	Paired ordinal / non-normal continuous	H0: $M_1 = M_2$ (no median difference) H1: $M_1 \neq M_2$ (median difference)	Reject H0 if P-value < 0.05
Mann-	Compare	Independent	H0: $M_1 = M_2$ (no	Reject H0 if P-value <

Whitney U Test	medians of two independent groups	ordinal / non-normal continuous	median difference) H1: $M_1 \neq M_2$ (median difference)	0.05
Kruskal-Wallis Test	Compare medians of three or more independent groups	Independent ordinal / non-normal continuous	H0: $M_1 = M_2 = M_3$ ... (all medians equal) H1: At least one median differs	Reject H0 if P-value < 0.05
Spearman's Correlation	Measure correlation between variables when normality is violated	Continuous (non-normal) / ordinal	H0: r = 0 (no correlation) H1: $r \neq 0$ (significant correlation)	Reject H0 if P-value < 0.05
Chi-Square Test of Independence	Test association between two categorical variables	Categorical only	H0: No association (independent) H1: Significant association (dependent)	Reject H0 if P-value < 0.05

Source: by the author based on the non-parametric tests section

4. Summary comparison between parametric and non-parametric tests:

The table (3) provides a comparative guide to choosing the appropriate test based on data type and assumptions.

Table N°3: Correspondence between Parametric Tests and Their Non-Parametric Alternatives

Purpose	Parametric Test	Non-Parametric Alternative
Compare mean of a sample to a population mean	One-Sample t-Test	- No direct non-parametric equivalent, but Sign Test can be used in some cases
Compare means between two independent groups	Independent Samples t-Test	Mann-Whitney U Test
Compare means between two related/paired samples	Paired Samples t-Test	Wilcoxon Signed-Rank Test
Compare means between three or more independent groups	One-Way ANOVA	Kruskal-Wallis Test
Measure correlation between two continuous variables	Pearson's Correlation Coefficient	Spearman's Rank Correlation

Test association between two categorical variables	–	Chi-Square Test of Independence

Source: by the author based on parametric and non-parametric tests sections

5. Conclusion:

Selecting the appropriate statistical test is a critical step that ensures the accuracy and validity of research findings. This paper provided a comprehensive comparison between parametric and non-parametric tests, highlighting their assumptions, appropriate data types, and hypotheses structures. Parametric tests are powerful when their strict assumptions are met, especially regarding normality and homogeneity of variances. However, when these conditions are violated, non-parametric tests offer flexible and robust alternatives suited for ordinal data, non-normal distributions, and small sample sizes.

By systematically outlining the most commonly used tests within each category, this paper serves as a practical guide for students and researchers navigating the complexities of statistical analysis. Understanding when and how to apply these methods not only enhances the reliability of research conclusions but also fosters more rigorous and informed scientific inquiry across various fields.

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