UNIT 1 RATIONALE FOR NON-PARAMETRIC STATISTICS

Structure

1.0 INTRODUCTION

Statistics is of great importance in the field of psychology. The human behaviour which is so unpredictable and cannot be so easily measured or quantified, through statistics attempts are made to quantify the same. The manner in which one could measure human behaviour is through normal distribution concept wherein it is assumed that most behaviours are by and large common to all and only a very small percentage is in either of the extremes of normal distribution curve. Keeping this as the frame of reference, the behaviour of the individual is seen and compared with this distribution. For analysis of obtained information about human behaviour we use both parametric and non-parametric statistics. Parametric statistics require normal distribution assumptions whereas non-parametric statistics does not require these assumptions and need not also be compared with normal curve. In this unit we will be dealing with non-parametric statistics, its role and functions and its typical characteristics and the various types of non-parametric statistics that can be used in the analysis of the data.

1.1 OBJECTIVES

After reading this unit, you will be able to:

- Define non-parametric statistics;
- Differentiate between parametric and non-parametric statistics;
- Elucidate the assumptions in non-parametric statistics;
- Describe the characteristics of non-parametric statistics; and
- Analyse the use of non-parametric statistics.

1.2 DEFINITION OF NON-PARAMETRIC STATISTICS

Non-parametric statistics covers techniques that do not rely on data belonging to any particular distribution. These include (i) distribution free methods (ii) non structural models. Distribution free means its interpretation does not depend on any parametrized distributions. It deals with statistics based on the ranks of observations and not necessarily on scores obtained by interval or ratio scales.

Non-parametric statistics is defined to be a function on a sample that has no dependency on a parameter. The interpretation does not depend on the population fitting any parametrized distributions. Statistics based on the ranks of observations are one example of such statistics and these play a central role in many non-parametric approaches.

Non-parametric techniques do not assume that the structure of a model is fixed. Typically, the model grows in size to accommodate the complexity of the data. In these techniques, individual variables are typically assumed to belong to parametric distributions, and assumptions about the types of connections among variables are also made.

Non-parametric methods are widely used for studying populations that are based on rank order (such as movie reviews receiving one to four stars). The use of non-parametric methods may be necessary when data have a ranking but no clear numerical interpretation. For instance when we try to assess preferences of the individuals, (e.g. I prefer Red more than White colour etc.), we use non parametic methods. Also when our data is based on measurement by ordinal scale, we use non-parametric statistics.

As non-parametric methods make fewer assumptions, their applicability is much wider than those of parametric methods. Another justification for the use of non-parametric methods is its simplicity. In certain cases, even when the use of parametric methods is justified, non-parametric methods may be easier to use. Due to the simplicity and greater robustness, non-parametric methods are seen by some statisticians as leaving less room for improper use and misunderstanding.

A statistic refers to the characteristics of a sample, such as the average score known as the mean. A parameter, on the other hand, refers to the characteristic of a population such as the average of a whole population. A statistic can be employed for either descriptive or inferential purposes and one can use either of the two types of statistical tests, viz., parametric Tests and non-parametric Tests (assumption free test).

The distinction employed between parametric and non-parametric test is primarily based on the level of measurement represented by the data that are being analysed. As a general rule, inferential statistical tests that evaluate categorical / nominal data and ordinal rank order data are categorised as non-parametric tests, while those tests that evaluate interval data or ratio data are categorised as parametric tests.

Differences between parametric and non-parametric statistics

The parametric and non-parametric statistics differ from each other on these various levels

Level of Differences	**Parametric**	**Non Parametric**
Assumed Distribution	Normal	Any
Assumed Variance	Homogeneous	Homogenous and Heterogeneous both
Typical data	Ratio or Interval	Ordinal or Nominal
Usual Central measure	Mean	Median
Benefits	Can Draw more conclusions	Simple and less affected by extreme score

Level of measurement is an important criterion to distinguish between the parametric and non-parametric tests. Its usage provides a reasonably simple and straightforward schema for categorisation that facilitates the decision making process for selecting an appropriate statistical test.

1.3 ASSUMPTIONS OF PARAMETRIC AND NON-PARAMETRIC STATISTICS

Assumptions to be met for the use of parametric tests are given below:

- Normal distribution of the dependent variable
- A certain level of measurement: Interval data
- Adequate sample size (>30 recommended per group)
- An independence of observations, except with paired data
- Observations for the dependent variable have been randomly drawn
- Equal variance among sample populations
- Hypotheses usually made about numerical values, especially the mean

Assumptions of Non-parametric Statistics test are fewer than that of the parametric tests and these are given below.:

- An independence of observations, except with paired data
- Continuity of variable under study

Characteristics of non-parametric techniques:

- Fewer assumptions regarding the population distribution
- Sample sizes are often less stringent
- Measurement level may be nominal or ordinal
- Independence of randomly selected observations, except when paired
- Primary focus is on the rank ordering or frequencies of data
- Hypotheses are posed regarding ranks, medians, or frequencies of data

There are three major parametric assumptions, which are, and will continue to be routinely violated by research in psychology: level of measurement, sample size, and normal distribution of the dependent variable. The following sections will discuss these assumptions, and elucidate why much of the data procured in health science research violate these assumptions, thus implicating the use of non-parametric techniques.

Self Assessment Questions

1) Define Non-parametric statistics.

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2) What are the charateristic featurs of non-parametric statistics?

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3) Differentiate between parametric and non-parametric statistics.

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4) What are the assumptions underlying parametric and non-parametric statistics?

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When statistical tests are to be used one must know the following:

1.3.1 Level of Measurement

When deciding which statistical test to use, it is important to identify the level of measurement associated with the dependent variable of interest. Generally, for the use of a parametric test, a minimum of interval level measurement is required. Non-parametric techniques can be used with all levels of measurement, and are most frequently associated with nominal and ordinal level data.

1.3.2 Nominal Data

The first level of measurement is nominal, or categorical. Nominal scales are usually composed of two mutually exclusive named categories with no implied ordering: yes or no, male or female. Data are placed in one of the categories, and the numbers in each category are counted (also known as frequencies). The key to nominal level measurement is that there are no numerical values assigned to the variables. Given that no ordering or meaningful numerical distances between numbers exist in nominal measurement, we cannot obtain the coveted 'normal distribution' of the dependent variable. Descriptive research in the health sciences would make use of the nominal scale often when collecting demographic data about target populations (i.e. pain present or not present, agree or disagree).

Example of an item using a nominal level measurement scale

1) Does your back problem affect your employment status? ☐Yes ☐No

2) Are you limited in how many minutes you are able to walk continuously with or without support (i.e. cane)? ☐Yes ☐No

1.3.3 Ordinal Data

The second level of measurement, which is also frequently associated with non-parametric statistics, is the ordinal scale (also known as rank-order). Ordinal level measurement gives us a quantitative 'order' of variables, in mutually exclusive categories, but no indication as to the value of the differences between the positions (squash ladders, army ranks). As such, the difference between positions in the ordered scale cannot be assumed to be equal. Examples of ordinal scales in health science research include pain scales, stress scales, and functional scales. One could estimate that someone with a score of 5 is in more pain, more stressed, or more functional than someone with a score of 3, but not by *how much.* There are a number of non-parametric techniques available to test hypotheses about differences between groups and relationships among variables, as well as descriptive statistics relying on rank ordering. Table below provides an example of an ordinal level item from the Oswestry Disability Index.

Table: Walking (Intensity of pain in terms of the ability to walk)

S. No.	Description	Intensity
1	Pain does not prevent me walking any distance	Lowest intensity of pain
2	Pain prevents me from walking more than 2 kilometres	Some level of intensity of pain
3	Pain prevents me from walking more than 1 kilometre	Moderate intensity of pain
4	Pain prevents me from walking more than 500 meters	High intensity of pain
5	I can only walk using a stick or crutches	Very high intensity of pain

1.3.4 Interval and Ratio Data

Interval level data is usually a minimum requirement for the use of parametric techniques. This type of data is also ordered into mutually exclusive categories, but in this case the divisions between categories are equidistant. The only difference between interval data and ratio data, is the presence of a meaningful zero point. In interval level measurement, zero does not represent the absence of value. As such, you cannot say that one point is two times larger than another. For example, 100 degrees Celsius is not two times hotter than 50 degrees because zero does not represent the complete absence of heat.

Ratio is the highest level of measurement and provides the most information. The level of measurement is characterised by equal intervals between variables, and a meaningful zero point. Examples of ratio level measurement include weight, blood pressure, and force. It is important to note that in health science research we often use multi item scales, with individual items being either nominal or ordinal.

1.3.5 Sample Size

Adequate sample size is another of the assumptions underlying parametric tests. In a large number of research studies, we do use small sample size and in certain cases we just use one case study and observe that case over a period of time. Some times, we take small sample sizes from a certain place and such samples are called as convenience samples, and limited funding. Thus, the assumption of large sample size is often violated by such studies using parametric statistical techniques.

The sample size required for a study has implications for both choices of statistical techniques and resulting power. It has been shown that sample size is directly related to researchers' ability to correctly reject a null hypothesis (power). As such, small sample sizes often reduce power and increase the chance of a type II error. It has been found that by using non-parametric techniques with small sample sizes, it is possible to gain adequate power. However, there does not seem to be a consensus among statisticians regarding what constitutes a small sample size. Many statisticians argue that if the sample size is very small, there may be no alternative to using a non-parametric statistical test, but the value of 'very small' is not delineated. It has been suggested by Wampold et al. (1990) , that the issue of sample size is closely related to the distribution of the dependent variable, given that as sample size increases, the sampling distribution approaches normal($n>100$).

At the same time, one can state that if the distribution of the dependant variable resembles closely the normal distribution, then it will amount to the sampling distribution of the mean being approximately normal. For other distributions, 30 observations might be required. Furthermore, in regard to decision about the statistical technique to be used, there is no clear cut choice but one can choose a technique depending on the nature of the data and sample size. Thus even the choice of parametric or non-parametric tests 'depends' on the nature of the data, the sample size, level of measurement, the researcher's knowledge of the variables' distribution in the population, and the shape of the distribution of the variable of interest. If in doubt, the researcher should try using both parametric and non-parametric techniques.

1.3.6 Normality of the Data

According to Pett (1997), in choosing a test we must consider the shape of the distribution of the variable of interest. In order to use a parametric test, we must assume a normal distribution of the dependent variable. However, in real research situations things do not come packaged with labels detailing the characteristics of the population of origin. Sometimes it is feasible to base assumptions of population distributions on empirical evidence, or past experience. However, often sample sizes are too small, or experience too limited to make any reasonable assumptions about the population parameters. Generally in practice, one is only able to say that a sample appears to come from say, a skewed, very peaked, or very flat population. Even when one has precise measurement (ratio scale), it may be irrational to assume a normal distribution, because this implies a certain degree of symmetry and spread.

Non-parametric statistics are designed to be used when we know nothing about the distribution of the variable of interest. Thus, we can apply non-parametric techniques to data from which the variable of interest does not belong to any specified distribution (i.e. normal distribution). Although there are many variables in existence that are normally distributed, such as weight, height and strength, this is not true of all variables in social or health sciences.

The incidence of rare disease and low prevalence conditions are both non-normally distributed populations. However, it seems that most researchers using parametric statistics often just 'assume' normality. Micceri et al. (1989) states that the naïve assumption of normality appears to characterise research in many fields.

However, empirical studies have documented non normal distributions in literature from a variety of fields. Micceri et al. (1989) investigated the distribution in 440 large sample achievement and psychometric measures. It was found that all of the samples were significantly non-normal ($p<0.01$).

It was concluded that the underlying tenets of normality assuming statistics appeared to be fallacious for the commonly used data in these samples. It is likely that if a similar study, investigating the nature of the distributions of data were to be conducted with some of the measures commonly used in health science research, a similar result would ensue, given that not all variables are normally distributed.

Self Assessment Questions

1) What are the aspects to be kept in mind before we decide to apply parametric or non-parametric tests?

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2) What is ordinal data? Give suitable examples?

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3) What are interval and ratio data ? Give examples.

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4) Why is sample size important to decide about usingparametric or non-parametric tests?

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5) What is meant by normality of a data? Explain.

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1.4 THE USE OF NON-PARAMETRIC TESTS

It is apparent that there are a number of factors involved in choosing whether or not to use a non-parametric test, including level of measurement, sample size and sample distribution. When the choice of statistical technique for a set of data is not clear, there is no harm in analysing the data with both these methods, viz., parametric and on parametric methods.

It must be remembered that for each of the main parametric techniques there is a non-parametric test available. Also, experiments with the data would also determine which test provides the best power, and the greatest level of significance. In general, these tests fall into the following categories:

- Tests of differences between groups (independent samples);
- Tests of differences between variables (dependent samples);
- Tests of relationships between variables.

1.4.1 Differences between Independent Groups

Usually, when we have two samples that we want to compare concerning their mean value for some variable of interest, we would use the *t*-test for independent samples). The non-parametric alternatives for this test are the Wald-Wolfowitz runs test, the Mann-Whitney U test, and the Kolmogorov-Smirnov two-sample test.

If we have multiple groups, we would use analysis of variance (see ANOVA/MANOVA. The non-parametric equivalents to this method are the KruskalWallis analysis of ranks and the Median test.

1.4.2 Differences between Dependent Groups

If we want to compare two variables measured in the same sample we would customarily use the t-test for dependent samples. For example, we want to compare the math skills of students just at the beginning of the year and again at the end of the year, we would take the scores and use the t-test for such comparison and state that there is a significant difference between the two periods. Non-parametric alternatives to this test are the *Sign* test and *Wilcoxon's matched pairs* test.

If the variables of interest are dichotomous in nature (i.e., "pass" vs. "no pass") then McNemar's Chi-square test is appropriate.

If there are more than two variables that were measured in the same sample, then we would customarily use repeated measures ANOVA.

Non-parametric alternatives to this method are Friedman's two-way analysis of variance and Cochran Q test (if the variable was measured in terms of categories, e.g., "passed" vs. "failed"). Cochran Q is particularly useful for measuring changes in frequencies (proportions) across time.

1.4.3 Relationships between Variables

To express a relationship between two variables one usually computes the correlation coefficient. Non-parametric equivalents to the standard correlation coefficient of Pearson 'r' are Spearman R, Kendall Tau.

The appropriate non-parametric statistics for testing the relationship between two variables are the Chi-square test, the Phi coefficient, and the Fisher exact test. In addition, a simultaneous test for relationships between multiple cases is available, as for example, Kendall coefficient of concordance. This test is often used for expressing inter rater agreement among independent judges who are rating (ranking) the same stimuli.

1.4.4 Descriptive Statistics

When one's data are not normally distributed, and the measurements at best contain rank order information, then using non prametric methods is the best. For example, in the area of psychometrics it is well known that the rated intensity of a stimulus (e.g., perceived brightness of a light) is often a logarithmic function of the actual intensity of the stimulus (brightness as measured in objective units of Lux). In this example, the simple mean rating (sum of ratings divided by the number of stimuli) is not an adequate summary of the average actual intensity of the stimuli. (In this example, one would probably rather compute the geometric mean.) Non-parametrics and Distributions will compute a wide variety of measures of location (mean, median, mode, etc.) and dispersion (variance, average deviation, quartile range, etc.) to provide the "complete picture" of one's data.

There are a number advantages in using non-parametric techniques in health science research. The most important of these advantages are the generality and wide scope of non-parametric techniques. The lack of stringent assumptions associated with non-parametric tests implies that there is little probability of violating assumptions, which implies robustness. The application of non-parametric tests in social and Health science researcsh is wide, given that they can be applied to constructs for which it is impossible to obtain quantitative measures (descriptive studies), as well as to small sample sizes.

1.4.5 Problems and Non-parametric Tests

The most common non-parametric tests used for four different problems include the following:

i) **Two or more independent groups:** The Mann-Whitney 'U' test and the Kruskal-Wallis one-way analysis of variance (H) provide tests of the null hypothesis that independent samples from two or more groups come from identical populations. Multiple comparisons are available by the Kruskal- Wallis test.

ii) **Paired observations:** The sign test and Wilcoxon Signed-rank test both test the hypothesis of no difference between paired observations.

iii) **Randomized blocks:** The Friedman two-way analysis of variance is the non-parametric equivalent of a two-way ANOVA with one observation per cell or a repeated measures design with a single group. Multiple comparisons are available for the Friedman test. Kendall's coefficient of concordanceis a normalization of the Friedman statistic.

iv) **Rank correlations:** The Kendall and Spearman rank correlations estimate the correlation between two variables based on the ranks of the observations.

The Table below gives an overview of when to use which test:

Choosing	**TEST**	
	PARAMETRIC	**NON PARAMETRIC**
Correlation test	Pearson	Spearman
Independent Measures, 2 Groups	Independent- Measures t-test	Mann-Whitney test ('U' Test)
Independent Measures, > 2 Groups	One Way Independent Measures ANOVA	Kruskal-Wallis Test
Repeated Measures, 2 Conditions	Matched-Pair t-Test	Wilcoxon test
Repeated Measures, > 2 Conditions	One-Way, Repeated Measures ANOVA	Friedman's Test

These statistics are discussed in many texts, including Siegel (1956), Hollander and Wolfe (1973), Conover (1980), and Lehmann (1975). Each of these non-parametric statistics has a parallel parametric test.

Self Assessment Questions

1) When do we use the non-parametric statistics?

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2) What is meant by descriptive statistics in the context of non-parametric statistics?

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3) State when to use which test – parametric or non-parametric?

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4) What are the four problems for which non-parametric statistics is used?

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1.4.6 Non-parametric Statistics

The primary barrier to use of non-parametric tests is the misconception that they are less powerful than their parametric counterparts (power is the ability to correctly reject the null hypothesis). It has been suggested that parametric tests are almost always more powerful than non-parametric tests. These assertions are often made with no references to support them, suggesting that this falls into the realm of 'common knowledge'. Evidence to support this is not abundant, nor conclusive. Rather, on closer examination, it is found that parametric tests are more powerful than non-parametric tests only if all of the assumptions underlying the parametric test are met.

Pierce (1970) suggests that unless it has been determined that the data do comply with all of the restrictions imposed by the parametric test; the greater power of the parametric test is irrelevant. This is because 'the purpose of applied statistics is to delineate and justify the inferences that can be made within the limits of existing knowledge - that purpose is defeated if the knowledge assumed is beyond that actually possessed'. Thus, the power advantage of the parametric test does not hold when the assumptions of the parametric test are not met, when the data are in ranks, or when the non-parametric test is used with interval or ratio data.

When comparison studies have been made between parametric and non-parametric tests, the non-parametric tests are frequently as powerful as parametric, especially with smaller sample sizes. Blair et al. (1985) compared the power of the paired sample t-test (a common parametric test), to the Wilcoxon signed-ranks test (non-parametric), under various population shapes and sample sizes (n=10, 25, 50), using a simple pre-post test design. It was found that in some situations the t-test was more powerful than the Wilcoxon.

However, the Wilcoxon test was found to be the more powerful test in a greater number of situations (certain population shapes and sample sizes), especially when sample sizes were small. In addition, the power advantage of the Wilcoxon test often increased with larger sample sizes, suggesting that non-parametric techniques need not be limited to studies with small sample sizes. It was concluded that insofar as these two statistics are concerned, the often-repeated claim that parametric tests are more powerful than non-parametric test is not justified.

Generally, the rationale for using the t-test over the Wilcoxon test is that the parametric tests are more powerful under the assumption of normality. However, it was shown in this study that even under normal theory, there was little to gain, in terms of power by using the t-test as opposed to the Wilcoxon.

It was suggested by Blair that 'it is difficult to justify the use of a t-test in situations where the shape of the sampled population is unknown on the basis that a power advantage will be gained if the populations does happen to be normal'. Blair concluded by saying that 'although there were only two tests compared here, it should be viewed as part of a small but growing body of evidence that is seriously challenging the traditional views of non-parametric statistics'. This study demonstrated that the use of non-parametric techniques is implicated whenever there is doubt regarding the fulfilment of parametric assumptions, such as normality or sample size.

Self Assessment Questions

Answer the following as True or False.

1) Parametric tests are equally assumptive as Non-parametric tests. T / F

2)	Non-parametric tests are most applicable when data is in rank form.	T / F
3)	Small sample size is not entertained by parametric tests.	T / F
4)	Parametric tests are more statistically grounded than Non-parametric tests.	T / F
5)	Non-parametric statistics cannot be used for complex research designs.	T / F

1.4.7 Advantages and Disadvantages of Non-parametric Statistics

Advantages

1) Non-parametric test make less stringent demands of the data. For standard parametric procedures to be valid, certain underlying conditions or assumptions must be met, particularly for smaller sample sizes. The one-sample t test, for example, requires that the observations be drawn from a normally distributed population. For two independent samples, the t test has the additional requirement that the population standard deviations be equal. If these assumptions/conditions are violated, the resulting P-values and confidence intervals may not be trustworthy. However, normality is not required for the Wilcoxon signed rank or rank sum tests to produce valid inferences about whether the median of a symmetric population is 0 or whether two samples are drawn from the same population.

2) Non-parametric procedures can sometimes be used to get a quick answer with little calculation.

   Two of the simplest non-parametric procedures are the sign test and median test. The *sign test* can be used with paired data to test the hypothesis that differences are equally likely to be positive or negative, (or, equivalently, that the median difference is 0). For small samples, an exact test of whether the proportion of positives is 0.5 can be obtained by using a binomial distribution. For large samples, the test statistic is:

   $(\text{plus} - \text{minus})^2 / (\text{plus} + \text{minus})$, where *plus* is the number of positive values and *minus* is the number of negative values. Under the null hypothesis that the positive and negative values are equally likely, the test statistic follows the chi-square distribution with 1 degree of freedom. Whether the sample size is small or large, the sign test provides a quick test of whether two paired treatments are equally effective simply by counting the number of times each treatment is better than the other.

   Example: 15 patients given both treatments A and B to test the hypothesis that they perform equally well. If 13 patients prefer A to B and 2 patients prefer B to A, the test statistic is $(13 - 2)^2 / (13 + 2)$ [= 8.07] with a corresponding P-value of 0.0045. The null hypothesis is therefore rejected.

   The *median test* is used to test whether two samples are drawn from populations with the same median. The median of the combined data set is calculated and each original observation is classified according to its original sample (A or B) and whether it is less than or greater than the overall median. The chi-square test for homogeneity of proportions in the resulting 2-by-2 table tests whether the population medians are equal.

3) Non-parametric methods provide an air of objectivity when there is no reliable (universally recognized) underlying scale for the original data and there is some

concern that the results of standard parametric techniques would be criticized for their dependence on an artificial metric. For example, patients might be asked whether they feel *extremely uncomfortable* / *uncomfortable* / *neutral* / *comfortable* / *very comfortable*. What scores should be assigned to the comfort categories and how do we know whether the outcome would change dramatically with a slight change in scoring? Some of these concerns are blunted when the data are converted to ranks[4].

4) A historical appeal of rank tests is that it was easy to construct tables of exact critical values, provided there were no ties in the data. The same critical value could be used for all data sets with the same number of observations because every data set is reduced to the ranks 1,...,*n*. However, this advantage has been eliminated by the ready availability of personal computers.

5) Sometimes the data do not constitute a random sample from a larger population. The data in hand are all there are. Standard parametric techniques based on sampling from larger populations are no longer appropriate. Because there are no larger populations, there are no population parameters to estimate. Nevertheless, certain kinds of non-parametric procedures can be applied to such data by using *randomization models*.

From Dallal (1988): Consider, for example, a situation in which a company's workers are assigned in haphazard fashion to work in one of two buildings. After a year physical tests are administered, it appears that workers in one building have higher lead levels in their blood. Standard sampling theory techniques are inappropriate because the workers do not represent samples from a large population—there is no large population. The randomization model, however, provides a means for carrying out statistical tests in such circumstances. The model states that if there were no influence exerted by the buildings, the lead levels of the workers in each building should be no different from what one would observe after combining all of the lead values into a single data set and dividing it in two, at random, according to the number of workers in each building. The stochastic component of the model, then, exists only in the analyst's head; it is not the result of some physical process, except insofar as the haphazard assignment of workers to buildings is truly random.

Of course, randomization tests cannot be applied blindly any more than normality can automatically be assumed when performing a t test. (Perhaps, in the lead levels example, one building's workers tend to live in urban settings while the other building's workers live in rural settings. Then the randomization model would be inappropriate.) Nevertheless, there will be many situations where the less stringent requirements of the randomization test will make it the test of choice. In the context of randomization models, randomization tests are the ONLY legitimate tests; standard parametric test are valid only as approximations to randomization tests.

Disadvantages

Such a strong case has been made for the benefits of non-parametric procedures that some might ask why parametric procedures are not abandoned entirely in favour of non-parametric methods!

The major disadvantage of non-parametric techniques is contained in its name. Because the procedures are *non-parametric*, there are no parameters to describe and it becomes more difficult to make quantitative statements about the actual difference between populations. (For example, when the sign test says two treatments are different, there is no confidence interval and the test does not say by how much the treatments differ.)

However, it is sometimes possible with the right software to compute estimates (and even confidence intervals!) for medians, differences between medians. However, the calculations are often too tedious for pencil-and-paper. A computer is required. As statistical software goes though its various iterations, such confidence intervals may become readily available, but are not there.

The second disadvantage is that non-parametric procedures throw away information. The sign test, for example, uses only the signs of the observations. Ranks preserve information about the order of the data but discard the actual values. Because information is discarded, non-parametric procedures can never be as powerful (able to detect existing differences) as their parametric counterparts when parametric tests can be used.

1.5 MISCONCEPTIONS ABOUT NON-PARAMETRIC TESTS

The lack of use of non-parametric techniques is owing to a series of common misconceptions about this branch of statistics.

Non-parametric statistics have long taken the back seat to parametric statistics, often being portrayed as inferior in practice and teaching. It has been suggested that researchers are hesitant to use these techniques, due to fears that peer reviewers may not be completely familiar with these statistics, and therefore unable to properly interpret, and review the results.

The above opinion could be due to the widespread case of limited exposure of researchers and clinicians to this type of statistics.

Non-parametric techniques are often left out of basic statistics courses, and relegated to the last chapter of texts, making them seem less important, while reinforcing the focus on parametric statistics.

Another common misconception concerning non-parametric statistics is that they are restricted in their application. It is thought that there are only a limited number of simple designs that can be analysed using these techniques.

However, there are non-parametric techniques which span from simple 2-group analysis, to complex structural equation modelling. Basically, for any parametric test, there is a non-parametric equivalent that would be equally, or in some cases, more appropriate for use.

Self Assessment Questions

1) What are the advantages of non-parametric statistics?

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2) What are the disadvantages of non-parametric statistics?

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3) What are the misconceptions about non-parametric statistic tests?

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1.6 LET US SUM UP

The key points of our discussion in this unit are:

1) **Characteristics common to most non-parametric techniques:**

- Fewer assumptions regarding the population distribution
- Sample sizes are often less stringent
- Measurement level may be nominal or ordinal
- Independence of randomly selected observations, except when paired
- Primary focus is on the rank ordering or frequencies of data
- Hypotheses are posed regarding ranks, medians, or frequencies of data

2) **Conditions when it is appropriate to use a non-parametric Test:**

- Nominal or ordinal level of measurement
- Small sample sizes
- Non-normal distribution of dependent variable
- Unequal variances across groups
- Data with notable outliers

3) **Advantages and disadvantages of Non-parametric Tests:**

- Methods quick and easy to apply
- Theory fairly simple
- Assumptions for tests easily satisfied
- Accommodate unusual or irregular sample distributions
- Basic data need not be actual measurements
- Use with small sample sizes
- Inherently robust due to lack of stringent assumptions
- Process of collecting data may conserve time and funds
- Often offer a selection of interchangeable methods
- Can be used with samples made up of observations from several different populations

1.7 UNIT END QUESTIONS

1) What are the major differences between parametric and non-parametric statistics?

2) Enumerate the advantages of non-parametric statistics.

3) Are there any assumptions for "Assumption Free tests"? If yes what are the assumptions of non-parametric statistics?

4) "Non-parametric Statistics has much wider scope than parametric statistics" support the statement with your arguments.

5) What are the major misconceptions regarding non-parametric statistics?

1.8 SUGGESTED READING

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