E-Learning Module on **Non Parametric Tests- Concept of NP tests**

Learning Objectives

At the end of this session, you will be able to know

- About Statistical tests
- Non Parametric tests
- Assumptions and Applications of the test
- Advantages and disadvantages of the test

Introduction

- A **statistical hypothesis test** is a method of making decisions using data, whether from a controlled experiment or an observational study (not controlled). In statistics , a result is called statistically significant , if it is unlikely to have occurred by chance alone, according to a pre-determined threshold probability, the significance level.

The phrase "test of significance" was coined by Ronald Fisher. "Critical tests of this kind may be called tests of significance, and when such tests are available we may discover whether a second sample is or is not significantly different from the first."

Statistical hypothesis testing is a key technique of statistical inference. The Bayesian approach to hypothesis testing is to base rejection of the hypothesis on the posterior probability. Other approaches to reaching a decision based on data are available via decision theory and optimal decisions.

Now that you have looked at the distribution of your data and perhaps conducted some descriptive statistics to find out the mean, median or mode, it is time to make some inferences about the data.

As previously covered in the module, inferential statistics are the set of statistical tests we use to make inferences about data.

These statistical tests allow us to make inferences because they can tell us if the pattern we are observing is real or just due to chance.

Types of statistical tests:

There are three types of Statistical tests

- Parametric tests
- Non Parametric tests
- Sequential tests

Already we discussed about the parametric tests and different types of test procedures available such as Z-test, t-test, F-test, Chi square test etc.

The majority of the hypothesis tests discussed in the parametric tests made inferences about the population parameters such as the mean and proportions.

These parametric tests have used the parametric statistics of samples that came from the population being tested.

To formulate these tests we made restrictive assumptions about the populations from which we drew our samples.

For example we assumed that our sample either were large or came from Normally distributed populations. But populations are not always Normal and even if a goodness of fit test indicates that a population is approximately Normal we cannot always be sure we are right because the test is not hundred percent reliable. For these cases we need alternatives to the parametric statistics and the specific hypothesis tests we have discussed so far.

Fortunately in recent times statisticians have developed useful techniques that do not make restrictive assumptions about the shape of the population distributions. These are known as distribution free or more commonly nonparametric tests

Now let us concentrate on Non parametric tests .

- Many statistical methods require assumptions to be made about the format of the data to be analyzed.
- For example, the paired t-test introduced in the previous topics requires that the distribution of the differences be approximately Normal, while the unpaired t-test requires an assumption of Normality to hold separately for both sets of observations.

- Fortunately, these assumptions are often valid in clinical data, and where they are not true of the raw data it is often possible to apply a suitable transformation.

There are situations in which even transformed data may not satisfy the assumptions, however, and in these cases it may be inappropriate to use traditional (parametric) methods of analysis.

•(Methods such as the t-test are known as 'parametric' because they require estimation of the parameters that define the underlying distribution of the data; in the case of the t-test, for instance, these parameters are the mean and standard deviation that define the Normal distribution.)

Nonparametric methods provide an alternative series of statistical methods that require no or very limited assumptions to be made about the data. There is a wide range of methods that can be used in different circumstances, but some of the more commonly used are the nonparametric alternatives to the t-tests

If the test does not require the knowledge of the parent population or in other words if the test does not require any such specification of the parameters it is known as Non Parametric tests.

For example : Chi-square test, Sign test, Run test, Mann Whitney U test etc.

Non Parametric methods

The first meaning of *non-parametric* covers techniques that do not rely on data belonging to any particular distribution. These include, among others:

Distribution free methods, which do not rely on assumptions that the data are drawn from a given probability distribution.

As such it is the opposite of parametric statistics. It includes non-parametric statistical models, inference and statistical tests

- *Non-parametric statistics* (in the sense of a statistic over data, which is defined to be a function on a sample that has no dependency on a parameter), whose interpretation does not depend on the population fitting any parameterized 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.

- There is at least one nonparametric test equivalent to a parametric test
- These tests fall into several categories
  - Tests of differences between groups (independent samples)
  - Tests of differences between variables (dependent samples)
  - Tests of relationships between variables

- Two samples – compare mean value for some variable of interest

Chi-squared tests of independence are used for deciding whether two variables are associated or are independent. The variables are

categorical rather than numeric. It can be used to decide whether the working women is correlated with house keeping (or not). The null hypothesis is that the variables are independent. The numbers used in the calculation are the observed and expected frequencies of occurrence (from contingency tables).

Nonparametric Assumptions

- Observations are independent
- Variable under study has underlying continuity
- The probability distribution function is continuous
- The lower order moments like mean and variance exists

The above assumptions are usually satisfied

Applications and purpose

Non-parametric methods are widely used for studying populations that take on a ranked 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, such as when assessing preferences.

In terms of levels of measurement, non-parametric methods result in "ordinal" data.

As non-parametric methods make fewer assumptions, their applicability is much wider than the corresponding parametric methods.

In particular, they may be applied in situations where less is known about the application in question.

Also, due to the reliance on fewer assumptions, non-parametric methods are more robust.

Another justification for the use of non-parametric methods is simplicity. In certain cases, even when the use of parametric methods is justified, non-parametric methods may be easier to use.

Due both to this simplicity and to their greater robustness, non-parametric methods are seen by some statisticians as leaving less room for improper use and misunderstanding

The wider applicability and increased robustness of non-parametric tests comes at a cost: in cases where a parametric test would be appropriate, non-parametric tests have less power.

In other words, a larger sample size can be required to draw conclusions with the same degree of confidence.

Advantages and disadvantages of nonparametric methods

Inevitably there are advantages and disadvantages to non-parametric versus parametric methods, and the decision regarding which method is most appropriate depends very much on individual circumstances. As a general guide, the following (not exhaustive) guidelines are provided.

Advantages of nonparametric methods

Nonparametric methods require no or very limited assumptions to be made about the format of the data, and they may therefore be preferable when the assumptions required for parametric methods are not valid.

Nonparametric methods can be useful for dealing with unexpected, outlying observations that might be problematic with a parametric approach.

Nonparametric methods are intuitive and are simple to carry out by hand, for small samples at least.

Nonparametric methods are often useful in the analysis of ordered categorical data in which assignation of scores to individual categories may be inappropriate. For eg, non-parametric methods can be used to analyze alcohol consumption directly using the categories never, a few times per year, monthly, weekly, a few times per week, daily and a few times per day. In contrast, parametric methods require scores (that is 1- 7) to be assigned to each category, with the implicit assumption that the effect of moving from one category to the next is fixed.

- Probability statements obtained from most nonparametric statistics are exact probabilities, regardless of the shape of the population distribution from which the random sample was drawn
- If sample sizes as small as N = 6 are used, there is no alternative to using a nonparametric test
- Treat samples made up of observations from several different populations.

- Can treat data which are inherently in ranks as well as data whose seemingly numerical scores have the strength in ranks
- They are available to treat data which are classificatory
- Easier to learn and apply than parametric tests

Disadvantages of nonparametric methods

Nonparametric methods may lack power as compared with more traditional approaches. This is a particular concern if the sample size is small or if the assumptions for the corresponding parametric method (For eg: Normality of the data) hold.

Nonparametric methods are geared toward hypothesis testing rather than estimation of effects. It is often possible to obtain nonparametric estimates and associated confidence intervals, but this is not generally straightforward. They ignore certain amount of information

Tied values can be problematic when these are common, and adjustments to the test statistic may be necessary.

Appropriate computer software for nonparametric methods can be limited, although the situation is improving. In addition, how a software package deals with tied values or how it obtains appropriate *P* values may not always be obvious.

The main drawback of Nonparametric methods is that they are not as efficient and powerful as parametric methods that are based on a known underlying distribution

The estimate of an interval at the 95% confidence level using a non parametric test may be twice as large as the estimate using the parametric test . When we use Non parametric tests , we make a trade off , we lose sharpness in estimating intervals but we gain the ability to use less information and to calculate faster

For example, if we are trying to use statistics to document that two groups of data should be treated as separate populations, and if we already know that it is reasonable to assume that the data values in both groups are normally distributed, test, such as the t-test, will be able to discriminate more effectively between the means of the two groups than would the corresponding nonparametric test

Criticism

- Losing precision/wasteful of data
- Low power
- False sense of security
- Lack of software
- Testing distributions only
- Higher-ordered interactions not dealt with

Power of a test

- Statistical power – probability of rejecting the null hypothesis when it is in fact false and should be rejected
  - Power of parametric tests – calculated from formula, tables, and graphs based on their underlying distribution
  - Power of nonparametric tests – less straightforward; calculated using Monte Carlo simulation methods

Non Parametric test are approximate tests and in case parametric tests exists they are more powerful than the Non parametric tests. Nonparametric tests are designed to test the statistical hypothesis only and for estimating the parameters.

Parametric tests are preferred because, in general, for the same number of observations, they are more likely to lead to the rejection of a false hull hypothesis.

That is, they have more power. This greater power stems from the fact that if the data have been collected at an interval or ratio level, information is lost in the conversion to ranked data (i.e., merely ordering the data from the lowest to the highest value).

Nonparametric tests are also referred to as **distribution-free** tests. These tests have the obvious advantage of not requiring the assumption of normality or the assumption of homogeneity of variance.

They compare medians rather than means and, as a result, if the data have one or two outliers, their influence is negated.

Generally, running nonparametric procedures is very similar to running parametric procedures, because the same design principle is being assessed in each case.

So, the process of identifying variables, selecting options, and running the procedure are very similar.

The final p-value is what determines significance or not in the same way as the parametric tests.

Parametric test	Non-parametric test
One-sample t-test	Nothing quite comparable
Paired sample t-test	Wilcoxon t Test
Independent samples t-test	Mann-Whitney U Test
Pearson's correlation	Spearman's correlation

To choose the appropriate statistical test, first categorize your variables as independent and dependent (intervening or nuisance variables are usually treated as additional independent variables).

Next, determine the number of independent and dependent variables in the study. Finally, determine the level of measurement (nominal, ordinal or interval) applied to each relevant variable.

How do you know what kind of test to use?

There are a wide range of statistical tests. The decision of which statistical test to use depends on the research design, the distribution of the data, and the type of variable.

In general, if the data is normally distributed you will choose from parametric tests.

If the data is non-normal you choose from the set of non-parametric tests.

The testing process

In the statistical literature, statistical hypothesis testing plays a fundamental role. The important steps in Non parametric tests are as follows:

- There is an initial research hypothesis of which the truth is unknown.
- The first step is to state the relevant null and alternative hypotheses which is usually based on the measure median unlike parametric tests which is based on mean , proportions or variance
- The 2nd step is to consider the statistical assumptions being made about the sample in doing the test.

- Decide which test is appropriate, and state the relevant test statistic .
- Derive the distribution of the test statistic under the null hypothesis from the assumptions.
- Select a significance level (α), a probability threshold below which the null hypothesis will be rejected. Common values are 5% and 1%.

- The distribution of the test statistic under the null hypothesis partitions the possible values of statistic into those for which the null-hypothesis is rejected, the so called critical region, and those for which it is not. The probability of the critical region is α.
- Compute from the observations the observed value of the test statistic .
- Decide to either fail to reject the null hypothesis or reject it in favor of the alternative.

The choice of the correct statistical test depends upon the definition of the variables, and particularly upon their level of measurement. It also depends upon the research design used, and the nature of the hypotheses: are they comparative or relationship; is there more than one independent variable?

The answers to six questions will isolate the correct statistical test:

1. How many independent variables co vary with the dependent variable?
2. At what level of measurement is the independent variable?
3. What is the level of measurement of the dependent variable?
4. Are the observations independent or dependent?
5. Are you comparing populations to populations, a sample to a population, or are you comparing two or more samples?
6. Is the hypothesis being tested comparative or relationship?

Non-parametric models

Non-parametric models differ from parametric models in that the model structure is not specified *a priori* but is instead determined from data.

The term *non-parametric* is not meant to imply that such models completely lack parameters but that the number and nature of the parameters are flexible and not fixed in advance.

- A histogram is a simple nonparametric estimate of a probability distribution
- Kernel density estimation provides better estimates of the density than histograms.
- Nonparametric regression and semi parametric regression methods have been developed based on kernels, splines, and wavelets.
- Data envelopment analysis provides efficiency coefficients similar to those obtained by multivariate analysis without any distributional assumption.

NP tests are often used in place of their parametric counterparts when certain assumptions about the underlying population are questionable. For eg: when comparing two independent samples, the Wilcoxon Mann-Whitney test does not assume that the difference between the samples is normally distributed whereas its parametric counterpart, the two sample t-test does. NP tests may be, and often are, more powerful in detecting population differences when certain assumptions are not satisfied.

All tests involving ranked data, that is data that can be put in order, are nonparametric.