Parametric and Nonparametric: Demystifying the Terms

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In More Good Reasons to Look at the Data, we looked at data distributions to assess center, shape and spread and described how the validity of many statistical procedures relies on an assumption of approximate normality. But what do we do if our data are not normal? In this article, we'll cover the difference between parametric and nonparametric procedures. Nonparametric procedures are one possible solution to handle non-normal data.

Definitions

If you've ever discussed an analysis plan with a statistician, you've probably heard the term "nonparametric" but may not have understood what it means. Parametric and nonparametric are two broad classifications of statistical procedures. The Handbook of Nonparametric Statistics 1 from 1962 (p. 2) says:

> "A precise and universally acceptable definition of the term 'nonparametric' is not presently available. The viewpoint adopted in this handbook is that a statistical procedure is of a nonparametric type if it has properties which are satisfied to a reasonable approximation when some assumptions that are at least of a moderately general nature hold."

That definition is not helpful in the least, but it underscores the fact that it is difficult to specifically define the term "nonparametric." It is generally easier to list examples of each type of procedure (parametric and nonparametric) than to define the terms themselves. For most practical purposes, however, one might define nonparametric statistical procedures as a class of statistical procedures that do not rely on assumptions about the shape or form of the probability distribution from which the data were drawn.

The short explanation

Several fundamental statistical concepts are helpful prerequisite knowledge for fully understanding the terms "parametric" and "nonparametric." These statistical fundamentals include random variables, probability distributions, parameters, population, sample, sampling distributions and the Central Limit Theorem. I cannot explain these topics in a few paragraphs, as they would usually comprise two or three chapters in a statistics textbook. Thus, I will limit my explanation to a few helpful (I hope) links among terms.

The field of statistics exists because it is usually impossible to collect data from all individuals of interest (population). Our only solution is to collect data from a subset (sample) of the individuals of interest, but our real desire is to know the "truth" about the population. Quantities such as means, standard deviations and proportions are all important values and are called "parameters" when we are talking about a population. Since we usually cannot get data from the whole population, we cannot know the values

of the parameters for that population. We can, however, calculate estimates of these quantities for our sample. When they are calculated from sample data, these quantities are called "statistics." A statistic estimates a parameter.

Parametric statistical procedures rely on assumptions about the shape of the distribution (i.e., assume a normal distribution) in the underlying population and about the form or parameters (i.e., means and standard deviations) of the assumed distribution. Nonparametric statistical procedures rely on no or few assumptions about the shape or parameters of the population distribution from which the sample was drawn.

Parametric tests and analogous nonparametric procedures

As I mentioned, it is sometimes easier to list examples of each type of procedure than to define the terms. Table 1 contains the names of several statistical procedures you might be familiar with and categorizes each one as parametric or nonparametric. All of the parametric procedures listed in Table 1 rely on an assumption of approximate normality.

Table 1

| Analysis Type	Example	Parametric Procedure	Nonparametric Procedure
Compare means between two distinct/independent groups	Is the mean systolic blood pressure (at baseline) for patients assigned to placebo different from the mean for patients assigned to the treatment group?	Two-sample t-test	Wilcoxon rank-sum test
Compare two quantitative measurements taken from the same individual	Was there a significant change in systolic blood pressure between baseline and the six-month follow-up measurement in the treatment group?	Paired t-test	Wilcoxon signed-rank test
Compare means between three or more distinct/independent groups	If our experiment had three groups (e.g., placebo, new drug #1, new drug #2), we might want to know whether the mean systolic blood pressure at baseline differed among the three groups?	Analysis of variance (ANOVA)	Kruskal-Wallis test
Estimate the degree of association between two quantitative variables	Is systolic blood pressure associated with the patient's age?	Pearson coefficient of correlation	Spearman's rank correlation

An example

Suppose you have a sample of critically ill patients. The sample contains 20 female patients and 19 male patients. The variable of interest is hospital length of stay (LOS) in

days, and you would like to compare females and males. The histograms of the LOS variable for males and females appear in Figure 1. We see that the distribution for females has a strong right skew. Notice that the mean for females is 60 days while the median is 31.5 days. For males, the distribution is more symmetric with a mean and median of 30.9 days and 30 days, respectively. Comparing the two groups, their medians are quite similar, but their means are very different. This is a case where the assumption of normality associated with a parametric test is probably not reasonable. A nonparametric procedure would be more appropriate.

This is the situation listed in the first row of Table 1 – comparing means between two distinct groups. Thus, the appropriate nonparametric procedure is a Wilcoxon rank-sum test. This test would give us a p-value of 0.63. Those of you familiar with p-values know that we typically compare our p-value to the value 0.05. We usually say that a p-value less than 0.05 is an indication of a statistically significant result. So, we would say that there is no significant difference between the genders with respect to length of stay based on the Wilcoxon rank-sum test. Incidentally, the p-value for the two-sample t-test, which is the parametric procedure that assumes approximate normality, is 0.04. You can see that in certain situations parametric procedures can give a misleading result.

Figure 1
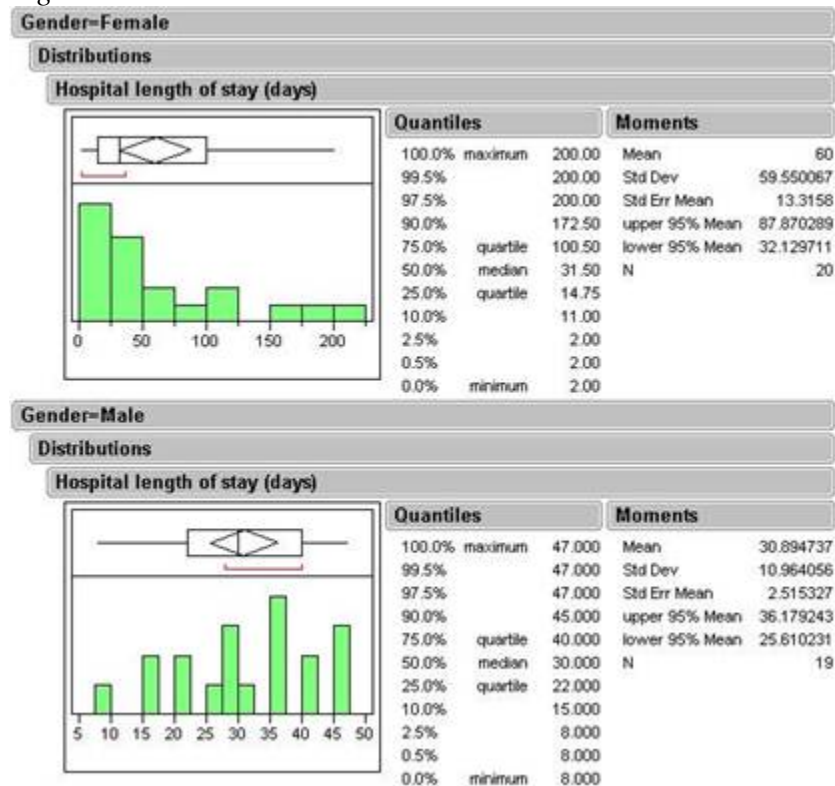
Why don't we always use nonparametric tests?
Although nonparametric tests have the very desirable property of making fewer assumptions about the distribution of measurements in the population from which we drew our sample, they have two main drawbacks. The first is that they generally are less

statistically powerful than the analogous parametric procedure when the data truly are approximately normal. "Less powerful" means that there is a smaller probability that the procedure will tell us that two variables are associated with each other when they in fact truly are associated. If you are planning a study and trying to determine how many patients to include, a nonparametric test will require a slightly larger sample size to have the same power as the corresponding parametric test.

The second drawback associated with nonparametric tests is that their results are often less easy to interpret than the results of parametric tests. Many nonparametric tests use rankings of the values in the data rather than using the actual data. Knowing that the difference in mean ranks between two groups is five does not really help our intuitive understanding of the data. On the other hand, knowing that the mean systolic blood pressure of patients taking the new drug was five mmHg lower than the mean systolic blood pressure of patients on the standard treatment is both intuitive and useful.

In short, nonparametric procedures are useful in many cases and necessary in some, but they are not a perfect solution.

Take-home points
Here is a summary of the major points and how they might affect statistical analyses you perform:

- Parametric and nonparametric are two broad classifications of statistical procedures.
- Parametric tests are based on assumptions about the distribution of the underlying population from which the sample was taken. The most common parametric assumption is that data are approximately normally distributed.
- Nonparametric tests do not rely on assumptions about the shape or parameters of the underlying population distribution.
- If the data deviate strongly from the assumptions of a parametric procedure, using the parametric procedure could lead to incorrect conclusions.
- You should be aware of the assumptions associated with a parametric procedure and should learn methods to evaluate the validity of those assumptions.
- If you determine that the assumptions of the parametric procedure are not valid, use an analogous nonparametric procedure instead.
- The parametric assumption of normality is particularly worrisome for small sample sizes (n < 30). Nonparametric tests are often a good option for these data.
- It can be difficult to decide whether to use a parametric or nonparametric procedure in some cases. Nonparametric procedures generally have less power for the same sample size than the corresponding parametric procedure if the data truly are normal. Interpretation of nonparametric procedures can also be more difficult than for parametric procedures.
- Visit with a statistician if you are in doubt about whether parametric or nonparametric procedures are more appropriate for your data.
- The book *Practical Nonparametric Statistics 2* is an excellent resource for anyone interested in learning about this topic in great detail. More general texts such as

Fundamentals of Biostatistics 3 and *Intuitive Biostatistics 4* have chapters covering the topic of nonparametric procedures.

More information

The Mayo Clinic CTSA provides a biostatistical consulting service through its BERD Resource. More information can be found on the [BERD home page](#).

References

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