Parametric vs. Non-Parametric Statistical Tests

If you have a continuous outcome such as BMI, blood pressure, survey score, or gene expression and you want to perform some sort of statistical test, an important consideration is whether you should use the standard parametric tests like t-tests or ANOVA vs. a non-parametric test.

Some of the most common statistical tests and their non-parametric analogs:

Parametric tests	**Nonparametric tests**
1-sample t test	1-sample Sign, 1-sample Wilcoxon
Paired t-test	Signed-rank test
2-sample t test	Mann-Whitney test
One-Way ANOVA	Kruskal-Wallis test

Is my data normally distributed? Can I use a parametric test?

1. Know your subject matter – can you justify the assumption of normality?
2. Plot your data (sample size permitting) – does it look close to normal/Gaussian?
3. Do you have extreme values?
4. Do you have many zero values or some natural limit?
    - Count data is a common example of this. We will likely have many zeroes
5. Is your data more discrete because of rounding or poor resolution?
6. Does your data follow another distribution? (ex: survival data)

My data do <u>not</u> look normally distributed. Should I always stick with a non-parametric test to be on the safe side?

The short answer is…NO! This may be a surprise, but parametric tests can perform well with continuous data that are non-normal (stats lingo: we say they are "*robust to departures from normality*") if:

1. **You have a decent sample size**

Parametric analyses	**Sample size guidelines for non-normal data**
1-sample t test	> 20
2-sample t test	Each group > 15 or 20
ANOVA	Each group > 15 or 20

2. **The spread of each group (within group SD) is different**

While nonparametric tests don't assume that your data follow a normal distribution, they <u>do have other assumptions</u> that can be hard to meet. For nonparametric tests that compare group medians, a common assumption is that the data for all groups must have the same spread (dispersion). If your groups have different spreads, the nonparametric test result just means that the distributions are different somehow (and not necessarily the median).

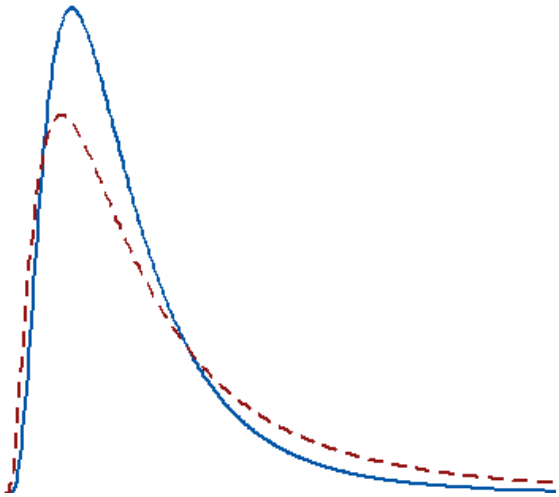
On the other hand, if you use the 2-sample t test or One-Way ANOVA, you can simply assume *unequal variances* with a slight modification to the test (see a statistician).

3. **you need power**

Converting data to ranks (which is what most non-parametric tests do) reduces power, and sometimes dramatically. Parametric tests usually have more statistical power than nonparametric tests. Thus, you are more likely to detect a significant effect when one truly exists.

When SHOULD you stick with a nonparametric test:

1. **Your area of study is better represented by the median**



2. **You have a very small sample size and non-normal looking data**

If you don't meet the sample size guidelines for the parametric tests and you are not confident that you have normally distributed data, you should use a non-parametric test or even a permutation-based test (see a statistician!).

In this scenario, you're in a tough spot with no valid alternative. Nonparametric tests have less power to begin with and it's a double whammy when you add a small sample size on top of that!

3. **You have ordinal data, ranked data, or outliers that you can't remove**

Typical parametric tests can only assess continuous data and the results can be significantly affected by outliers. Conversely, some nonparametric tests can handle ordinal data, ranked data, and not be seriously affected by outliers. Be sure to check the assumptions for the nonparametric test because each one has its own data requirements.