CHAPTER OVERVIEW

15: Nonparametric Tests

Introduction

t-tests and ANOVA are members of a statistical family of tests called **parametric tests.** Parametric tests assume that the

- sample of observations come from a particular probability distribution, e.g., normal distribution.
- samples among groups have equal variances.

Assumptions for parametric tests were introduced in Chapter 13. In the case of the t-test and ANOVA, we assume that the samples come from a **normal probability distribution** and that the probabilities of the test statistic follow the t distribution or the F distribution, respectively.

Providing these assumptions hold, we can then proceed to interpret our results as if we are talking about the population as a whole from which the samples were selected.

In other words, the t-test asks (infers) about properties of a population; hence, we are asking about parameters of the population.

t-tests, ANOVA, and other parametric tests are designed to work with quantitative ratio-scale data types. If the data are of this type and the probability distribution is known, they are the best tests to use… they allow you to make conclusions about experiments at a defined **Type I error rate** = 5%.

But what if you can't assume that distribution? Your options include

- transforming the data so as the data better meet the assumptions of parametric tests.
- apply nonparametric statistical tests.

That's where **nonparametric** statistics come in as an alternative to parametric tests.

Nonparametric tests make fewer assumptions

Nonparametric tests do not make the assumption about a particular distribution — **distribution-free tests** — nor are they used to make inferences about population parameters. Instead, nonparametric tests are used when the data type are ranks (ordinal). Now, when you think about it, all quantitative data can be converted to ranks. Hence, this is the argument for why there are nonparametric alternatives for tests like the t-test. There are a number of nonparametric alternatives to parametric tests. Another nonparametric option is to run a **permutation test** on the data.

Nonparametric tests lack statistical power

One downside for nonparametric tests is that they tend to have less statistical power compared to the parametric alternatives (see Chapter 11 for a review of **Statistical Power**). Thus, nonparametric tests tend to have higher Type II rates of error — they fail to properly reject the null hypothesis when they should. This problem tends to be less important for large sample sizes.

> **Note:**
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> Instead of **transformations** or other ad hoc manipulations of the data, modern statistical approaches favor modeling the error structure of the data within a Generalized Linear Model framework (St.-Pierre et al 2018). The advantage of the model approach is that parameter estimation occurs on the raw data. Use of transformations may, however, remain a better choice. While statistically justified, the generalized linear model approach may also tend to have higher rates of Type II error compared to simple transformations.

Thus, this chapter covers some of the more popular nonparametric alternative tests. Chapter 19 – Distribution-free statistical methods highlights use of permutation and randomization approaches, which also are alternatives to parametric tests.