## An Introduction to Nonparametric Statistics

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- ➤ Suppose I hypothesize that the mean weight of high school football players in Georgia is greater than 163 pounds.
- ➤ To test this hypothesis, suppose I collect a random sample of football players and find their mean weight and their sample standard deviation.
- ▶ Generally speaking, we learned in our introductory statistics courses that we would use a one-population t-test to test this hypothesis.

- ▶ However, one thing that we did not discuss in our introductory statistics courses is that the t-test assumes that the data is normally distributed or that the sample size is large enough for the Central Limit Theorem to apply.
- What if neither of these assumptions hold? Can we just ignore them and move on?
- Let's see why that might not be a good idea.

- Remember from earlier in the semester that the main way we compare competing process control charts is by calculating ARL, which is a function of statistical power.
- In words, statistical power is the probability of a hypothesis test (which a control chart is just an application of hypothesis tests) rejecting the null hypothesis for a given (read, specific) alternative hypothesis.

So for a given test statistic, T, and a given significance level,  $\alpha$ , the power of a hypothesis test is given by:

Power = 
$$P(T > t_{\alpha}|H_1$$
 is true)

where  $t_{\alpha}$  is the critical value of the test statistic for a given significance level,  $\alpha$ .

▶ Let's do a little simulation to estimate the power of a one-population *t*-test when the data is and is not normally distributed.

- As we can see, the power of the *t*-test can be severely impacted when the data is not normally distributed.
- But now we run into a new problem! If the data are non-normally distributed or if I am unable to reasonably assume that the data is normally distributed, how do I perform hypothesis tests?
- Nonparametric Statistics to the rescue!

- One alternative nonparametric test to the one-population *t*-test is called the *Sign Test*.
- First, the main difference with most every nonparametric method is that rather than testing the mean, we test the median.

$$H_0: \tilde{\mu}_0 = C$$
 vs.  $H_1: \tilde{\mu}_0 \neq C$ 

Suppose we take a random sample of size n. The test statistic for the Sign Test is given by:

$$T = \sum_{i=1}^{n} I(X_i > C)$$

where:

$$I(X_i > C) = \begin{cases} 1 & \text{if } X_i > C \\ 0 & \text{if } X_i \leq C \end{cases}$$

- If  $H_0$  is true and  $\tilde{\mu}=C$ , then we would expect T to be approximately n/2.
  - $\blacktriangleright$  Half of the observations greater than C and half less than C.
- $\blacktriangleright$  This suggests that if  $H_0$  is true, then:

 $T \sim \mathsf{Binomial}(n, 0.5)$ 

➤ To calculate the P-Value for the Sign Test, we would calculate:

$$P = P(|T \ge t_{\alpha}||H_0 \text{ is true})$$

▶ Let's look at an example with the Sign Test, as well as its power, using R.

- While the Sign Test is a good alternative to the one-population t-test, it is not the only alternative.
- ▶ Another (more famous and widely-used) alternative is the Wilcoxon Signed-Rank Test.
- ▶ Like the Sign Test, the WSRT tests the median of a population.

- ▶ To calculate the test statistic for the WSRT, we would:
  - 1. Rank the absolute values of the differences between the sample values and the hypothesized median.
  - 2. Sum the ranks of the positive differences.
  - 3. Calculate the test statistic as the sum of the ranks of the positive differences.
- Unlike the Sign Test, however, the WSRT's null distribution is more complicated and is based on the total possible number of combinations of observed signed ranks.

What do I mean by this? Let's look at how the null distribution of the WSRT statistic would be calculated and why we usually use an approximation as the sample size increases.