Effect Size For A One-Sample Z-Test

Now that we've calculated the z-test statistic, it becomes relatively easy to also determine the effect size that corresponds to this analysis. It's useful to report both test statistics and effect sizes because, together, they give you a sense of both *statistical significance* (via the hypothesis test) as well as *practical significance* (via the effect size). The former tells you whether we have evidence to believe that an effect exists, and the latter tells you whether the effect is big enough for us to care.

Let's take a look at the formula for the effect size of the one-sample z-test, as measured by Cohen's d:

$$d_z = \frac{\overline{x} - \mu_{\overline{x}}}{\sigma}$$

Notice that this formula is nearly identical to the formula for the z-test statistic, except that we have sigma (σ) in the denominator, rather than standard error ($\sigma_{\overline{x}}$, which is calculated using the formula $\frac{\sigma}{\sqrt{n}}$). This means that sample size (n) is not a factor for effect sizes, even though it is for hypothesis tests.

In the last *Guide*, we asked the question: Do people who attend college have different levels of intelligence than average? For this study, we collected a sample of college students and found that they had an average IQ of 110.47, which was significantly different than the population mean of 100. We also knew that the population standard deviation was 15. Already, then, we have everything we need to calculate the effect size:

$$\overline{x} = 110.47 \qquad \mu = 100 \qquad \sigma = 15$$

Let's plug these values into the formula for the effect size:

$$d_z = \frac{\overline{x} - \mu_{\overline{x}}}{\sigma} = \frac{110.47 - 100}{15} = 0.70$$

And you're done! Now we can interpret this effect size. We know that effect sizes between 0 and 0.2 are considered "*small*" effects, between 0.2 and 0.5 are considered "*medium*" effects, and above 0.5 are considered "*large*" effects. Therefore, this is a large effect.