Calculating required sample size in R and SAS

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An important question when designing an experiment is “How big a sample do I need?” A larger sample will give more accurate results, but at a cost. Use too small a sample, and you may get inconclusive results; too large a sample, and you’re wasting resources.

To calculate the required sample size, you’ll need to know four things:

1. The size of the response you want to detect
2. The variance of the response
3. The desired significance level
4. The desired power

Delta

Suppose you are comparing a treatment group to a placebo group, and you will be measuring some continuous response variable which, you hope, will be affected by the treatment. We can consider the mean response in the treatment group, μ_1, and the mean response in the placebo group, μ_2. We can then define $\Delta = \mu_1 – \mu_2$. The smaller the difference you want to detect, the larger the required sample size.

Variance

Of the four variables that go into the sample size calculation, the variance of the responses can be the most difficult to determine. Usually, before you do your experiment, you don’t know what variance to expect. Investigators often conduct a pilot study to determine the expected variance, or information from a previous published study can be used.

The **effect size** combines the minimal relevant difference and the variability into one measurement, Δ/σ.

Significance

Significance is equal to $1 – \alpha$, where α is the probability of making a Type 1 Error. That is, alpha represents the chance of a falsely rejecting H0 and picking up a false-positive effect. Alpha is usually set at 0.05, for a 95% significance.

Power

The power of a test is $1-\beta$, where beta is the probability of a Type 2 error (failing to reject the null hypothesis when the alternative hypothesis is true). In other words, if you have a 20% chance of failing to detect a real difference, then the power of your test is .8.