A Priori Power for Multiple Linear Regression Using G*Power

For a priori power, we can determine the total sample size needed for multiple linear regression given the estimated effect size $f^2$, $\alpha$ level, desired power, and number of predictors. We follow Cohen’s (1988) conventions for effect size (i.e., small $r^2 = .02$; moderate $r^2 = .15$; large $r^2 = .35$). If we had estimated a moderate effect $r^2$ of .15, alpha of .05, observed power of .80, and two independent variables, we would need a total sample size of 58.

18.9 Template and APA-Style Write-Up

Finally, here is an example paragraph for the results of the multiple linear regression analysis. Recall that our graduate research assistant, Marie, was assisting the assistant dean in Graduate Student Services, Jennifer. Jennifer wanted to know if GGPA could be predicted by the total score on the required graduate entrance exam (GRE total) and by UGPA. The research question presented to Jennifer from Marie included the following: Can GGPA be predicted from the GRE total and UGPA?

Marie then assisted Jennifer in generating a multiple linear regression as the test of inference, and a template for writing the research question for this design is presented as follows:

- Can [dependent variable] be predicted from [list independent variables]?
It may be helpful to preface the results of the multiple linear regression with information on an examination of the extent to which the assumptions were met. The assumptions include (a) independence, (b) homogeneity of variance, (c) normality, (d) linearity, (e) non-collinearity, and (f) values of X are fixed. Because the last assumption (fixed X) is based on interpretation, it will not be discussed here.

A multiple linear regression model was conducted to determine if GGPA (dependent variable) could be predicted from GRE total scores and UGPA (independent variables). The null hypotheses tested were that the multiple $R^2$ was equal to 0 and that the regression coefficients (i.e., the slopes) were equal to 0. The data were screened for missingness and violation of assumptions prior to analysis. There were no missing data.

**Linearity**: Review of the partial scatterplot of the independent variables (GRE total and UGPA) and the dependent variable (GGPA scores) indicates linearity is a reasonable assumption. Additionally, with a random display of points falling within an absolute value of 2, a scatterplot of unstandardized residuals to predicted values provided further evidence of linearity.

**Normality**: The assumption of normality was tested via examination of the unstandardized residuals. Review of the S-W test for normality ($SW = .973, df = 11, p = .918$) and skewness ($-.336$) and kurtosis (.484) statistics suggested that normality was a reasonable assumption. The boxplot suggested a relatively normal distributional shape (with no outliers) of the residuals. The Q-Q plot and histogram suggested normality was reasonable. Examination of casewise diagnostics, including Mahalanobis distance, Cook’s distance, DfBeta values, and centered leverage values, suggested there were no cases exerting undue influence on the model.

**Independence**: A relatively random display of points in the scatterplots of studentized residuals against values of the independent variables and studentized residuals against predicted values provided evidence of independence. The Durbin-Watson statistic was computed to evaluate independence of errors and was 2.116, which is considered acceptable. This suggests that the assumption of independent errors has been met.

**Homogeneity of variance**: A relatively random display of points, where the spread of residuals appears fairly constant over the range of values of the independent variables (in the scatterplots of studentized residuals against predicted values and studentized residuals against values of the independent variables) provided evidence of homogeneity of variance.

**Multicollinearity**: Tolerance was greater than .10 (.909), and the variance inflation factor was less than 10 (1.100), suggesting that multicollinearity was not an issue. However, the eigenvalues for the predictors were close to 0 (.012 and .007). A review of GRE total
regressed on UGPA, however, produced a multiple R squared of .091, which suggests noncollinearity. In aggregate, therefore, the evidence suggests that multicollinearity is not an issue.

Here is an APA-style example paragraph of results for the multiple linear regression (remember that this will be prefaced by the previous paragraph reporting the extent to which the assumptions of the test were met).

The results of the multiple linear regression suggest that a significant proportion of the total variation in GGPA was predicted by GRE total and UGPA, $F(2, 8) = 39.291, p < .001$. Additionally, we find the following:

1. For GRE total, the unstandardized partial slope (.012) and standardized partial slope (.614) are statistically significantly different from 0 ($t = 5.447, df = 8, p < .001$); with every one-point increase in the GRE total, GGPA will increase by approximately 1/100 of one point when controlling for UGPA.

2. For UGPA, the unstandardized partial slope (.469) and standardized partial slope (.567) are statistically significantly different from 0 ($t = 5.030, df = 8, p < .001$); with every one-point increase in UGPA, GGPA will increase by approximately one-half of one point when controlling for GRE total.

3. The CI around the unstandardized partial slopes do not include 0 (GRE total, .007, .018; UGPA, .254, .684), further confirming that these variables are statistically significant predictors of GGPA. Thus, GRETOT and UGPA were shown to be statistically significant predictors of GGPA, both individually and collectively.

4. The intercept (or average GGPA when GRE total and UGPA is 0) was .638, not statistically significantly different from 0 ($t = 1.954, df = 8, p = .087$).

5. Multiple $R^2$ indicates that approximately 91% of the variation in GGPA was predicted by GRE total scores and UGPA. Interpreted according to Cohen (1988), this suggests a large effect.

6. Estimated power to predict multiple $R^2$ is at the maximum, 1.00.

We note that the more advanced regression models described in this chapter can all be conducted using SPSS. For further information on regression analysis with SPSS, see Morgan and Griego (1998), Weinberg and Abramowitz (2002), and Meyers et al. (2006).

18.10 Summary

In this chapter, methods involving multiple predictors in the regression context were considered. The chapter began with a look at partial and semipartial correlations. Next, a lengthy discussion of multiple linear regression analysis was conducted. Here we