Interaction Effects in Regression

This handout is designed to provide some background and information on the analysis and interpretation of interaction effects in Multiple Regression (MR). This is a complex topic and the handout is necessarily incomplete. In practice, be sure to consult other references on Multiple Regression (Aiken & West, 1991; Cohen & Cohen, 1983; Pedhazur, 1996; Pedhazur & Schmelkin, 1991) for additional information.

Interaction effects represent the combined effects of variables on the criterion or dependent measure. When an interaction effect is present, the impact of one variable depends on the level of the other variable. Part of the power of MR is the ability to estimate and test interaction effects when the predictor variables are either categorical or continuous. As Pedhazur and Schmelkin (1991) note, the idea that multiple effects should be studied in research rather than the isolated effects of single variables is one of the important contributions of Sir Ronald Fisher. When interaction effects are present, it means that interpretation of the individual variables may be incomplete or misleading.

Kinds of Interactions. For example, imagine a study that tests the effects of a treatment on an outcome measure. The treatment variable is composed of two groups, treatment and control. The results are that the mean for the treatment group is higher than the mean for the control group. But what if the researcher is also interested in whether the treatment is equally effective for females and males. That is, is there a difference in treatment depending on gender group? This is a question of interaction. Inspect the results below. Interaction results whose lines do not cross (as in the figure at left) are called “ordinal” interactions. If the slope of lines is not parallel in an ordinal interaction, the interaction effect will be significant, given enough statistical power. If the lines are exactly parallel, then there is no interaction effect. In this case, a difference in level between the two lines would indicate a main effect of gender; a difference in level for both lines between treatment and control would indicate a main effect of treatment. However, when an interaction is significant and “disordinal”, interpretation of main effects is likely to be misleading. To determine exactly which parts of the interaction are significant, the omnibus F test must be followed by more focused tests or comparisons.
FOCUSED TESTS OF INTERACTIONS

Whenever interactions are significant, the next question that arises is exactly where are the significant differences? This situation is similar to the issues in post hoc testing of main effects, but it is also more complex in that interactions represent the combined effects of two forces or dimensions in the data not just one. The following section describes common approaches to obtaining more focused, specific information on where differences are in the interaction effect in two common situations: 1) the interaction of one continuous predictor and one categorical predictor, and 2) the interaction of two continuous predictors.

Method 1. Johnson-Neyman Regions of Significance. This is a common approach to the interpretation of the interaction between one continuous predictor, one categorical predictor and the criterion. The topic is covered in detail in Pedhazur (1997), chapter 14. The example used in Pedhazur in Table 14.3 (p. 588) is presented here. The data are available on the web site in the data subdirectory for EDPSY 604 named “ped14_3.sav”. A syntax file named “ped14_3.sps” is also available on the web site. If you run the syntax file, you will get the results of the regression analysis of the two predictors as well as the interaction of the two predictors. The syntax also produces a plot of the data. Editing the plot and requesting “chart-options-fit line-subgroups” will produce the figure below and the two regression lines fitted for each value of the categorical predictor variable.

One of the issues of greatest interest in interpreting the interaction displayed in the figure above is to determine at what points the two subgroup regression lines differ significantly from each other.
One approach to this question is the Johnson-Neyman procedure for determining regions of significance. This approach is described in Pedhazur. A syntax file that will calculate the regions of significance is also available on the web site and is named “regions.sps”.

**Method 2. Simple Slopes Tests.** This method is designed for the interpretation of the interaction effect of two continuous predictor variables. The method is not discussed in Pedhazur. Refer to Aiken and West (1991) or Cohen and Cohen (1983) for further information.

To illustrate some of the calculations, example 2.1 (p. 11) from Aiken and West is used. The data in matrix format is available on the web site named “aiken2_1.sav”. The regression analysis can be run using “aiken2_1.sps”. The regression analysis results in the following equation:

\[
Y' = 2.506 + .843(X) + 3.696(Z) + 2.621(XZ)
\]  (1)

To illustrate and test the significant interaction effect, separate regression lines are computed, plotted, and tested for individuals one standard deviation below the mean on predictor Z, at the mean of predictor Z, and one standard deviation below the mean of predictor Z. First the overall regression equation is rearranged so it can be expressed only in terms of values of X:

\[
Y' = ((.843 + 2.62(Z))(X) + (3.696(Z) + 2.506)
\]  (2)

To calculate an equation for Z one standard deviation above the mean, the standard deviation of Z (2.2) is substituted for Z in equation 2. This results in:

\[
Y' = 6.607(X) + 10.6372, \text{ for all those 1 SD above the mean on } Z
\]  (3)

For those at the mean of Z, a value of 0 is substituted for Z in equation 2. This results in:

\[
Y' = .843(X) + 2.506
\]  (4)

To calculate an equation for Z one standard deviation below the mean, the standard deviation of Z (-2.2) is substituted for Z and subtracted in equation 2. This results in:

\[
Y' = 4.921(X) - 5.6252, \text{ for all those 1 SD below the mean on } Z
\]  (5)

Actual values of Y’ can now be calculated by substituting values of predictor X. Commonly, values are computed for X at the mean, one standard deviation above the mean, and one standard deviation below the mean. Given that the standard deviation of X is 0.95, this results in:

<table>
<thead>
<tr>
<th>Equation</th>
<th>-1 SD on X</th>
<th>Mean X</th>
<th>+1 SD on X</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y’ for Z 1 SD Above</td>
<td>4.3606</td>
<td>10.6372</td>
<td>16.9139</td>
</tr>
<tr>
<td>Y’ for Mean Z</td>
<td>1.7052</td>
<td>2.5060</td>
<td>3.3069</td>
</tr>
<tr>
<td>Y’ for Z 1 SD Below</td>
<td>-0.9503</td>
<td>-5.6252</td>
<td>-10.3002</td>
</tr>
</tbody>
</table>
These values can be entered into SPSS for plotting. An example of this is in the file “aiken_lines.sav”. Using SPSS menus or the syntax below, the three regression lines can be plotted resulting in the figure below.

```
GRAPH
/LINE(MULTIPLE)=MEAN(above) MEAN(average) MEAN(below) BY time
/MISSING=LISTWISE REPORT.
```

The last step in this process is to test each line to determine whether there is a significant relationship to the criterion for each subset of the interaction effect. These tests are called “simple slopes” tests and are directly analogous to simple effects tests of interactions in the analysis of variance. The following syntax serves as an example:

```
compute zabove = z - 2.2.
compute zbelow = z - (-2.2).
compute xzabove = x * zabove.
compute xzbelow = x * zbelow.
execute.
```

A regression is then run using predictors X, zbelow, and xzbelow to test whether there is a significant relationship for those below the mean. A second regression analysis is run using predictors X, zabove, and xzabove to test whether there is a significant relationship for those above the mean. The t-test for xzbelow and xzabove are the simple slope tests.
References


