Abstract

Historically, deaf education in the United States has achieved poor results. An oft-quoted statistic is that on average, deaf students graduating from high school (at age 18-21) perform at the level of hearing 8-10 year olds in terms of reading and writing skills (Allen, 1994; Traxler, 2000). In this research, deaf children and their hearing siblings from a longitudinal database are tracked during their elementary and secondary school years. This presentation will focus on graphic displays of the longitudinal data, focusing on presenting individual data points and sub-group regression lines on a single graph (here, one regression line for the deaf sample, and one for the hearing siblings), tracking their school progress from K-12. These displays inform statistical data analysis. Detailed examples of code will be shared, as well as insights into the value of combining graphic displays with data analysis.

Introduction

This paper includes an intermediate presentation of statistical analysis, using regression methods. Individuals who have been exposed to predictive modeling in the mathematical or statistical sense should feel comfortable attending this session. The GLM, GPLOT, and GREPLAY Procedures in Base SAS® and SAS/GRAPH® were used in this paper.

The Study

In order to determine statistically significant differences in educational development between hearing and deaf children, four assessments were used. These scores measure basic math, verbal, and reading abilities from adolescence to early adulthood. The following four Peabody assessments were used:

The Peabody Individual Achievement Test for Math measures basic mathematical ability. It is one of the more widely used assessments of individual academic achievement.

The Peabody Individual Achievement Test in Reading Comprehension measures a child’s ability to derive the meaning of passages read silently.

The Peabody Individual Achievement Test in Reading Recognition measures a child’s word recognition and pronunciation abilities. Children were asked to read a word silently, and then say it aloud for an administrator.

The Peabody Picture Vocabulary Test is an assessment given to children that measures their hearing vocabulary for English words and provides an estimate of their verbal ability based on it.

The data supplied included scores for hearing children, as well as their deaf/hard of hearing siblings. Using sibling’s data removes the potential unwanted variation from family to family. It is worth noting that the sample size changes from variable to variable due to missing data points. However sample sizes from n=221 to n=341 were maintained.

To determine differences between hearing and deaf children, linear models will be constructed in which age is the predictor, and the scores in question are the response. As of now, if age was regressed onto scores, the linear model would be achieved, but wouldn’t be comparable to anything. Therefore, dummy variables will be implemented to separate the overall regression line into two unique regression lines, one for the deaf sample, and one for the hearing sample.
Method of Analysis

Sometimes in statistics, variables have two or more distinct levels, such as machines or operators. Often times these variables are referred to as categorical variables. In order to properly analyze the data using these types of variables, one must take into account the fact that variables with multiple levels may have separate deterministic effects on the response variable. In situations like this, the implementation of dummy variables is highly useful.

There are many ways to set up dummy variables so long as they are linearly independent of other variables in the model. The particular set up used in this research codes deaf = 1 and hearing = 0. It should be said that a variable with a levels will employ the use of a-1 dummy variables. Since the study only concerns deaf and hearing siblings, only one dummy variable is necessary.

As stated before, only one dummy variable was needed. The general model that will be constructed takes on the form:

\[ Y = (\beta_0 + \beta_1 X) + Z(\alpha_0 + \alpha_1 X) + \epsilon \]

In the model \( Z \) represents the dummy variable, and it can be seen that if \( Z = 0 \) the hearing model becomes:

\[ Y = \beta_0 + \beta_1 X \]

and when \( Z = 1 \) the deaf model becomes:

\[ Y = (\beta_0 + \alpha_0) + (\beta_1 + \alpha_1)X \]

Now with two regression models, differences between the deaf and hearing samples can be tested. It is easy enough to show the two samples are in fact different yet something else may be shown. A difference only concludes that there are two regression lines present, but does not show how the lines differ from one another. Four situations arise:

**Situation 1:** Two distinct regression models with different slopes, and different intercepts (4 parameters).

**Situation 2:** Two distinct regression models with equal slopes, and different intercepts (3 parameters).

**Situation 3:** Two distinct regression models with different slopes, and equal intercepts (3 parameters).

**Situation 4:** One distinct regression line with equal slopes and equal intercepts (2 parameters).

Identifying one of these situations gives even more information than a simple difference between the two samples. These situations tell us whether or not deaf and hearing siblings begin at the same levels, or different levels, and whether or not they progress at the same, or a different rate. As an aid to the analysis performed on the data, scatter plots have been provided.

Analysis

In order to test each situation, the appropriate F-tests must be constructed using extra sums of squares (ESS). The ESS are simply calculated as:

\[ ESS_{Test Parameter} = SS_{Regression} - SS_{Parameters not tested} \]

That is, the extra sums of squares that are produced by the addition of the respective test parameters. Once the ESS are obtained, the formal F-test may be performed as in any ANOVA or regression analysis.

Fortunately, SAS produces tests based on these ESS, which it calls Type III Sums of Squares. The trick in obtaining the Type III SS for a regression model involves using The GLM Procedure. The following code was used to obtain the necessary tests for deciding which situation is present:
Data RichD.Dualsample;
  input age deaf_flag <<variable>>;
  interaction = age*deaf_hear;
Run;
Proc Glm Data=RichD.Dualsample;
  model <<variable>> = age deaf_flag interaction / SS3;
Run;

The lack of the CLASS statement in PROC GLM treats each independent variable in the model as one degree of freedom, essentially fitting a regression model rather than an additive model. The SS3 option in the model statement suppresses the Type I Sums of Squares and produces the ESS needed to draw conclusions. Example output resulting from the code looks like:

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Squares</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>3</td>
<td>42005.30802</td>
<td>14001.76934</td>
<td>88.55</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Error</td>
<td>337</td>
<td>53289.45445</td>
<td>158.12894</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corrected Total</td>
<td>340</td>
<td>95294.76246</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Type III SS</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>1</td>
<td>25495.25056</td>
<td>25495.25056</td>
<td>161.23</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>deaf_flag</td>
<td>1</td>
<td>362.49076</td>
<td>362.49076</td>
<td>2.29</td>
<td>0.1309</td>
</tr>
<tr>
<td>interaction</td>
<td>1</td>
<td>1576.71421</td>
<td>1576.71421</td>
<td>9.97</td>
<td>0.0017</td>
</tr>
</tbody>
</table>

To test for situation 2, the F-test and resulting p-value associated with the interaction must be consulted. In the general case, this situation tests whether or not \( \alpha_i = 0 \) vs \( \alpha_i \neq 0 \). The ESS contributed by the interaction term to the model that already includes the age and deaf_flag variables is used to create the F-value used for the test. Since the p-value associated with the interaction is much less than any respectable level of alpha, lets say \( \alpha = .05 \), there is clearly a significant difference between the deaf and hearing samples and as a result two regression models are present.

To test for situation 3, the F-test and resulting p-value associated with the deaf_flag dummy variable must be consulted. In the general case, this situation tests whether or not \( \alpha_0 = 0 \) vs \( \alpha_0 \neq 0 \). The ESS contributed by the deaf_flag term to the model that already includes the age and interaction variables is used to create the F-value used for the test. Here, since the p-value is greater than an \( \alpha = .05 \) the two regression models have equal intercepts with different slopes.

Testing for situation 4 simply involves testing both the interaction as well as the deaf_flag variables. In the general case, this situation tests whether or not \( \alpha_e = \alpha_i = 0 \) vs at least one \( \alpha \neq 0 \). If both tests came back not significant, only one regression line would be present. Situation 1 would be when all terms are significant. This procedure was followed for each assessment, with the following results:

<table>
<thead>
<tr>
<th>Assessment</th>
<th>Situation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIAT Math</td>
<td>3</td>
</tr>
<tr>
<td>Peabody Picture Vocabulary</td>
<td>2</td>
</tr>
<tr>
<td>PIAT Reading Recognition</td>
<td>1</td>
</tr>
<tr>
<td>PIAT Reading Comprehension</td>
<td>1</td>
</tr>
</tbody>
</table>

As mentioned before, the use of scatter plots was employed as a visual aid to the conclusions drawn from the statistical analysis. The program used to obtain the graphical output follows as:
Since the graphs produced were treated as static graphs, they were stored as GIF files using the DEVICE= option which provide no opportunity for interactivity, and take up minimal space. Two SYMBOL statements were used in order to distinguish between the deaf and hearing sample. Colors, as well as shapes were used using the COLOR= and VALUE= options respectively to represent each sample as first a visual pleaser, and then in the event of the document printed in black and white, visual separation.

Axes were then set using appropriate scales. The only assessment which does not follow the same scaling in scores is the Peabody Picture Vocabulary Test, so the only modification necessary in the above code is the ORDER= option of the y-axis. Also, in the AXES2 statement, the label was rotated 90 degrees using the ANGLE= option in order to keep the graphs clean looking and compact.

Lastly, a legend was created which was given the dimension 2 x 1 using the ACROSS= and DOWN= options, and positioned in the upper left corner of the graph, with MODE=share specified. This last option ensures that the legend does not cover any data points which may impede the space where the legend was positioned.

Now, with the appropriate options specified, The GPLOT procedure was run.

```
Proc GPLOT Data=RichD.DualPlot;
   Plot <<variable>>*deaf_age <<variable>>*hearing_age / Overlay Legend=Legend1 NoFrame
   Haxis=axis1 Vaxis=axis2;
Quit;
```

In order to visually detect which situation is present, both populations were plotted on the same graphing window using the overlay option. Lastly, The GREPLAY procedure was used to condense the four graphs into one window.

```
Proc GREPLAY igout=work.gseg tc=sashelp.templt template=L2R2 nofs;
   Treplay 1:gplot 2:gplot1 3:gplot2 4:gplot3;
Quit;
```
As each graph is created in PROC GPLOT, it is stored in the work.gseg directory, with naming conventions related to the creation order of each graph. PROC GREPLAY allows users to augment graphs into matrix plots if desirable, giving users numerous templates to choose from, which are located in the sashelp.templt directory. The template chosen for this paper is the L2R2 template, which intuitively creates a square 2 x 2 matrix plot. Using the TREPLAY statement determines the placement of the specified graphs, and as a result, the following matrix plot is obtained.

As a recap, the graph displaying the PIAT Math scores shows that there are in fact two distinct regression models, with different slopes and same intercepts. Therefore, among deaf and hearing siblings, both start off at the same level regarding mathematical ability, however hearing siblings develop their math skills at a quicker rate than their deaf siblings. Regarding, the Peabody Picture Vocabulary Test, there are two distinct regression models, and the deaf and hearing siblings progress at the same rate, yet begin at different levels. As for the PIAT in Reading Recognition, there are two distinct regression models with different slopes and different intercepts. Graphically, it appears that the hearing sample starts off at a higher level, and progresses at a quicker rate. Lastly, the PIAT in Reading Comprehension shows the same situation as the recognition testing, however in this case, the deaf sample begins at a higher level than the hearing sample.

Conclusion

This study revealed interesting points about the relationship between deaf and hearing development. The use of the SAS system’s graphing and regression capabilities gives users a new approach to classic regression problems. The GPLOT procedure allows users to interpret the statistical conclusions in a concise manner with supporting visuals. While the data does not indicate that high school deaf children perform at a level of 8-10 year olds, the deaf sample scores did increase at a slower rate than the hearing sample in each of the four assessments.
References


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