Module 14: Missing Data
MLwiN/REALCOM Practical

Jonathan Bartlett & James Carpenter
London School of Hygiene & Tropical Medicine
www.missingdata.org.uk

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Pre-requisites

- You should be able to use MLwiN to fit single-level and multilevel regression models (see MLwiN practicals for Modules 3 and 5)
- Single-level logistic regression in MLwiN (Module 6)
- You need to have installed the MLwiN and REALCOM Impute packages, which are available from www.bristol.ac.uk/cmm.

Online resources:
www.missingdata.org.uk

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Introduction to the Class Size Data

You will be analysing data derived from the class size study carried out by Peter Blatchford and colleagues at the Institute of Education, London, and kindly made available to us. Some study findings are described in Blatchford et al. 2002. Please note that the dataset we use here has been extracted from the original project for the purposes of illustrating missing data concepts and methods, and so it is not representative of the original data. Furthermore, note that the dataset we use here contains different variables to the one referred to in the corresponding Concepts document.

To open the worksheet:

From within the LEMMA Learning Environment

- Go to Module 14: Missing Data, and scroll down to MLwiN Datafiles
- If you do not already have MLwiN to open the datafile with, click (get MLwiN).
- Click “14.1.wsz”

The Names window will appear.

Table 14.1. Variables contained in the class size data

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description and coding</th>
</tr>
</thead>
<tbody>
<tr>
<td>pupil</td>
<td>Pupil identifier</td>
</tr>
<tr>
<td>school</td>
<td>School identifier</td>
</tr>
<tr>
<td>nlitpre</td>
<td>Pre-reception literacy score, with 1,741 missing values</td>
</tr>
<tr>
<td>nlitpost</td>
<td>Literacy score at the end of reception</td>
</tr>
<tr>
<td>fsmn</td>
<td>Eligible for free school meals (1=yes, 0=no)</td>
</tr>
<tr>
<td>gend</td>
<td>Gender (1=boys, 0=girls)</td>
</tr>
<tr>
<td>tentry</td>
<td>Term of school entry (1=Spring or Summer, 0=Autumn)</td>
</tr>
<tr>
<td>cons</td>
<td>Constant, set to 1</td>
</tr>
<tr>
<td>nlitpre_full</td>
<td>Pre-reception literacy score, with no missing values</td>
</tr>
</tbody>
</table>

The dataset contains literacy scores from pupils in the year before the reception year and scores from the end of the reception year. Note that the test scores have been normalised.
It also contains information on the child’s gender and whether they were eligible to receive free school meals. The `nlitpre` variable contains 1,741 missing values. We have made these values missing artificially, in order to illustrate some of the concepts and methods we will use. We thus also have the variable `nlitpre_full`, which is the `nlitpre` variable before any values were made missing. We emphasize that in practice the `nlitpre_full` variable would not be available.

The dataset is multilevel (clustered, hierarchical), because children are nested within schools. For the moment, we will completely ignore this multilevel structure in order to illustrate the concepts and methods in the more standard single-level setting. At the end of the practical, in P14.7, we consider a multilevel analysis of the data.

**P14.1 The Model of Interest**

Our model of interest throughout will be the linear regression of post-reception literacy scores on a child’s pre-reception literacy score, eligibility for free school meals, and their gender.

We begin by fitting the model of interest to the full data, i.e. by using the `nlitpre_full` variable as a covariate, rather than `nlitpre`. We again emphasize that in practice this would not be possible, since only the partially observed variable `nlitpre` would be available.

- Click on the Model menu and then Equations to open the Equations window
- Check that the model matches the one shown in Figure 14.1
- Click the Start button to estimate the model parameters

![Figure 14.1. Model of interest fitted to full data](image)

Figure 14.1 shows the fitted model, using the full data (note the message that 4873 of 4873 cases are in use). Comparing the coefficients to their standard errors, we see that all three covariates are statistically significantly associated with the post-reception literacy score. Children with high pre-reception scores tended to have higher post-reception
literacy scores. Those who were eligible for free school meals had lower scores than those who were not, and boys had lower scores on average than girls.

We will take the coefficients shown in Figure 14.1 as the gold standard, to which we compare subsequent estimates which are based on the partially observed `nlitpre` variable (rather than `nlitpre_full`).

**P14.2 Investigating Missingness**

In this section we investigate the missing data in the class size dataset. We have already noted that the `nlitpre` variable contains missing values. First, open the worksheet:

From within the LEMMA Learning Environment

- Go to Module 14: Missing Data, and scroll down to MLwiN Datafiles
- If you do not already have MLwiN to open the datafile with, click (get MLwiN).
- Click “14.2.wsz”

The number of missing values in each variable can be easily viewed in the Names window. The Names window should appear when you load the worksheet (otherwise click on Data Manipulation, then Names). This shows that `nlitpre` is the only variable with missing values.

![Names window](image)

*Figure 14.2. The Names window for the class size dataset (14.2.wsz)*
P14.2.1 Investigating the missingness mechanism

We now investigate the missingness mechanism for the \textit{nlitpre} variable. This will help inform us as to what assumptions might be plausible for the mechanism, and consequently which approaches to handling the missing values will be appropriate. To do this, we first generate a variable which indicates whether the \textit{nlitpre} variable is observed for a child or not.

- Click on Data Manipulation and then Command interface
- In the Command interface window which opens, type the following commands:
  
  \begin{verbatim}
  eqmi 0
  calc c10 = 1*(\textit{nlitpre}'!=MISSING)
  name c10 'r'
  eqmi 1
  \end{verbatim}

We use the \texttt{eqmi} command to temporarily change MLwiN’s treatment of missing values. In the \texttt{calc} command we then set column 10 to equal one when \textit{nlitpre} is not missing and zero otherwise, and rename this column to \textit{r}. Lastly we restore the \texttt{eqmi} setting back to its original value. To check that this worked:

- Using the Names window, highlight \textit{nlitpre} and \textit{r} and, under Data, click View.

Figure 14.3 shows these two columns for the first 16 rows in the dataset. This confirms that when \textit{nlitpre} is missing, the new \textit{r} variable is set to zero, and it is one when \textit{nlitpre} is observed.
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