

# Linking Antenatal Factors to Non-Communicable Diseases in Children and Adults

## A Fight Against Missing Data

Anthony Chapman  
University of Aberdeen

### Abstract

There is a large body of evidence linking reduced birth weight and increased risk for non-communicable diseases (NCD) such as type II diabetes and asthma, which implicates factors driving fetal growth in NCD aetiology. We are exploring the potential for a computing approaches to relating repeated measurements of fetal size during a pregnancy to post natal outcomes using routinely acquired data for the population of Grampian.

### Introduction

Our group has related fetal measurements to postnatal outcomes in childhood which include asthma and eczema in a local population [1, 2, 3] and also from Saudi Arabia [4]. We are exploring the possibility for a computational approach to relate repeated measurements of fetal size during a pregnancy to post natal outcomes using routinely acquired data for the population of Grampian. If successful, our approaches have the potential to be used nationwide or even internationally. One of the biggest problems we face are missing values in the routinely acquired data, . For our project to be valid, missingness is one of the first problems we will have to remedy.

### Current Objective

Our current efforts are towards the creation of artificially complete data, that is to generate a dataset which is complete (i.e. no missing values) out of a dataset with only partial completeness. As you can see in Table 1, missingness ranges from 0% to 35% in each individual column.

By analysing the dataset we noticed that 100% of the records have at least 1 value present. On the other hand, we also noticed that only 15% of the records are complete in all fields. In order for any analytical result to be reliable, we will need to use more than 15% of the dataset, otherwise we can't justify any results on such a small sample of any population. Thus we would like to find a way to complete the missing data and then evaluate how good (i.e. close to the truth) our new data is.

Table 1: Summary of the sample data, N is out of 2000

Statistic	N	Mean	St. Dev.	Min	Max
matism	1,999	0.297	0.457	0	1
Quintile_SIMD_2006	1,986	3.602	1.454	1	5
Z_CRL_our	852	-0.000	0.999	-4.930	4.799
z_BPD_our	1,480	0.000	1.000	-4.040	3.737
Z_BWT_ICH	1,716	0.208	0.989	-2.300	11.020
Z_BMI_5years	754	0.518	0.940	-2.550	4.320

### Methods

#### Benchmark databases

In order to evaluate any imputation method, we will need to have a benchmark to compare any results. For this benchmark to be relevant to our project, it needs to behave similarly to our own database. Thus we are going to use a subset of our database as our benchmark and then imitate the original database with an artificial one. Illustrated in Figure 1, we are able to replicate the distribution of missingness from a benchmark database which itself was obtained from the original database. Thus we can test what impact imputation has on any database and have something to compare it to.

#### Imputation

Imputation is the process of replacing missing data with some values[5]. We have chosen MICE [6], an R [7] package, for the creating of artificially complete data. MICE works by approximating a missing value by looking at not only the known fields in the same record but also by analysing the distribution of all the other records in a dataset.

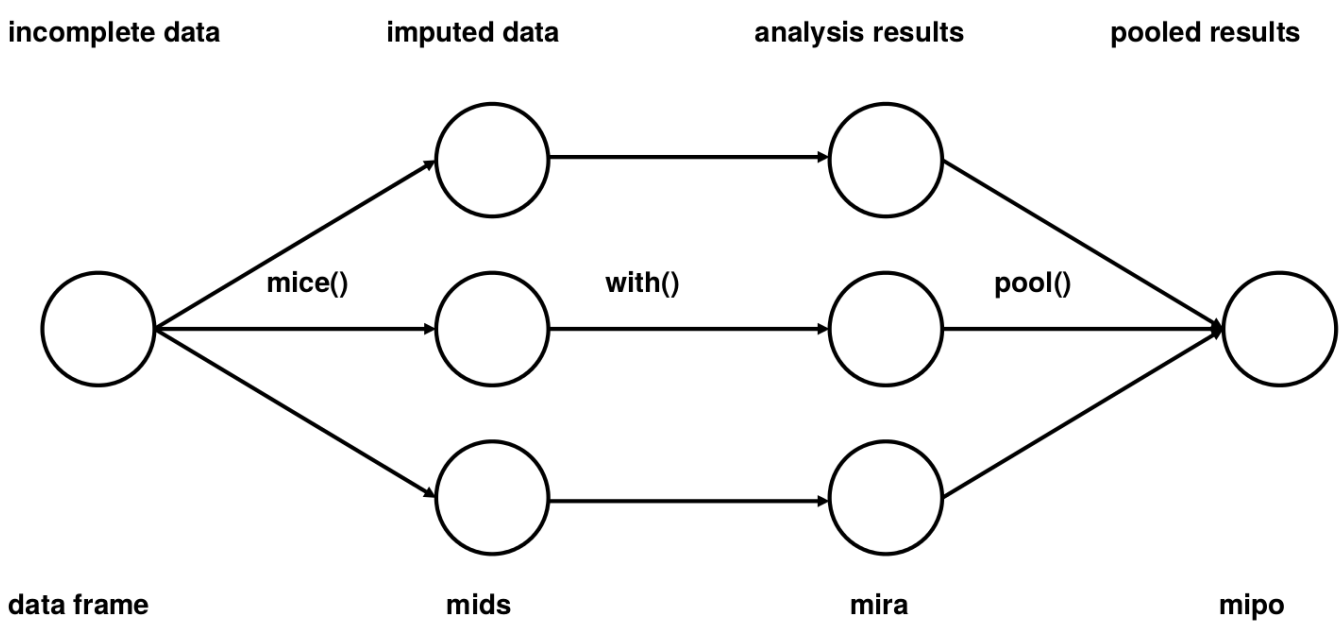


Figure 2: Main steps in MICE

#### Evaluating Imputation

In order to evaluate whether MICE creates a good artificially complete dataset, we will use the already mentioned benchmarks, we start with an incomplete dataset, we extract a complete subset (our benchmark) from it, we then create several artificially incomplete datasets to mimic the original. Once we have these artificially incomplete datasets, we are able to apply MICE to them and compare the results to the benchmark database and decide whether imputation worked or not.

### Contact Information:

Department of Applied Health Sciences  
Computing Science Department  
University of Aberdeen  
238 Meston Building, Old Aberdeen

Phone: 07708288138  
Email: r01ac14@abdn.ac.uk



### Results

In Table 2, column (1) represents the complete dataset and columns (2) and (3) represent two artificially complete datasets. The values in the columns are the regression coefficients for each values in the first column. Essentially we are regressing Z\_BWT\_ICH in terms of the other values. In the table one can see that the values are very close to each other. This is enough to indicate that imputation works on this dataset.

Table 2: (1)- regression model of complete data, (2) - regression model of first artificially complete data, (3) - regression model of second artificially complete data

	Dependent variable:		
	Z_BWT_ICH		
	(1)	(2)	(3)
z_BPD_our	0.148*** (0.054)	0.173*** (0.055)	0.201*** (0.054)
Quintile_SIMD_2006	0.056 (0.036)	0.050 (0.037)	0.059* (0.034)
matasevYes	-0.150 (0.126)	-0.102 (0.127)	-0.121 (0.121)
matism	-0.182 (0.118)	-0.218* (0.122)	-0.223* (0.114)
bsexmf24Male	-0.247*** (0.093)	-0.320*** (0.094)	-0.329*** (0.090)
Constant	0.217 (0.166)	0.266 (0.169)	0.223 (0.160)
Observations	334	334	334
R <sup>2</sup>	0.091	0.090	0.113
Adjusted R <sup>2</sup>	0.075	0.073	0.097
Residual Std. Error (df = 327)	0.828	0.833	0.799
F Statistic (df = 6; 327)	5.482***	5.399***	6.942***
Note:	*p<0.1; **p<0.05; ***p<0.01		

### Conclusions

From the results, as the imputed datasets are so close to the benchmark, we can conclude that MICE creates efficient artificially complete datasets. We mimicked the missingness distribution of the dataset and the replicated it onto a benchmark dataset so we could compare the effect of applying MICE to it. The results are so close to the benchmark that we can confidently impute the real data for analysis.

### Forthcoming Research

Our next steps will be to apply these imputation methods to the real data (waiting for approvals), then we can analyse the dataset without any missing values. We will then use clustering techniques to find relationships within the data.

### References

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