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An Analysis of the Missing Data Methodology for Different Types of Data

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Abstract

Missing data is an eternal problem in data analysis. It is widely recognised that data is costly to collect, and the methods used to deal with missing data in the past relied on case deletion. There is no one overall best fix, but many different methodologies to use in different situations.

This study was motivated by the writer's time spent analysing data in the nutrition study, and realising how much data was wasted by case deletion, and subsequently how this could bias inferences formed from the results. A better method (or methods), of dealing with missing data (than case deletion) is required, to ensure valuable information is not lost.

What is being done: What is in the literature? The literature on this topic has exploded with new methods in recent times. Algorithms have been written and incorporated based on these methods into a number of statistical packages and add-on libraries.

Statistical packages are also reviewed for their practicality and application in this area. The nutrition data is then applied to different methodologies, and software packages to assess different types of imputation.

A set of questions are posed; based on type of data, type of missingness, extent of missingness, the required end use of the data, the size of the dataset, and how extensive that analysis needs to be. This can guide the investigator into using an appropriate form of imputation for the type of data at hand.

A comparison of imputation methods and results is given with the principal result that imputing missing data is a very worthwhile exercise to reduce bias in survey results, which can be achieved by any researcher analysing their own data.

Further to this, a conjecture is given for using Data Augmentation for ordinal data, particularly Likert scales. Previously this has been restricted to either person or item mean imputation, or hot deck methods. Using model based methods for imputation is far superior for other types of data. Model based methods for Likert data are achieved by means of inserting the linear by linear association model into standard missing data methodology.

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Blessed is the man who perseveres under trial,
because when he has stood the test,
he will receive the crown of life that
God has promised to those who love him.
James 1:12

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Notation and Abbreviations

BLR	Binary Logistic Regression
CD	Case Deletion
EM	Expectation Maximisation (algorithm)
EM Imp	Imputation via the EM algorithm
GLM Imp	General Location Model Imputation
HD	Hotdeck (Imputation)
iid	Independent identically distributed
LUM	Look up methods
LVCF	Last Value Carried Forwards
MCAR	Missing Completely at Random
MAR	Missing at Random
Mean Imp	Mean family of Imputation
MI	Multiple Imputation
MI BB	Multiple Imputation Bayesian Bootstrap
MICE	Multiple Imputation by Chained Equations
MI DA	Multiple Imputation via Data Augmentation
MI EM	Multiple Imputation via the EM algorithm
N.Neighbour	Nearest Neighbour
N Nets	Neural Networks
NLR	Nominal Logistic Regression
NMAR	Not Missing at Random (Informatively Missing)
OLR	Ordinal Logistic Regression
PMM	Predictive Mean matching
Reg Imp	Regression Imputation
SHHD	Sequential and/or Hierarchical Hotdeck
SI	Single Imputation
St Reg	Stochastic regression Imputation

W	Indicator for Missingness
X	Co-variate in model
Y	Variable of interest
$\hat{\alpha}$	Gamma Parameter (Ch 8)
$\hat{\beta}$	Gamma Parameter (Ch 8)
$\hat{\beta}$	Regression Coefficient Estimate (Ch 9)
θ	Distribution Parameter
$\hat{\theta}$	Maximum Likelihood Estimate of the Parameter
ψ	Missingness Parameter in Model