Missing the Point: Non-Convergence in Iterative Imputation Algorithms

Anonymous Authors[1]

Abstract

Iterative imputation is a popular tool to accommodate missing data. While it is widely accepted that valid inferences can be obtained with this technique, these inferences all rely on algorithmic convergence. There is no consensus on how to evaluate the convergence properties of the method. This paper provides insight into identifying non-convergence in iterative imputation algorithms. Our study found that—in the cases considered—inferential validity was achieved after five to ten iterations, much earlier than indicated by diagnostic methods. We conclude that it never hurts to iterate longer, but such calculations hardly bring added value.

1. Introduction

A popular method to accommodate missing data is to impute (i.e., 'fill in') the missing values in an incomplete dataset. It is widely accepted that imputation techniques such as multiple imputation (MI; @rubin76) can yield statistically valid inferences. The validity of these inferences relies on the method through which imputations are obtained—often iterative algorithms. Iterative imputation algorithms are employed in e.g., `SPSS`, `Stata`, and the `R` packages `MI`, and `mice`. Or use: Convergence of the algorithm used to solve the missing data problem is a topic that has not received much attention but is ever so important, as most imputation software packages draw inference from iterative imputation procedures.

The validity of the inference all depends on the state space of the algorithm at the final iteration. If the algorithm does not reach convergence, "the imputed datasets will not be truly independent and the variability among them may understate the true levels of missing-data uncertainty" (Schafer and Olsen, p. 556).

But when is this the case? Current practice of visually inspecting imputations is not sufficient because 1) no objective point at which convergence is established, 2) only severely pathological cases of non-convergence may be identified, and 3) diagnosing non-convergence can be challenging to the untrained eye. On top of that, the statistics to inspect are either univariate or dependent on the substantive model of interest. Converged univariate statistics do not guarantee multivariate convergence, and with a model-dependent statistic there is no guarantee that the algorithm is converged enough for other models of scientific interest. This negates the advantages of MI: solving the missing data problem and complete data problem separately.

Therefore, we propose a novel parameter to inspect. We use this parameter to identify non-convergence with two quantitative diagnostic methods: Rhat and AC.

We simulate and investigate the plausibility of identifiers for non-convergence for iterative imputation algorithms ...

2. Discussion

Valid inferences may be obtained when there is still non-convergence in the algorithm.

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[1]Anonymous Institution, Anonymous City, Anonymous Region, Anonymous Country. Correspondence to: Anonymous Author <anon.email@domain.com>.

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