

Handling missing observations with multiple imputation

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Introduction

Handling missing observations

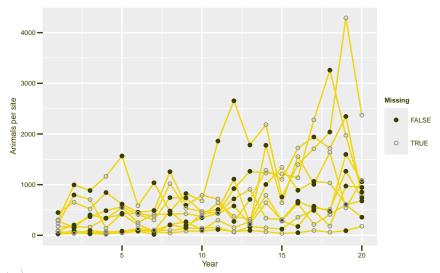
The best solution to handle missing data is to have none.

– Sir Ronald Aylmer Fisher

- ▶ In practice we can only try to minimise the missingness
- ▶ An increase in missingness will lead to a decrease in power
- Analysis can handle missing data (e.g. average number of animals)
 - No need for imputation
- Analysis cannot handle missing data (e.g. population totals)
 - Imputation is required

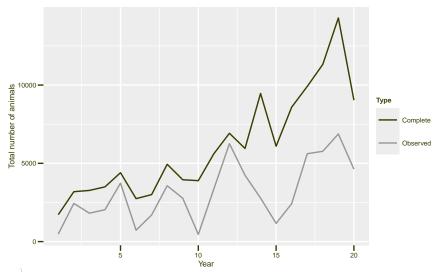


Number of animals per site





Population totals





Some imputation methods

- Popular in ecology for analysis of population trends
 - Underhill index, 118 citations (Underhill & Prys-Jones, 1994)
 - ► TRIM, 310 citations (Pannekoek & Van Strien, 2005)
 - birdSTATs, Access shell around TRIM (Meij, 2013)
 - All are single imputation methods
- Popular in medical and social science
 - Multiple imputation, 9625 citations (Rubin, 1987)
 - Only emerging in field of ecology





Single imputation versus multiple imputation

The similarities

- Replace missing values with imputed values
- Imputed values are based on a model
 - ► The model can be very basic
 - A constant
 - The overal mean
 - The model can be elaborate
 - Use available covariates (e.g. year, season, site, climate, ...)
 - Use correlation structures (e.g. temporal, spatial, ...)
 - ▶ Use a relevant distribution (e.g. Poisson, negative binomial, ...)
 - Use zero-inflation
- Final analysis on the augmented dataset

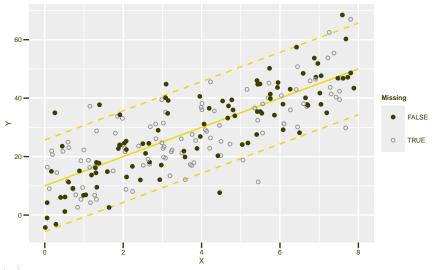


The differences

- Single imputation replaces missing values only once
 - It uses the best available single value: the predicted value of the model
 - Single imputation ignores model uncertainty and natural variability
- Multiple imputation replaces missing values several times
 - It uses each time a different random value
 - Based on
 - ▶ The distribution of predicted values of the model
 - The noise of the model
 - Multiple imputation takes both model uncertainty and natural variability into account

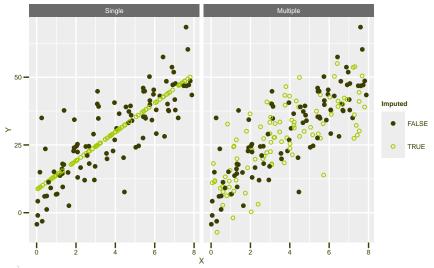


Example dataset





Example of one imputation set





How to handle the randomness in multiple imputation?

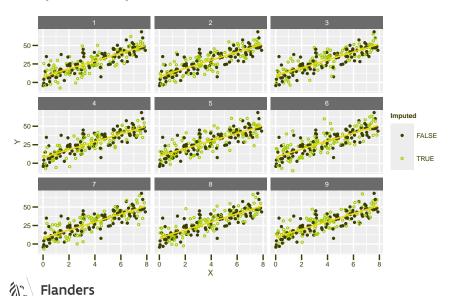
- Since the imputed values are random, every imputation set will have different values
- ► Hence the results of the analysis after imputation will be different among imputation sets
- Solution:
 - Create L imputation sets
 - 2 Run the analysis on each imputation set
 - Average the parameter of interest B and its standard error σ_B among imputation sets using the formulas below

$$\overline{B} = \frac{1}{L} \sum_{l=1}^{L} \hat{B}_{l}$$

$$\overline{\sigma}_{B}^{2} = \frac{1}{L} \sum_{l=1}^{L} \hat{\sigma}_{B_{l}}^{2} + \frac{L+1}{L} \sum_{l=1}^{L} \frac{(\hat{B}_{l} - \overline{B})^{2}}{L-1}$$



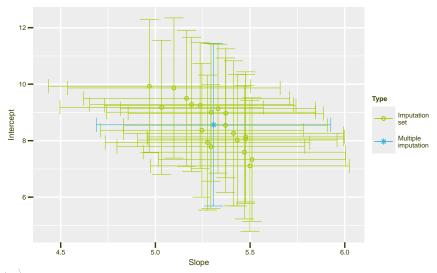
Example of 20 imputation sets



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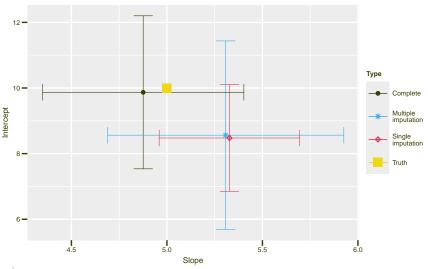
State of the Art

Analysis of 20 imputation sets





Comparison of results







Advice on imputation

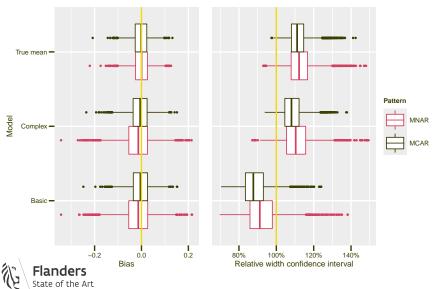
General recommendations

- Forget single imputation
 - Use multiple imputation
- Use a reasonable complex model
 - ► Too simple: model will smooth too much
 - Too complex: unstable or unreliable model
 - Use the relevant distribution!
- Number of imputations (Graham et al., 2007)
 - ightharpoonup Aim for L=100 when computational effort is reasonable
 - L=3 can be sufficient (<10% missing and <5% power falloff)
- Proportion of missingness
 - Multiple imputation is robust, even with 50% to 75% missing data
- Type of missingness
 - Missing not at random (MNAR) can introduce biased results



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Effect of imputation model and type of missingness (Onkelinx et al., 2016a)



Available R packages

- ▶ R (R Core Team, 2013) is free and open source software for statistical computing
- Some packages for multiple imputation

Package	Counts	Mixed model	GUI	Missing covariate	Reference
multimput Amelia mice	X X	Х	Х	X X	Onkelinx et al. (2016b) Honaker et al. (2011) van Buuren & Groothuis-Oudshoorn (2011)



References I

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Onkelinx T., Devos K. & Quataert P. (2016a). Working with population totals in the presence of missing data. Comparing imputation methods in terms



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