The algorithmic Search for the optimal Number of Imputations

Gedeon Alexander Vogt

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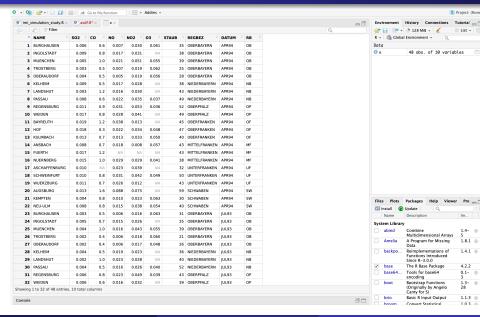
Outline

- Multiple Imputation: An Introduction
- 2 Properties of Multiple Imputation
- 3 The iterative Multiple Imputation Procedure
- 4 Simulation Study

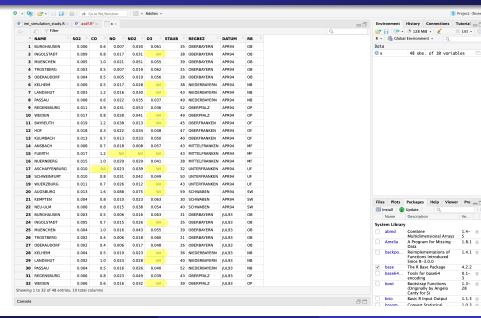
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The Problem



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Possible Solutions

(i) Drop rows containing NAs

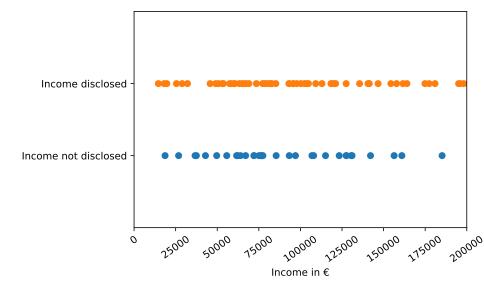
Possible Solutions

- (i) Drop rows containing NAs
- (ii) Single imputation

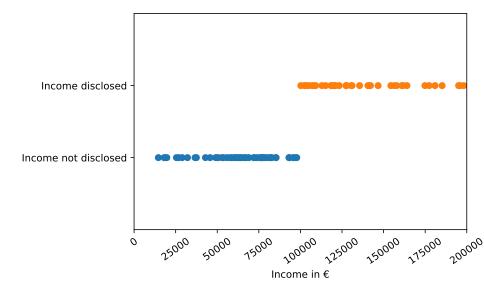
Possible Solutions

- (i) Drop rows containing NAs
- (ii) Single imputation
- (iii) Multiple imputation

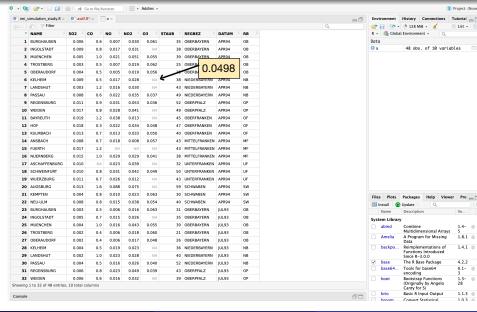
Possible Solutions - Drop Rows containing NAs



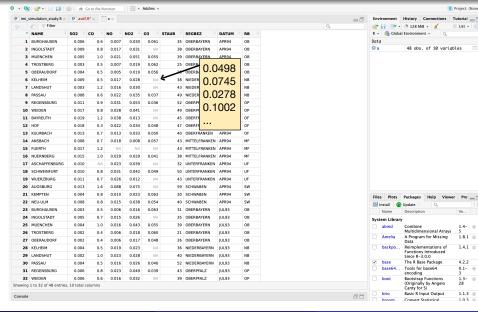
Possible Solutions - Drop Rows containing NAs



Possible Solutions – Single Imputation



Possible Solutions – Multiple Imputation



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- + easy to implement
- + the knowledge of the data collector that goes into the process of creating appropriate imputes
- increased running time

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Prior- & Posterior Distribution

$$\pi(\vartheta|Y_{obs}, D) \equiv \pi(\vartheta|Y_{obs}) = constant \times \pi(\vartheta) \times f(Y_{obs}|\vartheta)$$

Expected Value & Variance

3.3 Proposition: (Approximated Expected Value and Variance)

The expected values of ϑ can be approximated as

$$E_{\vartheta}(\vartheta|Y_{obs}) \approx \bar{\vartheta},$$

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$$extstyle extstyle Var_{artheta}(artheta|Y_{obs}) pprox rac{1}{D} \sum_{d=1}^{D} extstyle Var_{artheta}(artheta|Y_{mis}^{(d)},Y_{obs}) + rac{1}{D-1} \sum_{d=1}^{D} [E_{artheta}(artheta|Y_{mis}^{(d)},Y_{obs}) - ar{artheta}]^2.$$

Within- and Between Variability

3.4 Definition: (Within- and Between Variability)

The summands of Prop. (3.3) can be denoted as

$$\hat{W} := \frac{1}{D} \sum_{d=1}^{D} Var_{\vartheta}(\vartheta|Y_{mis}^{(d)}, Y_{obs})$$

$$\hat{B} := \frac{1}{D-1} \sum_{d=1}^{D} [E_{\vartheta}(\vartheta | Y_{mis}^{(d)}, Y_{obs}) - \bar{\vartheta}]^2 = \frac{1}{D-1} \sum_{d=1}^{D} (\hat{\vartheta}_d - \bar{\vartheta})^2.$$

Asymptotic Distribution and finite Imputations Correction

3.5 Corollary:

Let $(\hat{\vartheta}_{(d)})_{n\in\mathbb{N}}$ be a sequence of random variables, that are i.i.d. with $\sigma^2 = Var(\hat{\vartheta}_{(1)}) = \hat{B} + \hat{W} < \infty$ and $\mu = E(\hat{\vartheta}_{(1)}) = \vartheta$. If $\hat{\vartheta}_{(d)}$ is a random vector and $\hat{\vartheta}_{(1)}, \hat{\vartheta}_{(2)}, \hat{\vartheta}_{(3)}, \dots$ i.i.d., then for $D \longrightarrow \infty$, $\bar{\vartheta}$ is distributed as:

$$\bar{\vartheta}^{\mathsf{as}} \mathcal{N}(\vartheta, \hat{B} + \hat{W}).$$

Asymptotic Distribution and finite Imputations Correction

3.6 Proposition: (Total Variance for finite D)

The total variance for finite D can be written as

$$\hat{V}_D := (1 + D^{-1}) \hat{B} + \hat{W}.$$

For $D \longrightarrow \infty$ we get $\hat{V} := \hat{B} + \hat{W}$.

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The Algorithm

- 1. **Start.** Select an initial number of imputed datasets, D_0 , $\bar{\vartheta}_{D_0} = \sum_{i=1}^{D_0} \hat{\vartheta}_i/D_0$
- 2. **Update.** For $D > D_0$,

$$\bar{\vartheta}_{D+1} = \frac{D\,\bar{\vartheta}_D + \hat{\vartheta}_{D+1}}{D+1}$$

- 3. **Distance.** Compute: $d_{D+1} = d(\bar{\vartheta}_{D+1}, \bar{\vartheta}_D)$ using an appropriate distance.
- 4. Stopping rule. $d_j < \varepsilon$ for $j = D + 1, ..., D + k_0$

(Nassiri et al., 2020)

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Simulation Set Up

Settings:

- *n*-dimensional random vector: $\mathbf{Y}_i \sim N(\mu \mathbf{1}_n, \sigma^2 I_n + \tau J_n)$
- 100 random draws
- create missing data with mice
- create imputed data sets with Amelia
- variate the following parameters: Missing data percentage, ϱ , ε , k_0

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The Models:

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The Models:

- (i) Compound-Symmetry (estimated parameters: μ , σ^2 , τ)
- (ii) Logistic Regression (estimated parameters: β_1 , β_2 , β_3)

Simulation Results

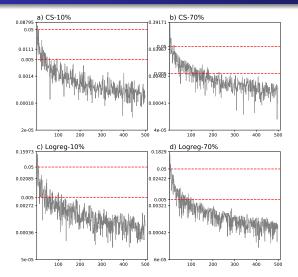


Figure: Convergence rates of the distances for CS and Logreg for $\sigma^2 = 0.25$, $\rho = 0.1$, $k_0 = 5$ and $\beta = (0.2, -2, 0.5)^T$.

Simulation Results

$k_0 = 1$								
Model	ρ	ε	Mean	SD	$\mu(\beta_1)$ MAD	$\sigma^2(\beta_2)$ MAD	$\tau(\beta_3)$ MAD	
CS-10%	0.1	0.005	25.55	10.11	0.02	0.02	0.01	
		0.05	4.98	1.66	0.02	0.01	0.01	
	0.9	0.005	12.86	4.79	0.14	0.02	0.29	
		0.05	3.7	1.01	0.12	0.01	0.26	
CS-70%	0.1	0.005	53.58	16.97	0.03	0.02	0.01	
		0.05	10.28	3.52	0.03	0.02	0.01	
	0.9	0.005	25.42	9.33	0.13	0.01	0.26	
		0.05	5.72	2.49	0.12	0.02	0.25	
Logreg- 10%	0.1	0.005	22.57	9.01	0.11	0.14	0.06	
		0.05	4.82	1.6	0.10	0.13	0.05	
	0.9	0.005	22.16	9.26	0.11	0.15	0.11	
		0.05	4.93	1.79	0.1	0.16	0.11	
Logreg- 70%	0.1	0.005	22.21	8.57	0.1	0.14	0.06	
		0.05	4.91	1.46	0.1	0.15	0.05	
	0.9	0.005	24.45	9.92	0.1	0.17	0.11	
		0.05	4.65	1.48	0.1	0.15	0.11	

(a) Validation	steps:	k_0	=	1
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$k_0 = 5$							
Model	ρ	ε	Mean	SD	$\mu(\beta_1)$ MAD	$\sigma^2(\beta_2)$ MAD	$\tau(\beta_3)$ MAD
CS-10%	0.1	0.005	65.36	19.83	0.02	0.01	0.01
		0.05	7.73	2.67	0.02	0.01	0.01
	0.9	0.005	42.42	17.87	0.12	0.01	0.29
	0.5	0.05	5.36	2.43	0.12	0.01 (0.23
	0.1	0.005	152.23	27.11	0.02	0.01	0.01
CS-70%		0.05	19.06	4.47	0.02	0.01	0.01
C3-1076	0.9	0.005	91.55	26.09	0.11	0.02	0.24
	0.5	0.05	12.94	4.85 0.12	0.01	0.28	
Logreg- 10%	0.1	0.005	57.61	18.04	0.1	0.14	0.06
		0.05	6.52	2.42	0.1	0.12	0.06
	0.9	0.005	57.88	20.02	0.11	0.14	0.1
	0.3	0.05	7.56	3.43		0.12	
Logreg- 70%	0.1	0.005	60.93	17.99	0.1	0.14	0.05
		0.05	7.04	2.94	0.11	0.14	0.06
	0.9	0.005	60.7	22.02	0.11	0.16	0.11
	0.9	0.05	7.49	2.85	0.11	0.15	0.1

(b) Validation steps: $k_0 = 5$

Figure: Mean, SD and their mean absolute deviation from the true parameter (β_i corresponds to the Logreg model and μ , σ^2 , τ the CS model) for selected D given $\sigma^2=0.25$ and different values for ε and ϱ using the Mahalanobis distance with $S=\hat{V}$.

Thank you for your attention!

References

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