POLS/CS&SS 503: Advanced Quantitative Political Methodology

MISSING DATA

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Methods of Dealing with Missing Data

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Types of Missingness

- MCAR Missingness completely at random
- MAR Missingness at random
- MNAR Missingness that depends on unobserved variables, or NI Non-ignorable missingness

Funamental Problem with Missing Data

Cannot tell from data alone whether missingness is MAR or MNAR.

What we will cover and not cover

- Covering: MCAR
 - * Missing values in \boldsymbol{X}
 - · Methods: listwise-deletion, multiple imputation
- Not-covering: MNAR models
 - Selection models
 - Censoring, Truncation

Methods of Dealing with Missing Data

Methods

- Complete case (Listwise deletion)
 - Consistent and valid inferences when MCAR (or MAR but missingness does not depend on the dependent variable)
 - Even in MCAR, inefficient
- Available case (pairwise deletion):
 - E.g. Covariance matrix. Calculate $\sum_i (x_{i,j} \bar{x}_j)(x_{i,k} \bar{x}_k)$ for all obs in which $x_{i,j}, x_{i,k}$ are not-missing, regardless of missingness of other variables.
 - Does not work for all analyses
 - Can result in nonsensical results
- Unconditional Mean Imputation (Mean substitution)
 - preserves mean of variables; reduced variance
 - attenuates relationships between variables
 - overstates certainty—increases "effective" sample size and distorts inference

Overview of Multiple Imputation



When is Listwise Deletion Preferable to MI?

- 1. All of the following need to hold
 - Analysis model is conditional on \boldsymbol{X} and correctly specified
 - There is NI missingness in \boldsymbol{X}
 - Missingness in X is not a function of Y, and unobserved variable affecting $Y \mbox{ do not exist}$
 - Number of observations after deletion is large
- 2. Know X well enough that we don't trust it to impute, but trust it enough to analyze Y
- 3. Rarely would you prefer listwise deletion to multiple imputation

Multiple Imputation Estimator Combines Individual Estimates

Given $B_j^{(1)}, \ldots, B_j^{(g)}$, and SE $(B_j^{(1)}), \ldots,$ SE $(B_j^{(g)})$ from g imputations: Estimate for single coefficients is:

$$\begin{split} \text{Point Estimate} \qquad & \tilde{\beta}_j = \frac{\sum_{l=1}^g B_j^{(l)}}{g} \\ \text{Std. Error.} \quad & \tilde{\text{SE}}\left(\tilde{\beta}_j\right) = \sqrt{V_j^{(W)} + \frac{g+1}{g}V_j^{(B)}} \\ \text{Within Imputation Variance} \qquad & V_j^{(W)} = \frac{1}{g}\sum_{l=1}^g \text{V}(B_j^{(l)}) \\ \text{Between Imputation Variance} \qquad & V_j^{(B)} = \frac{1}{g-1}\sum_{l=1}^g \left(B_j^{(l)} - \tilde{\beta}_j\right)^2 \end{split}$$

where $\tilde{\beta}_j$ distributed t with complicated d.f. (see Fox, 564)

Why we don't need to run many imputations

Relative efficiency of multiple imputation

$$RE(\tilde{\beta}_j) = V(\tilde{\beta}_j^{MLE}) / V(\tilde{\beta}_j^{MI}) = \frac{g}{g + \gamma_j}$$

where γ_{j} is the relative rate of missing information

$$\gamma_j = \frac{R_j}{R_j + 1} \qquad \qquad R_j = \frac{g + 1}{g} \times \frac{V_j^{(B)}}{V_j^{(W)}}$$

Main point!

Suppose $R_j=\gamma$, then with g=5 iterations, then efficiency is

$$\frac{5}{5+0.5} = 0.91$$

Advice on Missing Data

- Include all relevant variables in the imputation; at least all used in the estimation, including the dependent variable.
- Even if data are not multivariate normal, multivariate normal works okay.
- Transform data to approximate normality (Amelia has options)
- See TSCS extensions in Amelia
- Post-hoc adjustments okay. Impute naively and adjust, e.g.round to integers, or 0/1.
- If need to save time, work with a single iteration until "final" analysis.
- Potential problems: complex interactions between variables
- Try default methods; they often work.
- If not ...
 - Multiple Chained Equations: mice, mi packages
 - Hot-deck imputation
 - Full Bayesian models

Methods of Dealing with Missing Data

- · Gelman and Hill, Ch. 25 "Missing Data Imputation"
- Fox, Ch 20 "Missing Data in Regression Models"
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 "Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Imputation." *American Political Science Review* null (01): 49–69. http://journals.cambridge.org/article_S0003055401000235 (May 19, 2015).