Workshop on Integrative Data Analysis

Using Imputation to Enhance Multiple Iterations of HINTS Data

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Outline

- Missing Data Principle
  - Missing data mechanisms
  - Basic principles for imputing missing data
- Applications
  - Impute missing data for income
  - Generate synthetic data for variables for which data are not collected at certain iterations - Use the internet to look for health information for self
- Concluding Remarks

Item Missing Data

ID	Design Variables	X	Y	Z
1	O	O	O	O
2	O	O	O	M
3	O	O	M	M
4	O	O	M	O
	O	O	O	O
⋮	O	O	O	O
	O	O	M	O
n	O	O	O	M

O: Observed
M: Missing

Complex Survey Design Variables:

- Stratum
- Cluster or Replicate Weights
- Survey Weights

Missing Data Mechanisms

- Missing Completely At Random (MCAR)
  - Missingness doesn't depend on anything.
  - Unbiased using deletion approach, but less efficient
- Missing At Random (MAR)
  - Missingness doesn’t depend on the missing data, but can depend on the observed data
  - Unbiased if MAR is accounted for properly
- Not Missing At Random (NMAR)
  - Missingness depends on the missing data
  - Need to model missingness

How to determine the missing mechanism

- MCAR test for multivariate normal data
  - *Little R.J., JASA 1988*
- Unverifiable for MAR and NMAR because we don't know the missing data
  - Based on theoretical and/or substantive knowledge
- MAR works reasonably well for most applications

Imputation Under MAR

- Fill in missing values with plausible values using an imputation model
- Create a MAR situation by modeling covariates that are predictive to
  - Outcome that is subject to missing (M1)
  - Probability of missingness in outcome (M2)
- M1 is more useful than M2 in bias reduction
  - *Little, R.J. and Vartivarian, S., Survey Methodology, 2005)*

Single Imputation

- One imputed value for each missing observation
- Treat imputed values as if they were the observed, thus standard errors tend to be underestimated
- Remedy: Resampling procedures to incorporate imputation uncertainty in variance estimation
  - *Bootstrap (Efron, The Annals of Statistics 1979)*
  - *Jackknife (Miller, Biometrika 1974)*
  - Adjusted versions for simple random samples

Traditional Single Imputation Methods

- Mean substitution
  - Mean of observed data for all missing data
- Regression substitution
  - Predictive value from a regression model
- Stochastic regression substitution
  - Add random error to predictive value
- Hot deck (vs. Cold deck)

Multiple Imputation

- Generate imputed values
  - Frequentist approach: predict missing values, then add random error drawn from its residual distribution
  - Bayesian approach: randomly draw from the posterior predictive distribution of the variable
  - Estimate values explicitly or through MCMC
- Repeat multiple times
- Each imputed data is analyzed using standard statistical procedures separately
- Combine multiple estimates using a simple rule

Combining Rule

- *Rubin D., "Multiple Imputation for Nonresponse in Surveys", Wiley & Sons 1987, Chapter 3*

Point: $\bar{q} = \sum_{i=1}^{M} q_i \Big/ M$

where, q_i is the estimate from analyzing each imputed data d_{i}, i=1,2,…,M, and M is the number of imputation

Variance: $T = \bar{u} + \left(1 + \frac{1}{M}\right) * b$

where, $\bar{u}$ is the average of within imputation variance

b is the between imputation variance.

Validity of Multiple Imputation

- Depends on how imputation is carried out
- Adequately fit predictive model
- Model reflects MAR assumption
- “Congenial” to the analytic model: model assumptions are compatible
  - *Meng X.L., Statistical Science 1994*

Validity of Multiple Imputation cont’

- Assumptions are compatible
  - More relaxed assumptions → Less efficient
  - More strict assumptions → More efficient
- Assumption are not compatible
  - Omit an important term → biased (attenuation)
  - Include an unrelated term → unbiased but less efficient
- Imputation model need to be general to incorporate known and unknown statistical terms that may be included in an analytic model

Application 1

Imputing Item Missing Income Data
HINTS4 Cycle 1

Item Missing Data at a Glance

Background Variables	Missing Obs (N)	Unwgted Missing Rate (%)
Age	68	1.7
Occupation	160	4.0
Marital Status	111	2.8
Education	85	2.1
Race/Ethnicity	220	5.6
Rent or Own Home	89	2.2
Comfortable Spk English	155	3.9
U.S. Born	47	1.2
Income	401	10.1

Weighted Sequential Hot Deck Imputation

- *Cox, B.G., ASA Proceedings 1980, Cox, B.G. and Folsom, ASA Proceedings 1981*
- Substitute the missing value using response from a donor who is similar to the recipient
- Means estimated using imputed data match weighted means using observed data in expectation
- *Not depends on the distribution of outcome, thus less sensitive to model failure*
- Variations of hot deck: random hot deck, predictive mean, predictive propensity, etc.

Select Covariates

- Select important covariates associated with
  - Income and/or Probability of missing income
  - Race/ethn, Education, Renter/Owner, Speak English, Nativity
  - Implemented in SUDAAN Hotdeck Procedure
- Records with missing data on covariates are not imputed
- Have the option for multiple imputation which is not ‘proper’ because the same donor pool is repeatedly used and variance is underestimated
- Modified by adding a Bayesian Bootstrap procedure before each imputation

Application 2

Data Enhancement: Synthetic Data for Variables not Collected in a Iteration of HINTS

Motivation

- Concern over response burden and data quality
- Not all items are asked in every iteration
- Limit the usefulness of the data for analyzing temporal trends
- A solution is to use imputation method to recover such ‘missing’ information based on reasonable model assumptions

Item Comparability

- Pattern of item comparability across all iterations
- Same inference population
- Survey designs vary slightly: sampling frame, design factors, and data collection mode

	Design Variables	X	Y	Z	T	U	V	W
Iteration 1 (2003)	O	O	O	O	M	O	M	M
Iteration 2 (2005)	O	O	O	M	O	M	O	M
Iteration 3 (2007)	O	O	M	O	O	M	M	O
Iteration 4 (2012)	O	O	O	O	O	O	O	O

4’s 3’s 2’s

O: Observed; M: Not Asked and Treated as Missing

Example: Have you used the Internet to look for health or medical info. for self in the past 12 months?

- Not asked in 2007
- Large gap of 7 yrs btwn iteration 2 and 4
- Basic idea is to
  - Stack data from all iterations to create a concatenated data set
  - Turn to a typical missing data problem
  - Treat the 2007 data as missing
  - Fill in with multiple imputes

	Design Variables	Year	X	Y
Iteration 1 (2003)	O	2003	O	O
Iteration 2 (2005)	O	2005	O	O
Iteration 3 (2007)	O	2007	O	M
Iteration 4 (2012)	O	2012	O	O

Question: Have used the Internet to look for health or medical info. for self in the past 12 months?

- Missing At Random (MAR)?
- Missing data may depend on time, thus making MAR is a strong assumption
- In this illustration, we hope to use the correlations between X and Y, and Time and X to recover the not otherwise missing information on the correlation between Time and Y.

Distribution of Outcome

Year of Data Collection	N		% of Look for Health Info. for Self	
	Use internet	Missing	Point	S.E.
HINTS 1 (2003)	3,982	8	50.6	1.0
HINTS 2 (2005)	3,244	95	56.9	1.3
HINTS 3 (2008)	5,078	5,078	-	-
HINTS 4 (2011)	2,914	14	77.6	1.3

Note: Complex Survey Design Features are Incorporated in all Estimates.

Covariates

Demographics

- Age
- Gender
- Race/Ethnicity
- Interview in Spanish
- Marital Status
- Rural

Health Status

- Overall Health Status
- BMI
- Ever Had Cancer
- Family Member Ever Had Cancer.

Socioeconomics

- Education
- Employment Status
- Household Income

Health Care and Cancer Communication

- Health Insurance Coverage
- Seek Health Care For Self
- Seek Cancer Information

Internet Use

- Internet Use
- Use The Internet For Medication Purchase
- Use The Internet For Participating In Online Health Group
- Use The Internet For Communications With The Doctors
- Use The Internet To Look For Health and Medical Information For Others

Imputation Method

- Most covariates have missing data
  - Most ~ 1-5%, Max 14% for income
- Item missing data are simultaneously imputed together with the iteration missing data
- Sequential regression multivariate imputation (SRMI)

– Raghunathan T.E., Lepkowski J.M. et al, Survey Methodology 2001

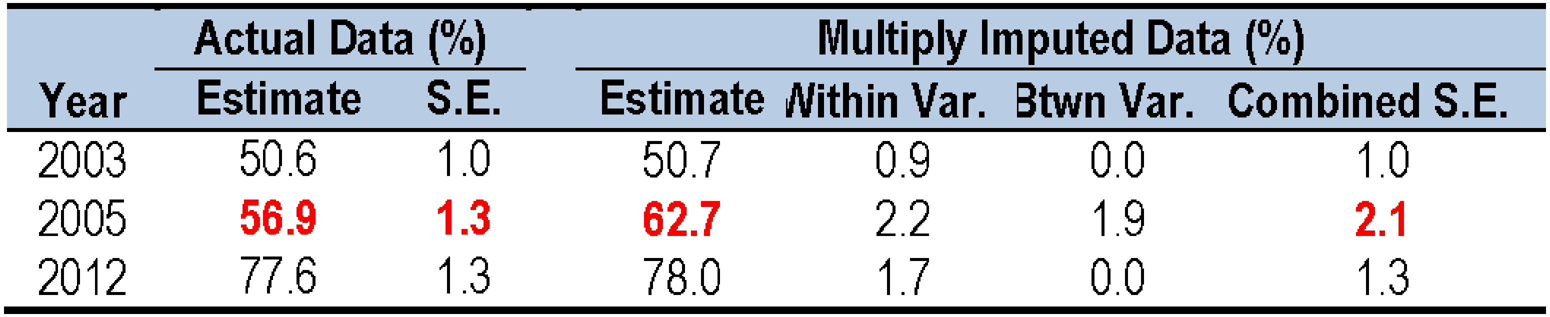
– IVEware in SAS, MICE in R, ICE in Stata

Sequential regression multivariate imputation

- Different conditional multivariate regression model depends on the type of outcome
  - Continuous: linear model based on normality
  - Binary: logistic model
  - Categorical: multinomial model
  - Count: Poisson model
- Handle skip pattern and higher order terms
  - For example, internet activity related items are only imputed for those who use the Internet
  - Interaction terms

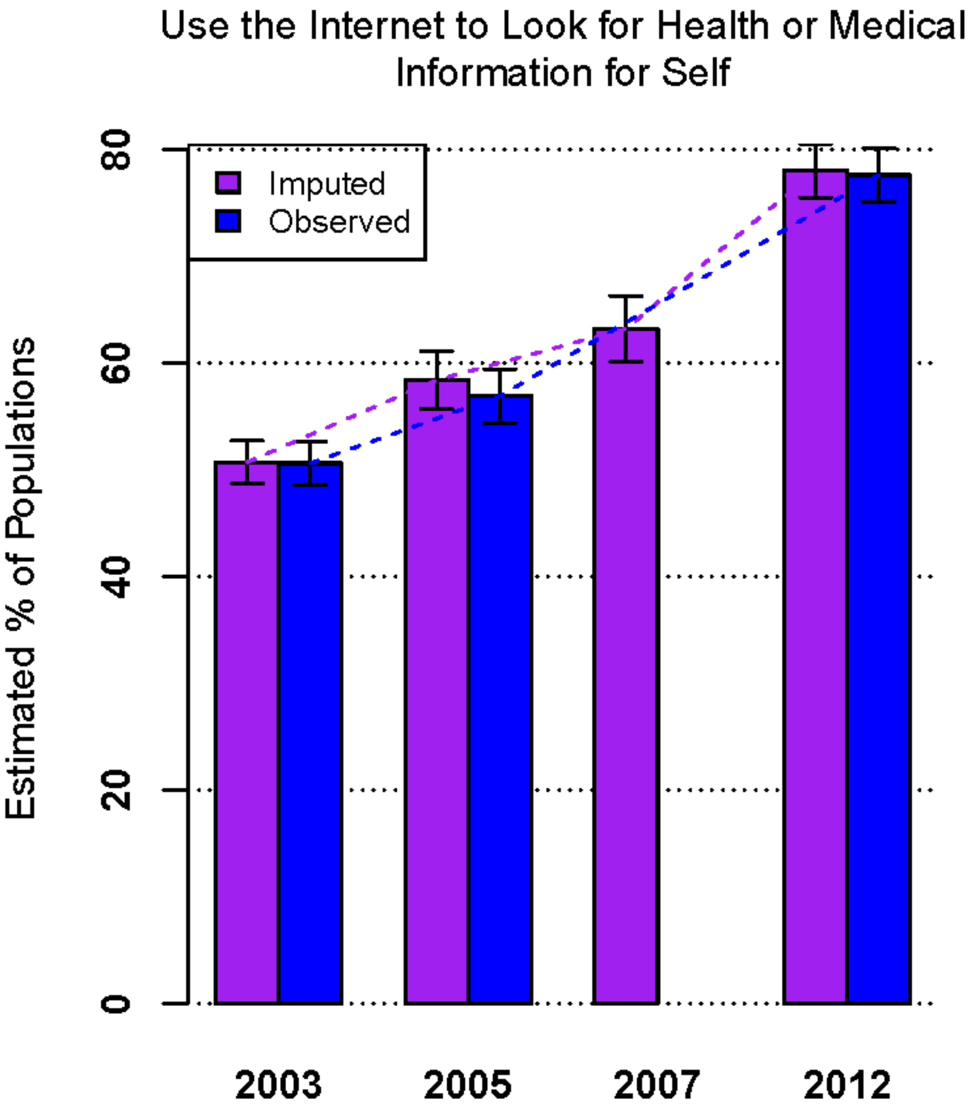
Model Validation

- Simulated data using data from 2003, 2005, and 2012
- Delete outcome data for 2005
- Build imputation model to impute 2005 data
- Compare to the original 2005 estimates
- Similar estimates suggests valid imputation models; Large differences warrants further model improvements



	Actual Data (%)		Multiply Imputed Data (%)			
Year	Estimate	S.E.	Estimate	Within Var.	Btwn Var.	Combined S.E.
2003	50.6	1.0	50.7	0.9	0.0	1.0
2005	**56.9**	**1.3**	**62.7**	2.2	1.9	**2.1**
2012	77.6	1.3	78.0	1.7	0.0	1.3

Final Analysis Results



Thoughts on Future Survey Planning

	Design Variables	Year	X	Y
Iteration 1 (2003)	O	2003	O	O
Iteration 2 (2005)	O	2005	O	O
Iteration 3 (2007)	O	2007	O	O
	O		O	M
Iteration 4 (2012)	O	2012	O	O

A random subsample (10-20% of sample)

- This current approach is limited by the lack of information on the correlation between time and Y for 2007
- Improved by building a bridge btwn Time and Y by measuring Y on a random sample in 2007
- Some cost in precision, but large gain in data availability.

Concluding Remarks

- Imputation method is a flexible tool for enhancing the data usability by recovering missing information
- Key issue is to model reasons for missing data, if not ignorable.
- “General” model assumptions to protect against assumption failure
- Model diagnosis also apply to imputation to ensure an adequate fit

Questions and Suggestions

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More details on SRMI approach

SRMI

- Sort variables in increasing order by the amount of missing data
- Each variable is sequentially imputed
  - Step 1: impute 1st variable using fully observed sample
  - Step 2: impute 2nd variable on fully observed plus imputed sample in Step 1
  - Step 3: cycle through all variables with missing data completes the first iteration
  - Step 4: repeat Step 1-3, but conditional on all variables, each time use updated imputed values
- Typically 5-10 iterations are sufficient

SRMI: Simple Illustration

ID	Design Variables	X	Y	Z
1	O	O	O	O
2	O	O	O	M
3	O	O	M	O
4	O	O	M	M
5	O	O	O	M

For Iteration 1

1. Fit $Y \sim X$, e.g. $E(Y|X) = X\beta + \epsilon$, and generate imputed values $(\hat{y}_3, \hat{y}_4)$ use this model
2. Fit $Z \sim X + \binom{Y}{\hat{Y}}$, generate imputed values $(\hat{z}_2, \hat{z}_4, \hat{z}_5)$ use this 2nd model

For subsequent Iterations

1. Fit $Y \sim X + \binom{Z}{\hat{Z}}$, and generate updated values $(\hat{y}_3, \hat{y}_4)$
2. Fit $Z \sim X + \binom{Y}{\hat{Y}}$, and generate updated values $(\hat{z}_2, \hat{z}_4, \hat{z}_5)$