Survey Inference with Incomplete Data

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Goals

- Importance of dealing with missing data in national surveys
- Weighting and Imputation as a general purpose solutions for missing data
- Why we need multiple imputation?
- Enhance the use of all available information for the creation of public-use datasets
- Design implications and future directions
- Other two talks provide several applications and software related issues

Missing Data

- A pervasive problem and is getting worse
  - Response rates are generally declining in all surveys (unit nonresponse)
  - Subjects who are willing to participate in surveys hesitate to provide all information (item nonresponse)
- Threat to quintessential notion of a representative sample from the population
  - Leading to bias of unknown direction and magnitude
  - Loss of efficiency

What is the reasons for missing data? (Missing Data Mechansim)

X	Y_{obs}
X	?

Missing Completely at random (MCAR)

$$Y_{obs} \overset{distribution}{=} ?$$

Missing at random (MAR)

$$Y_{obs} \mid X = x \overset{distribution}{=} ? \mid X = x$$

Not Missing At random (NMAR)

$$Y_{obs} \mid X = x \overset{distribution}{\neq} ? \mid X = x$$

Analysis

- Most complete-case (available case) analyses are valid under MCAR assumption
  - Default in most software packages
  - Unreasonable assumption
- MAR assumption is much weaker
  - Depends on how good are the X as predictors of Y
  - Non-testable assumption
- NMAR
  - Need explicit formulation of differences between respondents and non-respondents
  - Need External data
  - Non-testable assumption

Weighting (Unit Nonresponse)

- MAR assumption
- Group respondents and non-respondents based on X (Adjustment Cells)
- Attach weights to respondents in each group to compensate for non-respondents in the same group
  - Example : White females aged 25-35 living in Southwest Region

100 in sample

80 nonrespondents

20 nonrespondents

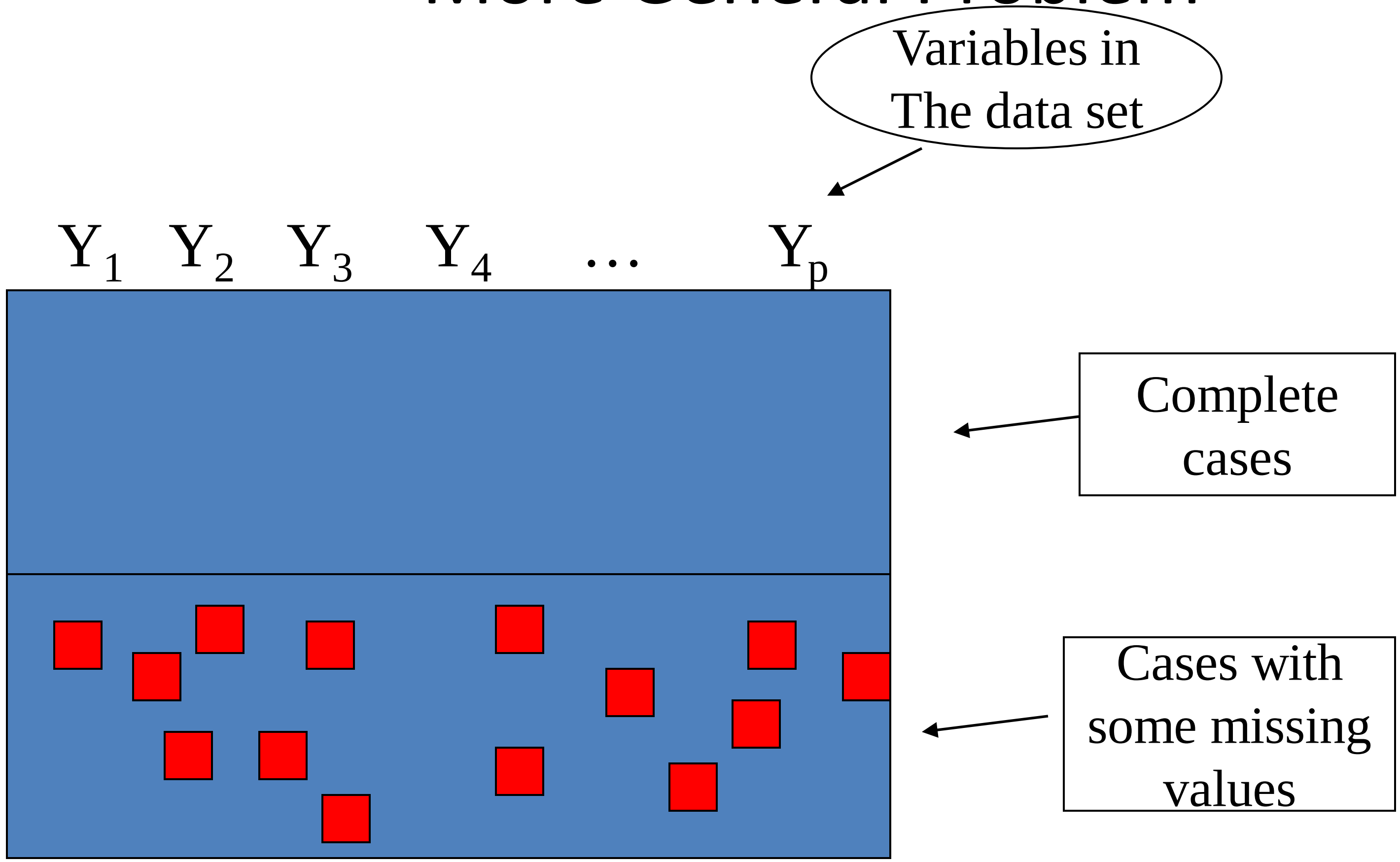
pr(response in cell) = 0.8

response weight = 1.25

Formation of Adjustment Cells

- Need X that are predictive of Y (or a collection of Y's in a multi-purpose survey)
- Using X's that are not predictive of Y will not reduce bias but will increase variance
- Current survey practice focuses too much on finding X's that differentiate respondents from non-respondents but predictive power of X for Y is more critical
- Need to think proactively in collecting X's that are related to multiple Y's through design modification

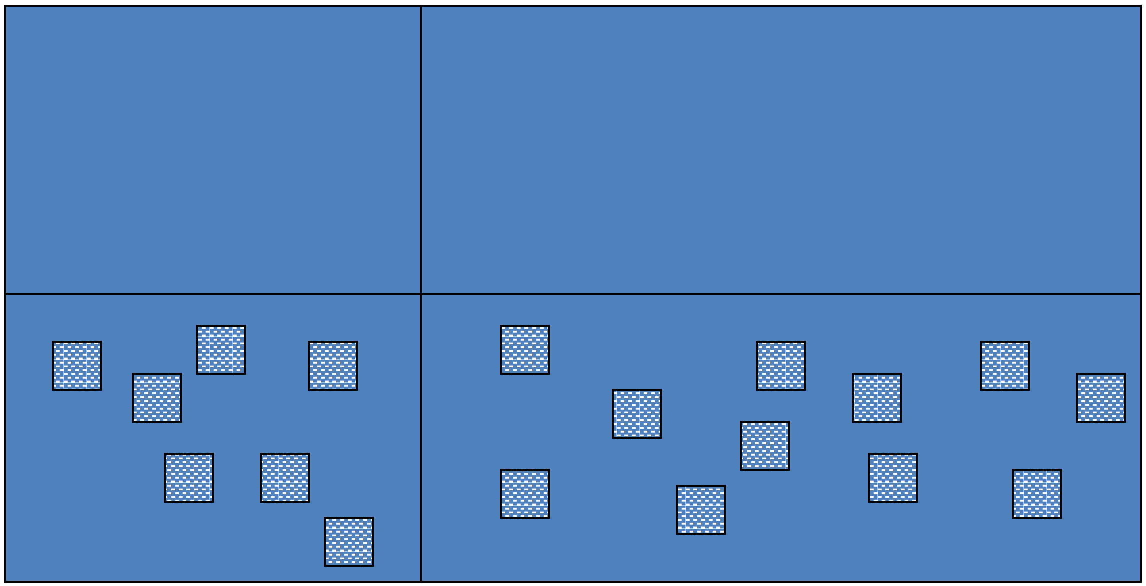
More General Problem



D_{obs} = Observed data:

D_{miss} = Missing data:

Imputation



Imputation refers to filling in a value for each missing datum based on other information (e.g., a model and observed data)

$Imputation:$

$Draws\ from\ predictive\ distribution\ \Pr(D_{miss} \mid D_{obs})$

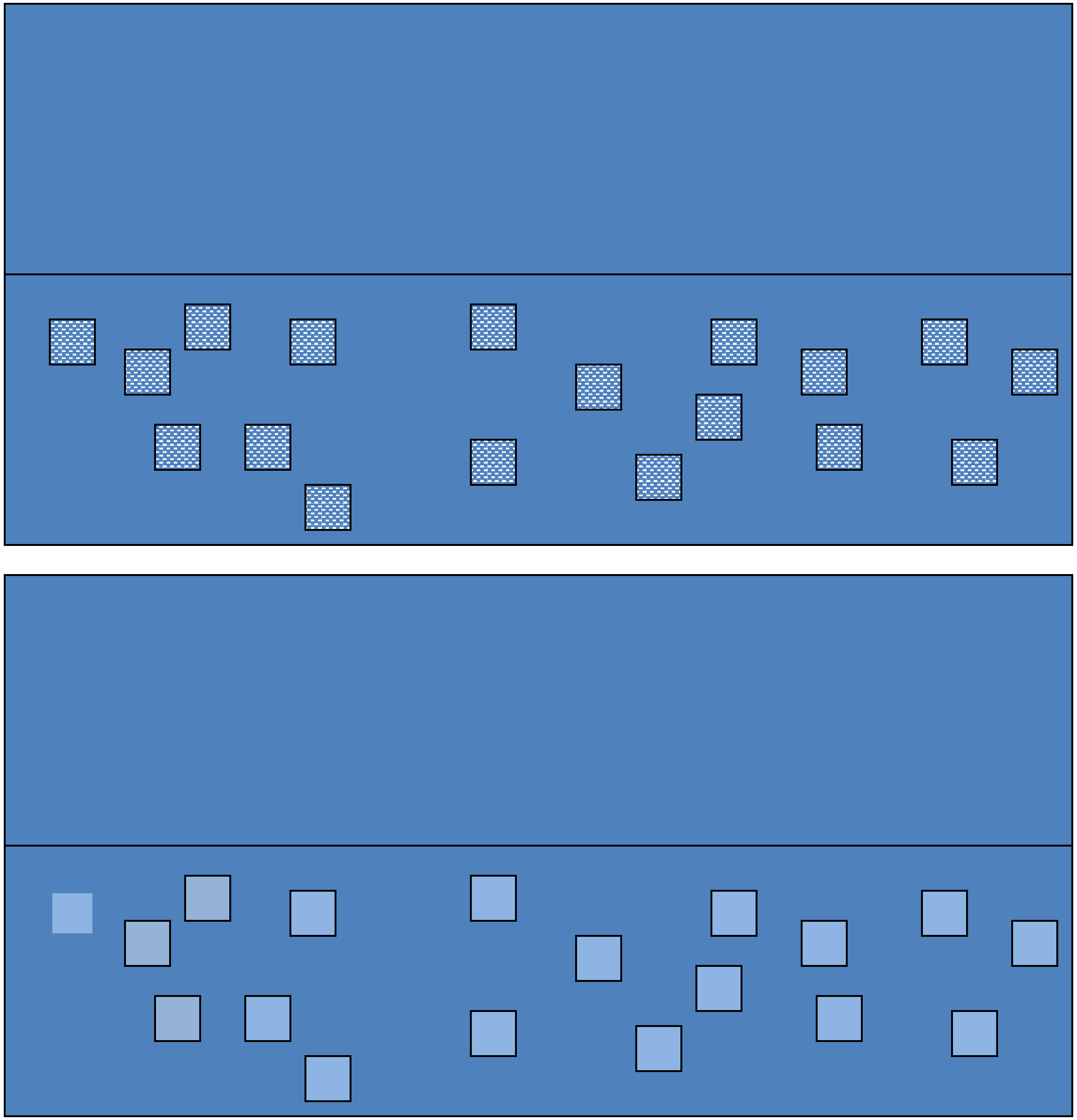
Imputation

- **Typically used for item nonresponse**
- **Benefits of imputation**
  - **Completes the data matrix**
  - **If imputation is performed by a producer of public-use data:**
    - **Missing data are handled comparably across secondary data analyses**
    - **Information available to the data producer but not the public can be used in creating imputations**

Imputation

- Important issues:
  - Imputations are not real values
  - Single imputation fed into standard software package treats the imputed values as real values
  - Underestimates the variance estimates due to ignoring uncertainties associated with imputes
- Goes against our “culture” where approximations of the sample designs (collapsing, combing PSUs, strata etc) avoid underestimation

Multiple Imputation



Repeat Imputation process several times (say M times)

Uncertainty due to imputation is captured by the "between Imputed Data" Variation

Analysis of Multiply Imputed Data

- Analyze each imputed data separately

$$Estimate: e_1, e_2, \ldots, e_M$$

$$Variance(= SE^2): v_1, v_2, \ldots, v_M$$

- Combine Estimates

$$\overline{e} = (e_1 + e_2 + \ldots + e_M)/M$$

- Combine variances

$$\left.\begin{aligned} \overline{v} &= (v_1 + v_2 + \ldots + v_M)/M \\ b &= \mathrm{var}(e_1, e_2, \ldots, e_M) \end{aligned}\right\} \quad T = \overline{v} + (1 + 1/M)b$$

Software for Creating Imputations

- SAS
  - PROC MI
  - User-developed IVEWARE (www.isr.umich.edu/src/smp/ive)
- Stata
  - ICE
- R
  - MICE
  - MI
- SOLAS
- AMELIA
- SPSS
- Stand-Alone
  - SRCWARE (www.isr.umich.edu/src/smp/ive)
  - NORM
  - PAN (www.stat.psu.edu/~jls)
  - CAT

Another good source:
www.multiple-imputation.com

Software for Analysis of Imputed Data

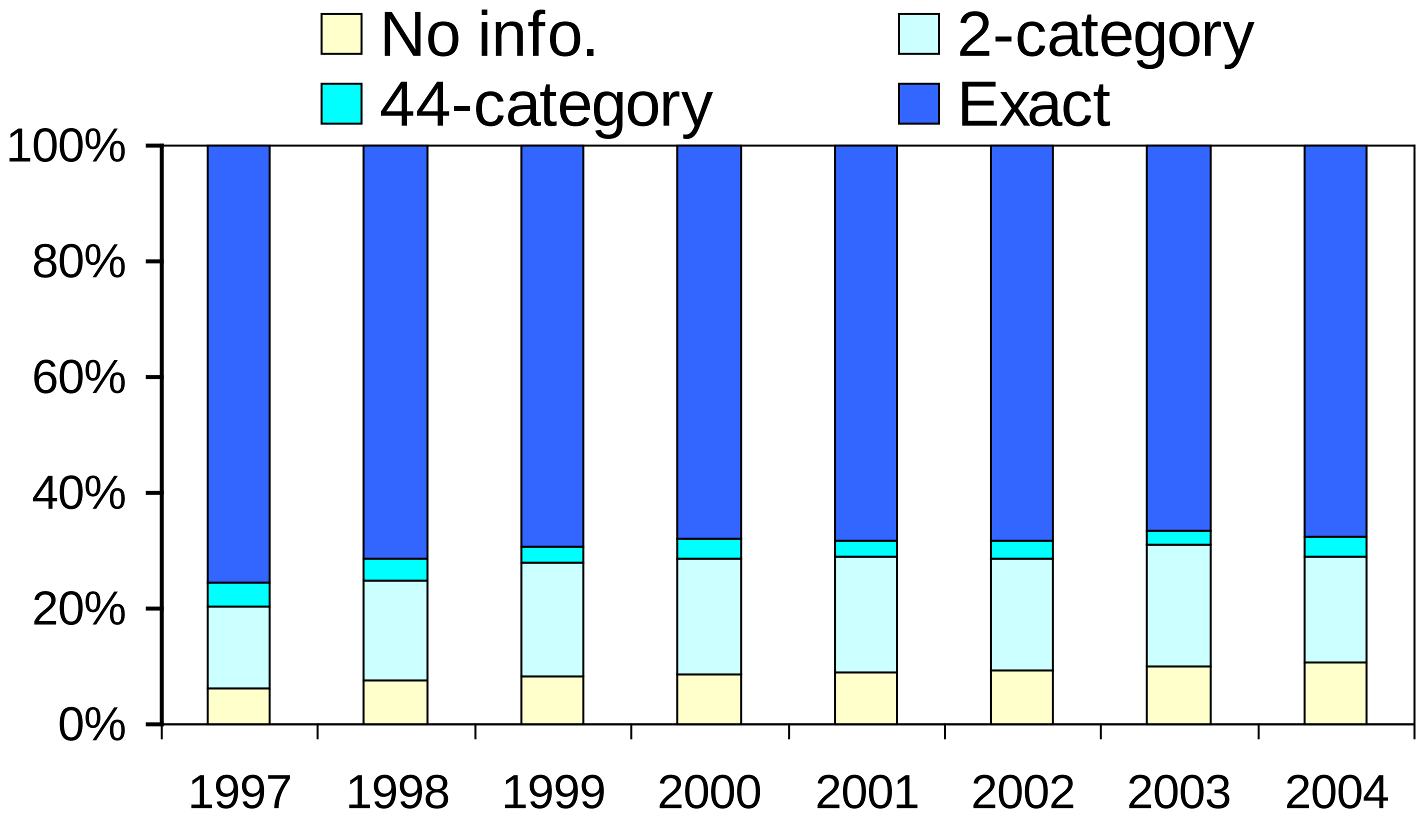
- SAS
  - MIANALYZE
  - IVEWARE
- SUDAAN
- STATA
  - MICOMBINE
  - MI
    - Newest version has excellent interface
- R (user defined macros)
- SRCWARE (Stand alone)

MULTIPLE IMPUTATION FOR MISSING INCOME DATA IN THE NATIONAL HEALTH INTERVIEW SURVEY

- Schenker, Raghunathan, Chiu, Makuc, Zhang, and Cohen (2006, JASA)
- National Health Interview Survey (NHIS)
  - Principal source of information on the health of the civilian non-institutionalized population
  - Data collected at both family and person levels
  - Contains items on health, demographic, and socioeconomic characteristics (e.g., income)
  - Allows the study of relationships between health and other characteristics

NHIS

- **Percent distribution of types of family income responses by year for the NHIS in 1997 – 2004**



Missingness appears to be related to several other characteristics, such as health, health insurance, age, race, country of birth, and region of residence

- **Missing income data multiply imputed for NHIS beginning with 1997**
  - ***M* = 5 sets of imputations of:**
  - **employment status for adults (< 4% missing)**
  - **personal earnings for adults who worked for pay**
  - **family income (and ratio of family income to Federal poverty threshold)**
- **Imputed income files since 1997, with documentation, available at NHIS Web site: www.cdc.gov/nchs/nhis/2008imputedincome.htm**
- **Used adaptation of IVEware**

- Complicating issues handled during imputation
  - Hierarchical structure of data
    - Families and persons
    - Sometimes, one variable (e.g., personal earnings) restricted based on another variable (e.g., whether worked for pay), but both variables missing
    - Imputation within bounds
      - e.g., families for which categories rather than exact dollar values reported for income
- Several variables used as predictors (including design variables)
- Different types (continuous, categorical, count)
  - Small amounts of missingness (mostly $< 2\%$)

Results

- **Estimated percentage of persons of ages 45-64 in fair or poor health, by ratio of family income to Federal poverty threshold: 2001 NHIS**

Ratio to Poverty Threshold	No Imp. (NI)		Single Imp. (SI)		Mult. Imp. (MI)		Ratio of SEs	
	Est.	SE	Est.	SE	Est.	SE	NI ÷ MI	SI ÷ MI
< 1.00	45.6	1.68	39.4	1.34	39.9	1.54	1.09	0.87
1.00 – 1.99	32.7	1.32	29.8	1.03	29.3	1.11	1.19	0.93
2.00 – 3.99	16.1	0.63	16.0	0.51	15.9	0.55	1.15	0.94
4.00+	5.9	0.34	6.1	0.27	6.2	0.30	1.11	0.90

Summary of Multiple Imputation

- Retains advantages of single imputation
  - Consistent analyses
  - Data collector's knowledge
  - Rectangular data sets
- Corrects disadvantages of single imputation
  - Reflects uncertainty in imputed values
  - Corrects inefficiency from imputing draws
    - estimates have high efficiency for modest *M*, e.g. 5
- For this approach to be successful, we need to collect good correlates of variables that are expected to have large amounts of missing values