

Bayesian Data Editing for Continuous Microdata

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Problem Statement

Setting Numerical microdata that may be

- Missing
- Erroneous

Dataset of Interest U.S. Census Bureau's every-five-years Census of Manufactures (CM)

Goal Simultaneously (and multiply) impute edit constraint-satisfying replacements for *both* missing values and erroneous values

Impact

- Improve data quality
- Reduce cost: editing is estimated to consume 20–40% of survey costs

Notation

- i = subject
- j = numerical attribute
- $X_i(j)$ = “true” value of attribute j for subject i
- $Y_i(j)$ = reported value of attribute j for subject i
- $S_i(j)$ = binary error indicator for attribute j for subject i
 - *Conceptually*, $S_i(j) = \mathbf{1}(Y_i(j) \neq X_i(j))$
 - *Operationally*, $S_i(j) = 1$ means that a replacement will be imputed for $Y_i(j)$

Classes of Edit Constraints

Range Constraints $L(j) \leq Y_i(j) \leq U(j)$

Ratio Constraints $Y_i(j)/Y_i(\ell) \leq \alpha_{j,\ell}$ (better as $Y_i(j) \leq \alpha_{j,\ell} Y_i(\ell)$)

Balance Constraints $Y_i(j_1) + Y_i(j_2) + \dots + Y_i(j_\ell) = Y_i(j_m)$

Compatibility Constraints (usually only for categorical data):
 $Y_i(j_1) = y_1$ and $Y_i(j_2) = y_2$ are incompatible

Two Steps in Automated Data Editing

Error Localization Determine (estimate) $S_i(j)$

- Multiple approaches, discussed momentarily

Error Correction Determine (calculate) replacement values for those $Y_i(j)$ for which $S_i(j) = 1$

- Generally, some form of imputation
- Violations of balance edits sometimes resolved by definition (not always a good idea)

This Talk: Compare Three Methods

Fellegi-Holt (FH) (*JASA*, 1976)

- Error Localization: Use optimization algorithm to determine [weighted] minimum number of attributes to impute
- Error Correction: Historically, hot deck or In this talk, constraint-preserving imputation algorithm of Kim, et al. (*JBES*, 2014, to appear)

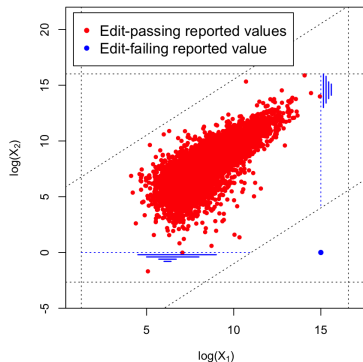
Flag All Active Items (AAI)

- Error Localization: Flag every $Y_i(j)$ that is involved in an edit violation
- Error Correction: Constraint-preserving imputation algorithm of Kim, et al.

Bayesian Editing (BE) Integrate localization and correction

What's Wrong with Fellegi-Holt

- 1 Have to enumerate all implied constraints (otherwise can't be sure that minimization has been achieved)
- 2



Structure of the BE Model

More Notation

- \mathcal{X} = feasible region defined by range and ratio constraints
- T = set of variables that are not “sums” in balance constraints
- $A_i \in \{0, 1, 2, 3\}$ = “nature of errors” indicator for subject i

Model for $\{X_i(j) : j \in T\}$ Mixed multivariate normal restricted to \mathcal{X} : parameters K, μ_k, Σ_k, π

Model for π Dirichlet process (stick-breaking representation)

Model for $\{X_i(j) : j \notin T\}$ Equal to sum of components

Model Structure—2

Model for $A_i|X_i$ May involve parameters ψ , but $f(a|x, \psi) \propto 1$

Model for $S_i|(X_i, A_i)$ May involve parameters ψ , but $f(s|x, a, \psi) \propto 1$

Model for $Y_i|(X_i, S_i)$ $E_i = \{j : S_i(j) = 1\}$ (erroneous components)

- $S_i(j) = 0 \Rightarrow Y_i(j) = X_i(j)$
- $Y_i(E_i)$ uniform on (subset of bounding hypercube) $\setminus \mathcal{X}$

Model for Missingness At the moment, MAR

- $Y_i(j)$ missing $\Rightarrow S_i(j) = *$

Priors The standard noninformative choices

BIG Inference Assumptions

AAI and BE $Y_i \in \mathcal{X} \Rightarrow S_i = 0$

- Tempting interpretation: $Y_i \in \mathcal{X} \Rightarrow X_i = Y_i$
- Safer interpretation: If $Y_i \in \mathcal{X}$, no basis for changing it

AAI $Y_i(j)$ involved in an edit violation $\Rightarrow S_i(j) = 1$

The MCMC

- Gibbs update for all but a few steps
- Data augmentation techniques to ease estimation of truncated normal distributions (O'Malley and Zaslavsky, *JASA*, 2008)
- Simultaneously draw imputed values X and editing indicators S
 - 1 Propose S^* from neighbors of current S using birth-death process
 - 2 Generate X^* given S^* from constrained mixture of normals
 - 3 Accept/reject (X^*, S^*) by Metropolis-Hastings

Structure

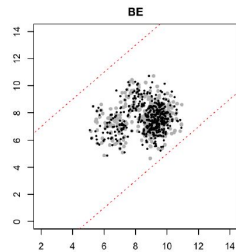
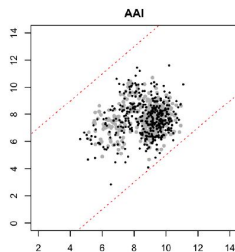
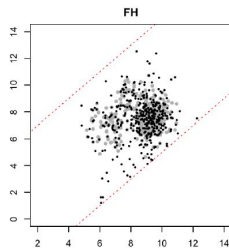
- 9 variables
 - Range constraints for every variable
 - Ratio constraints for some pairs of variables
 - Two balance constraints: $X(4) = X(1) + X(2) + X(3)$ and $X(7) = X(5) + X(6)$
- $n = 2000$ error-free values of

$$(X_i(1), X_i(2), X_i(3), X_i(5), X_i(6), X_i(8), X_i(9))$$

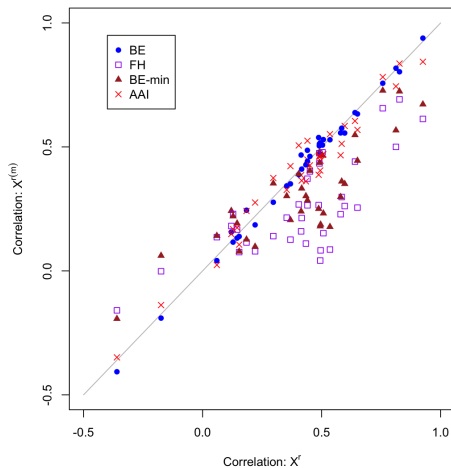
from mixture of normals; calculate $X_i(4)$ and $X_i(7)$ from balance constraints

- For 1000 out of 2000 records, introduce edit-failing records using model (so no mis-specification)
- 5% missingness, CAR
- 500 simulations

Pictorial Results: Data



Pictorial Results: Correlations



Numerical Results: 95% CI Coverage for Population Means

Variable	True X	E-P X	True S	FH	AAI	BE
$X(1)$	95.2	95.4	96.2	90.0	96.2	95.8
$X(2)$	93.0	95.4	95.6	6.4	97.0	95.4
$X(3)$	94.4	95.6	94.0	95.2	97.6	96.2
$X(4)$	93.4	93.0	94.6	96.6	94.8	95.2
$X(5)$	93.8	94.0	94.4	0.0	93.4	92.4
$X(6)$	94.8	94.2	93.8	0.8	97.8	93.0
$X(7)$	94.8	94.4	94.2	10.8	94.4	92.2
$X(8)$	95.0	95.6	94.6	96.6	95.8	93.8
$X(9)$	95.6	92.2	96.4	67.0	94.0	95.4

Numerical Results: Relative Bias for Regression Coefficients

Model $X_i(9) = \beta(0) + \beta(1)X_i(1) + \beta(5)X_i(5) + \beta(9)X_i(9) + \varepsilon_i$

Variable	True X	E-P X	True S	FH	AAI	BE
$\beta(0)$	0.2	0.1	0.3	-2.6	-1.8	0.9
$\beta(1)$	-0.8	-1.6	-0.3	51.7	10.3	-2.9
$\beta(5)$	0.0	0.4	0.3	-41.6	-3.3	1.7
$\beta(9)$	0.2	0.5	-0.3	-0.4	-2.2	-0.4

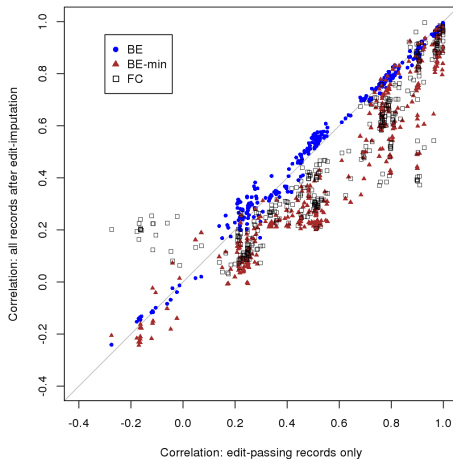
$$\text{Relative Bias} = \frac{1}{|Q|} \left(\frac{1}{R} \sum_{r=1}^R \hat{Q}_r - Q \right)$$

Basics

- Part of Economic Census (most recent data: 2007)
- Example attributes: (logs of) cost of materials, total employment, total value of shipments, . . . (so linear regressions are Cobb-Douglas production functions)
- Industry-specific ratio and balance constraints
- Current method: combination of manual and FH + hot deck (SPEER), labeled FC (Final Census)

Our Study One NAICS code, 1869 establishments, 27 variables, Title 13-protected (so worked in RDC)

Pictorial Results: Correlations



AAI or BE?

Criterion	Winner
Specification of constraints	Tie
Intellectual appeal	BE: borrows more strength
“Right” amount of imputation	BE
Incorporate domain knowledge of errors	BE: prior on S
Estimated distribution of S	BE: posterior distribution
Bayes “shock factor”	AAI
Computational burden	AAI: 10× speed
Information about measurement error	Neither

Unresolved Issues: Specific

- 1 What are the effects of model mis-specification?
- 2 What are the tradeoffs between record-level correctness and inferential correctness?
- 3 Should the same imputation model be used for both missing and erroneous data?
- 4 What about weights?

Unresolved Issues: Broad

- 1 What if administrative data are available?
- 2 Do we need a taxonomy for erroneousness: erroneous completely at random, at random, non-ignorably?
- 3 What difference would it make to have a (good) measurement error model?
- 4 Can we integrate edit, imputation and disclosure limitation?

Acknowledgements and More Information

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Technical Report Kim, Cox, Karr, Reiter, Wang, “Simultaneous Edit-Imputation for Continuous Microdata,” NISS Technical Report 189: <http://www.niss.org/sites/default/files/tr189.pdf> (submitted to *JASA*)

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