Data Integration for Split Questionnaire

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Outline

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Introduction: motivation

Korea Rural Economic Institute (KREI) has been conducted two annual surveys from 2018:

1. Consumer Behavior Survey for Foods (CBSF).
2. Consumer Attitude Survey for Processed Foods (CASPF).

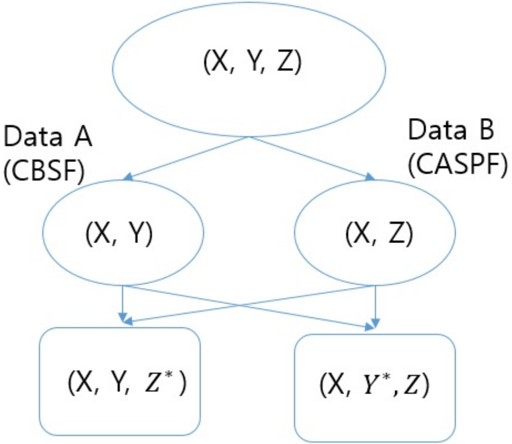
Long-term goal: Split questionnaire survey

Short-term goal: Analysis combining two surveys in micro-level.

For example, interested in $Y \mid Z$:

- (CBSF) Y: Changes in HMR consumption relative to last year.
- (CASPF) Z
  - frequency of dining-out.
  - evaluation on food safety of HMRs (Home Meal Replacements).

Introduction: data structure



Data structure

- X are commonly observed on both A and B.

Introduction: goals

Under our basic setup, interested in

$$(Y_i, X_i) \longrightarrow (Y_i, X_i, Z_i^*) \ \ i \in A,$$

Suffices to know the distribution of Z conditional on Y and X,

$$f(Z \mid Y, X) \propto f_1(Y \mid X, Z) f_2(Z \mid X)$$

Or, to know the conditional distribution of f_1 when f_2 can be correctly estimated from Data B.

Introduction: some poplar methods

1. Conditional independent assumption

$$f(Z \mid Y, X) = f_2^*(Z \mid X)$$

   - f_2^* can be estimated from Data B.
   - Weired if we are interested in a regression of $Y \mid X, Z$.

2. Record Linkage

   - Often there exists common units between two data sets.
   - Require key variables in X such as identification variables or demographic variables.

3. Nearest Neighbor Imputation

   - Find donors using commonly observed X values.
   - Hard to represent the relationship between Y and Z given X.

Fractional Imputation: short review

- Initially proposed by Kalton and Kish (1984) and extensively discussed in Fay (1996).
- Kim and Fuller (2004) and Fuller and Kim (2005) proposed fractional hot deck imputation (FHDI) as a repeated imputation.
- Kim (2011) proposed a parametric fractional as a general tool for missing data analysis. (MCEM)
- Im, Kim, Fuller (2015) investigated a multivariate version of FHDI and the R package 'FHDI' was developed by Im, Cho and Kim (2018).

Fractional Imputation: basic idea

- $E(y_{i,mis} \mid y_{i,obs})$ is approximated by

$$E(y_{i,mis} \mid y_{i,obs}) \cong \sum_{j=1}^{M} w_{ij}^{*} y_i^{*(j)},$$

  - $(y_{i,mis}, y_{i,obs})$ is the (observed, missing) part of y_i.
  - M: a size of imputed values on the unit i
  - $y_i^{*(j)}$: j-th imputed value for $y_{i,mis}$, $j = 1, \ldots, M$.
  - w_{ij}^{*}: fractional weight assigned to the j-th imputed value (vector) of unit i.

- Split the record with missing item into $M(> 1)$ imputed values.
- Assign fractional weights on imputed values.
- The final product is a single data file with size $\leq nM$.
- For variance estimation, the fractional weights are replicated.

Fully Nonparametric FHDI 1

Fully Nonparametric FHDI

1. Both f_1 and f_2 are estimated non-parametrically.
2. Relatively easy to extend for multivariate variables.

Assumption

- All variables are categorical. (Note: can apply categorization for interval data in practice).
- Some of X are instrumental variables for Z.

Fully Nonparametric FHDI 2

(Step 1) Estimate joint cell probabilities $P(X, Z)$ and $P(X_2, Z)$ from data B, where $X = (X_1, X_2)$.

(Step 2) Impute all possible Z values for each observation in data A.

Table: An illustrative example with binary responses

ID	Y	X_1	X_2	Z^*
1	1	1	1	1^*
1	1	1	1	2^*
2	2	2	1	1^*
2	2	2	2	2^*

Fully Nonparametric FHDI 3

(Step 3) Compute fractional weights w_{ij}^*.

E-step

$$
\begin{aligned}
w_{ij}^* &\propto P(Y \mid X, Z^*)P(Z^* \mid X) \\
&\propto \frac{P(Y, X, Z^*)}{P(Z^*, X)} P(Z^*, X) \\
&= \frac{P(Y, X_2, Z^*)}{P(Z^*, X_2)} P(Z^*, X) \quad \text{(Asumption)}
\end{aligned}
$$

- $P(Z^*, X)$ and $P(Z^*, X_2)$ were estimated on data B (Step 1).
- $P(Y, X_2, Z^*)$ is estimated on imputed data A (M-step).
- X_1 in $X = (X_1, X_2)$ plays a role of instrumental variable for identification.
- w_{ij}^* are normalized so that $\sum_j w_{ij}^* = 1$ for all i's.

Fully Nonparametric FHDI 4

(Step 3) Compute fractional weights w_{ij}^*.

M-step: update joint cell probabilities of $P(Y, X, Z^*)$

$$P(Y = y, X = x, Z^* = z) = \frac{\sum_{i,j} w_i w_{ij}^* I(Y_i = y, X_i = x, Z_i^{*(j)} = z)}{\sum_{i,j} w_i w_{ij}^*}.$$

(Step 4) Select M imputed values for each recipient $i \in A$ with the probability proportional to w_{ij}^*.

Note that the current algorithm allows missing values on both data A and data B.

Simulation Study 1

- X_1, X_2 and Z are separately generated from Bernoulli distribution ($p = 0.5$), but linked through a Gaussian copula with the correlation matrix.

$$\begin{pmatrix} 1 & 0.3 & 0.5 \\ 0.3 & 1 & 0.5 \\ 0.5 & 0.5 & 1 \end{pmatrix}$$

- Y is generated from a logit model

$$P(Y = 1 \mid X_1, X_2, Z) = \{1 + \exp(-\beta_0 - \beta_1 X_2 - \beta_2 Z)\}^{-1},$$

  where $\beta_0 = 0$, $\beta_1 = 0.5$ and $\beta_2 = 1$.
- $n = 2,000$ samples with $n_A = 1,000$ and $n_B = 1,000$: (Y, X_1, X_2) in data A and (X_1, X_2, Z) for data B.
- Working model: $Y \mid (X_2, Z)$.

Simulation Study 2

Table: MC results for simulation study 1

	Full		NNI		FHDI		
	EST	SE	EST	SE	EST	SE	SE2
β_1	0.50	0.16	0.87	0.16	0.50	0.28	0.16
β_2	1.01	0.18	-0.01	0.17	1.00	0.45	0.18

- Nearest neighbor was found in comparison X_1 and X_2.
- Single value $M = 1$ is generated for each Z_i.
- EST denotes point estimates.
- SE denotes MC variance and SE2 denotes the estimated SE as if the imputed values were originally observed.

Real Data analysis 1

1. 2019년 '식품소비 행태조사'와 '가공식품 소비자 태도조사'의 연계분석 가능성을 검정하기 위하여 총 1,519 가구에 대하여 추가 조사가 이뤄졌음.

2. 성별, 연령대, 식품첨가물 인식, MSG 인식, 간편식 이용 여부가 모두 관측되는 validation sample이 존재.

변수 구분	변수명	내용
공통변수	X_1	성별(남성/여성)
	X_2	연령대(20-30/40-50/60+)
가공식품	Y_1	식품첨가물인식 (상관없음/먹지않음)
소비자태도조사	Y_2	MSG인식(상관없음/먹지않음)
식품소비행태조사	Z	간편식이용 여부 (예/아니오)

Real Data analysis 2

(X_2, Y_1, Y_2, Z)	Full	CI	NNI	FHDI
(1,1,1,1)	0.053	0.048	0.049	0.049
(1,1,1,2)	0.007	0.048	0.011	0.011
(1,1,2,1)	0.026	0.026	0.025	0.026
⋮	⋮	⋮	⋮	⋮
(3,2,1,2)	0.030	0.027	0.27	0.023
(3,2,2,1)	0.027	0.040	0.38	0.035
(3,2,2,2)	0.049	0.040	0.38	0.041

- Full-validation sample; CI-Conditional Independence; NNI-Nearest Neighbor imputation; FI-fractional hot deck imputation
- RMSE: CI-0.0233, NNI:0.0031, FHDI:0.0021.
- FHDI additionally represents the relationship between Y and Z.

Concluding Remarks

- FHDI can be used to handle split questionnaires (intended non-response).

- When the items are not so large, the proposed method works well.

- For the large items, we need more entity observations. It would be appropriate for big data analysis.

- For non-survey data, we first need to adjust selection bias if we have benchmark information.

$$\begin{aligned} \sum_{i \in A} w_i x_i &= X \\ \sum_{j \in B} w_j x_j &= X \end{aligned}$$

- Identification issue is under development as the future study.