

Multiple Imputation

Summer Workshops

June 10, 2009

What is MI and Why do I have to use it?

- MI is a Monte Carlo technique.
 - Missing data are imputed with conditional random values
 - Each new dataset is analysed
 - Combining for the results
- Make your dataset as small as possible

What is MI and Why do I have to use it?

- Extreme missing data can decrease sample size, statistical power, and increase the possibility of bias
- Data are expected to be missing at random
 - The probability of missing data on any variable is not related to its particular value.

How do I do MI in SAS?

Output - (Untitled)

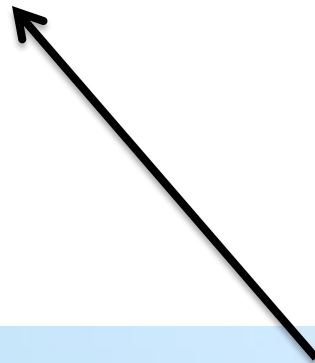
Command ==>

The SAS System

09:55 Monday, June 1, 2009 5

The MEANS Procedure

Variable	N Miss	Maximum	Minimum	Mean
wabused	25	12.0000000	0	2.4154786
habused	19	12.0000000	0	1.8209256



The MI technique in SAS assumes that the variables are multivariate normal. If the missing are small it will be ok. Also, you can use the transform command.

How do I do MI in SAS?

Command ==>

```
proc mi data=mi seed=24 out=outmi ;  
var wabused habused;  
run;
```

```
proc reg data=outmi outest=outreg covout noprint;  
model kids= wabused habused;  
by _Imputation_;  
run;
```

```
proc mianalyze data=outreg;  
modeleffect Intercept wabused habused;  
run;  
|
```

```

Command ==>
Parameter Estimates from Imputed Data Sets
09:55 Monday, June 1, 2009

The MI Procedure
Model Information

Data Set          WORK.MI
Method            MCMC
Multiple Imputation Chain Single Chain
Initial Estimates for MCMC EM Posterior Mode
Start            Starting Value
Prior            Jeffreys
Number of Imputations 5
Number of Burn-in Iterations 200
Number of Iterations 100
Seed for random number generator 24

Missing Data Patterns

-----Group Means-----
Group  wabused  habused  Freq  Percent  wabused  habused
1      X      X      473   91.67   2.410148 1.803383
2      X      .      18    3.49   2.555556 .
3      .      X      24    4.65    .      2.166667
4      0      0      1     0.19    .      .

EM (Posterior Mode) Estimates

   _TYPE_  _NAME_  wabused  habused
MEAN
COV      wabused  10.057401 1.573766
COV      habused   1.573766 6.873918

Multiple Imputation Variance Information

Variable  -----Variance-----
          Between  Within  Total  DF
wabused  0.001011  0.019614  0.020827  342.29

Multiple Imputation Variance Information

Variable  Relative Increase in Variance  Fraction Missing Information  Relative Efficiency
wabused  0.061830  0.059822  0.988177

```

This tells use if our data are monotone or arbitrary in missing pattern



Proc Mianalyze

- This is needed to produce univariate and multivariate results for the variables.
- The Proc MI procedure will create a variable called `_imputation`
 - Use this as a by variable

This output tells what is going on with the variance when we have the new dataset

The MIANALYZE Procedure

Model Information

Data Set WORK.OUTREG
Number of Imputations 5

Multiple Imputation Variance Information

Parameter	-----Variance-----			DF
	Between	Within	Total	
Intercept	0.000159	0.003224	0.003415	1286.2
wabused	0.000010523	0.000175	0.000188	886
habused	0.000014963	0.000258	0.000275	941.65

Multiple Imputation Variance Information

Parameter	Relative Increase in Variance	Fraction Missing Information	Relative Efficiency
Intercept	0.059061	0.057232	0.988683
wabused	0.072031	0.069290	0.986331
habused	0.069719	0.067155	0.986747

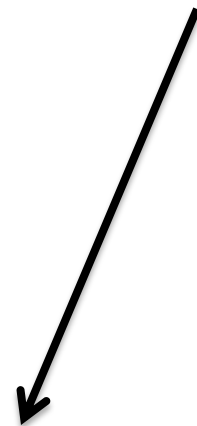
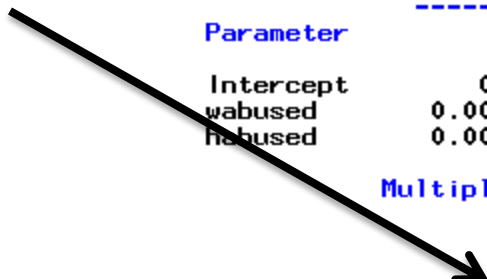
Multiple Imputation Parameter Estimates

Parameter	Estimate	Std Error	95% Confidence Limits		DF
Intercept	0.425682	0.058437	0.31104	0.540324	1286.2
wabused	0.023758	0.013709	-0.00315	0.050664	886
habused	0.035350	0.016598	0.00278	0.067923	941.65

Multiple Imputation Parameter Estimates

Parameter	Minimum	Maximum	Theta0	t for H0:	
				Parameter=Theta0	Pr > t
Intercept	0.406227	0.440495	0	7.28	<.0001
wabused	0.019762	0.027856	0	1.73	0.0834
habused	0.031986	0.039810	0	2.13	0.0334

This gives us the standard error and parameter estimate for each variable in our model.



What you can use with Proc Mi

- Proc Reg
- Proc Genmod
- Proc Logit
- Proc Mixed
- Proc GLM

SAS IVEware

- <http://www.isr.umich.edu/src/smp/ive/>
- Perform a variety of descriptive and model based analyses accounting for such complex design features as clustering, stratification, and weighting.
- Perform multiple imputation analyses for both descriptive and model-based survey statistics.

SAS IVEware

- Currently the following SAS PROCs can be called: CALIS, CATMOD, GENMOD, LIFEREG, MIXED, NLIN, PHREG, and PROBIT
- Variables can be: continuous, binary, categorical, counts, or mixed

How do I do MI in STATA?

- First make sure you have the ice program
- Findit ice
- Findit mim

How do I do MI in STATA?

```
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
respid_w	516	11329.81	826.6325	10008	12700
wabused	491	2.415479	3.183261	0	12
habused	497	1.820926	2.632406	0	12
kids	516	.5465116	.9429181	0	6

set more off

ice kids wabused habused, /*

***/saving (R:\CFDR\CFDR\HEIDI\workshop_imputed.dta, replace) m(5)
genmiss (m_)/***

***/ seed(123)**

use R:\CFDR\CFDR\HEIDI\workshop_imputed.dta, clear

tab _mj

mim: regress kids wabused habused

```

Results
College Station, Texas 77845 USA
800-STATA-PC      http://www.stata.com
979-696-4600     stata@stata.com
979-696-4601 (fax)

Single-user Stata for Windows perpetual license:
  Serial number: 199048108
  Licensed to:  CFDR computer
                CFDR computer

Notes:
  1. (/m# option or -set memory-) 1.00 MB allocated to data

. use "R:\CFDR\CFDR\HEIDI\CM\ice.dta", clear
. do "R:\CFDR\CFDR\HEIDI\CM\workshop.txt"
.
. set more off
.
. ice kids wabused habused, /*
> */saving (R:\CFDR\CFDR\HEIDI\workshop_imputed.dta, replace) m(5) genmiss (m_)/
> */ seed(123)

```

#missing values	Freq.	Percent	Cum.
0	473	91.67	91.67
1	42	8.14	99.81
2	1	0.19	100.00
Total	516	100.00	

Variable	Command	Prediction equation
kids		[No missing data in estimation sample]
wabused	regress	kids habused
habused	regress	kids wabused

```
Imputing .....1.....2.....3.....4.....5
file R:\CFDR\CFDR\HEIDI\workshop_imputed.dta saved
```

```
. use R:\CFDR\CFDR\HEIDI\workshop_imputed.dta, clear
```

```
. tab _mj
```

imputation number	Freq.	Percent	Cum.
0	516	16.67	16.67
1	516	16.67	33.33
2	516	16.67	50.00
3	516	16.67	66.67
4	516	16.67	83.33
5	516	16.67	100.00
Total	3,096	100.00	

```
. mim: regress kids wabused habused
```

```
Multiple-imputation estimates (regress)           Imputations =      5
Linear regression                                Minimum obs =    516
                                                Minimum dof =   178.2
```

kids	Coef.	Std. Err.	t	P> t	[95% Conf. Int.]	MI,df
wabused	.023559	.01402	1.68	0.095	-.004107 .051225	178.2
habused	.039167	.016678	2.35	0.020	.006317 .072016	246.5
_cons	.4184	.057147	7.32	0.000	.306107 .530692	475.2

```
. end of do-file
```


A more complex example- Add Health

ice happy rsat rschool hs twoyear grad notenrolled work parttime
fulltime married lwp cohab consequences risks behavior
depressed fitin notfuture rnocrowd maturity female hadsex
responsibilities bio income momed rrace black hisp otherrace
mlhs mhs msomec money, /*

*/saving (T:\Users\hlyons\min_impute.dta, replace) m(3) genmiss
(m_)/*

svyset [pweight=gswgt3_2], strata(region)psu(psuscid)

```
*/cmd(happy rsat consequence behavior risks fitin notfuture  
rnocrowd maturity responsibilities rschool momed: ologit, work  
: mlogit, married lwp cohab bio female hadsex : logit)/*
```

```
*/passive
```

```
(hs:rschool==1\twoyear:rschool==2\grad:rschool==4\notenrolle  
d:rschool==5\parttime:work==2\fulltime:work==3\mlhs:momed=  
=1\mhs:momed==2\msomec:momed==3)/*
```

```
*/substitute (rschool: hs twoyear grad notenrolled, work: parttime  
fulltime, momed: mlhs mhs msomec)
```

```
*/ seed(123)
```

```
use T:\Users\hlyons\min_impute.dta, clear
```

```
tab _mj
```

- **mim:svy,subpop(marker):ologit happy
twoyear grad notenrolled parttime
fulltime married lwp cohab
consequences behavior risks fitin
notfuture rnocrowd bio income mlhs
mhs msomec black hisp otherrace age
hadsex female money rsat,or**

What Svy commands Mim can do?

- Svy: regress
- Svy: mean
- Svy: proportion
- Svy: ratio
- Svy: logistic
- Svy: ologit
- Svy: mlogit
- Svy: probit
- Svy: oprobit
- Svy: poisson

SPSS

- Now, using SPSS Missing Values 17.0, you can impute missing values for categorical or continuous variables by multiple imputation.



Questions?

Next workshop:

***Introduction to Structural
Equation Modeling***

Wednesday, June 17, 12:00-1:00

Room 314