Missing Data & How to Deal: An overview of missing data

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Goals

- Discuss ways to evaluate and understand missing data
- Discuss common missing data methods
- Know the advantages and disadvantages of common methods
- Review useful commands in Stata for missing data

General Steps for Analysis with Missing Data

- 1. Identify patterns/reasons for missing and recode correctly
- 2. Understand distribution of missing data
- 3. Decide on best method of analysis

Step One: Understand your data

- Attrition due to social/natural processes
  - Example: School graduation, dropout, death
- Skip pattern in survey
  - Example: Certain questions only asked to respondents who indicate they are married
- Intentional missing as part of data collection process
- Random data collection issues
- Respondent refusal/Non-response

Find information from survey (codebook, questionnaire)

- Identify skip patterns and/or sampling strategy from documentation

86A. **Have you ever worked for pay, not counting work around the house?**

(CIRCLE ONE)

No . . . . 1 **(SKIP TO QUESTION 93 ON PAGE 59)**
Yes, and I am currently employed . . . . 2 **(SKIP TO QUESTION 87)**
Yes, but I am not currently employed . . . . 3 **(GO TO QUESTION 86B)**

86B. **When did you last work for pay, not counting work around the house?**

(WRITE IN)

|__|__| Month   19 |__|__| Year

```
. tab F2S86BYR
```

YEAR, LAST TIME R WORKED	Freq.	Percent	Cum.
81	1	0.10	0.10
87	1	0.10	0.19
88	4	0.39	0.58
89	7	0.68	1.25
90	35	3.38	4.63
91	234	22.59	27.22
92	81	7.82	35.04
97: REFUSED	5	0.48	35.52
98: MISSING	19	1.83	37.36
99: LEGITIMATE SKIP/NOT IN WAVE	649	62.64	100.00
Total	1,036	100.00	

Recode for analysis: mvdecode command

```
.         tab worked,m

 HAS R EVER
 WORKED FOR
PAY OUTSIDE
       HOME |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |        160       13.41       13.41
          2 |        488       40.91       54.32
          3 |        383       32.10       86.42
          7 |          1        0.08       86.50
          8 |          8        0.67       87.18
          . |        153       12.82      100.00
------------+-----------------------------------
      Total |      1,193      100.00

.         mvdecode worked, mv(7 8)
      worked: 9 missing values generated

.         tab worked,m

 HAS R EVER
 WORKED FOR
PAY OUTSIDE
       HOME |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |        160       13.41       13.41
          2 |        488       40.91       54.32
          3 |        383       32.10       86.42
          . |        162       13.58      100.00
------------+-----------------------------------
      Total |      1,193      100.00
```

Recode for analysis: mvdecode command

```
.         tab worked,m

  HAS R EVER |
 WORKED FOR |
PAY OUTSIDE |
       HOME |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |        160       13.41       13.41
          2 |        488       40.91       54.32
          3 |        383       32.10       86.42
          7 |          1        0.08       86.50
          8 |          8        0.67       87.18
          . |        153       12.82      100.00
------------+-----------------------------------
      Total |      1,193      100.00

.         mvdecode worked, mv(7 8)
      worked: 9 missing values generated

.         tab worked,m

  HAS R EVER |
 WORKED FOR |
PAY OUTSIDE |
       HOME |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |        160       13.41       13.41
          2 |        488       40.91       54.32
          3 |        383       32.10       86.42
          . |        162       13.58      100.00
------------+-----------------------------------
      Total |      1,193      100.00
```

```
. tab worked if worked>2,m

  HAS R EVER |
 WORKED FOR |
PAY OUTSIDE |
       HOME |      Freq.     Percent        Cum.
------------+-----------------------------------
          3 |        383       70.28       70.28
          . |        162       29.72      100.00
------------+-----------------------------------
      Total |        545      100.00
```

Note: Stata reads missing (.) as a value greater than any number.

Analyze missing data patterns: misstable command

```
. misstable sum
                                                               Obs<.
                                                   +------------------------------
    Variable |     Obs=.     Obs>.     Obs<.      | Unique
             |                                    | values        Min         Max
-------------+------------------------------------+------------------------------
      SCH_ID |        91               1,102      |   >500       1249       91991
       BYS75 |        91               1,102      |      6          0           8
      BYS81B |        91               1,102      |      8          1          98
    BY2XRIRR |        91               1,102      |   >500      10.91       99.99
    BY2XMIRR |        91               1,102      |   >500       16.5       99.99
       F1S74 |        92               1,101      |      4          1           8
     F1S80AA |        92               1,101      |      6          0           8
       F1S82 |        92               1,101      |      7          1          98
-------------------------------------------------------------------------------

. misstable pattern, freq

         Missing-value patterns
           (1 means complete)

            |   Pattern
  Frequency |  1  2  3  4    5  6  7  8
  ----------+---------------------------
      1,028 |  1  1  1  1    1  1  1  1
            |
         74 |  1  1  1  1    1  0  0  0
         73 |  0  0  0  0    0  1  1  1
         18 |  0  0  0  0    0  0  0  0
  ----------+---------------------------
      1,193 |

  Variables are  (1) BY2XMIRR  (2) BY2XRIRR  (3) BYS75  (4) BYS81B  (5) SCH_ID  (6) F1S74  (7) F1S80AA  (8) F1S82
```

Step Two: Missing data Mechanism (or probability distribution of missingness)

- Consider the probability of *missingness*
  - Are certain groups more likely to have missing values?
    - Example: Respondents in service occupations less likely to report income
  - Are certain responses more likely to be missing?
    - Example: Respondents with high income less likely to report income
- Certain analysis methods assume a certain probability distribution

Missing Data Mechanisms

- Missing Completely at Random (MCAR)
  - Missing value (y) neither depends on x nor y
    - Example: some survey questions asked of a simple random sample of original sample
- Missing at Random (MAR)
  - Missing value (y) depends on x, but not y
    - Example: Respondents in service occupations less likely to report income
- Missing not at Random (NMAR)
  - The probability of a missing value depends on the variable that is missing
    - Example: Respondents with high income less likely to report income

Exploring missing data mechanisms

- Can’t be 100% sure about probability of missing (since we don’t actually know the missing values)
- Could test for MCAR (t-tests)—but not totally accurate
- Many missing data methods assume MCAR or MAR but our data often are MNAR
  - Some methods specifically for MNAR
    - Selection model (Heckman)
    - Pattern mixture models

Good News!!

- Some MAR analysis methods using MNAR data are still pretty good.
  - May be another measured variable that indirectly can predict the probability of missingness
    - Example: those with higher incomes are less likely to report income BUT we have a variable for years of education and/or number of investments
  - ML and MI are often unbiased with NMAR data even though assume data is MAR
    - See Schafer & Graham 2002

Step 3: Deal with missing data

- Use what you know about
  - Why data is missing
  - Distribution of missing data
- Decide on the best analysis strategy to yield the least biased estimates
  - Deletion Methods
    - Listwise deletion, pairwise deletion
  - Single Imputation Methods
    - Mean/mode substitution, dummy variable method, single regression
  - Model-Based Methods
    - Maximum Likelihood, Multiple imputation

Deletion Methods

- Listwise deletion
  - AKA complete case analysis
- Pairwise deletion

Listwise Deletion (Complete Case Analysis)

- Only analyze cases with available data on each variable
  - Advantages:
    - Simplicity
    - Comparability across analyses
  - Disadvantages:
    - Reduces statistical power (because lowers n)
    - Doesn't use all information
    - Estimates may be biased if data not MCAR*

Gender	8^{th} grade math test score	12^{th} grade math score
~~F~~	~~45~~	~~.~~
~~M~~	~~.~~	~~99~~
F	55	86
F	85	88
F	80	75
~~.~~	~~81~~	~~82~~
F	75	80
~~M~~	~~95~~	~~.~~
M	86	90
F	70	75
~~F~~	~~85~~	~~.~~

*NOTE: List-wise deletion often produces *unbiased regression slope estimates* as long as missingness is not a function of outcome variable.

Application in Stata

- Any analysis including multiple variables automatically applies listwise deletion.

```
. sum id BYS75 BY2XRIRR_1 F22XMIRR

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
          id |      1193     4596533     2612696     124932    9199152
       BYS75 |      1089    1.221304    2.003138          0          8
  BY2XRIRR_1 |      1043    27.02079    8.850781      10.83      43.83
    F22XMIRR |      1193    61.06244    26.49801      18.01      99.99

. mean id BYS75 BY2XRIRR_1 F22XMIRR

Mean estimation                     Number of obs    =     1043

--------------------------------------------------------------
             |       Mean   Std. Err.     [95% Conf. Interval]
-------------+------------------------------------------------
          id |    4544590    81565.86      4384538     4704642
       BYS75 |   1.155321    .0590753     1.039401    1.271241
  BY2XRIRR_1 |   27.02079    .2740561     26.48302    27.55855
    F22XMIRR |   60.31022    .7925299     58.75508    61.86536
--------------------------------------------------------------
```

Pairwise deletion (Available Case Analysis)

- Analysis with all cases in which the variables of interest are present.
  - Advantage:
    - Keeps as many cases as possible for each analysis
    - Uses all information possible with each analysis
  - Disadvantage:
    - Can't compare analyses because sample different each time

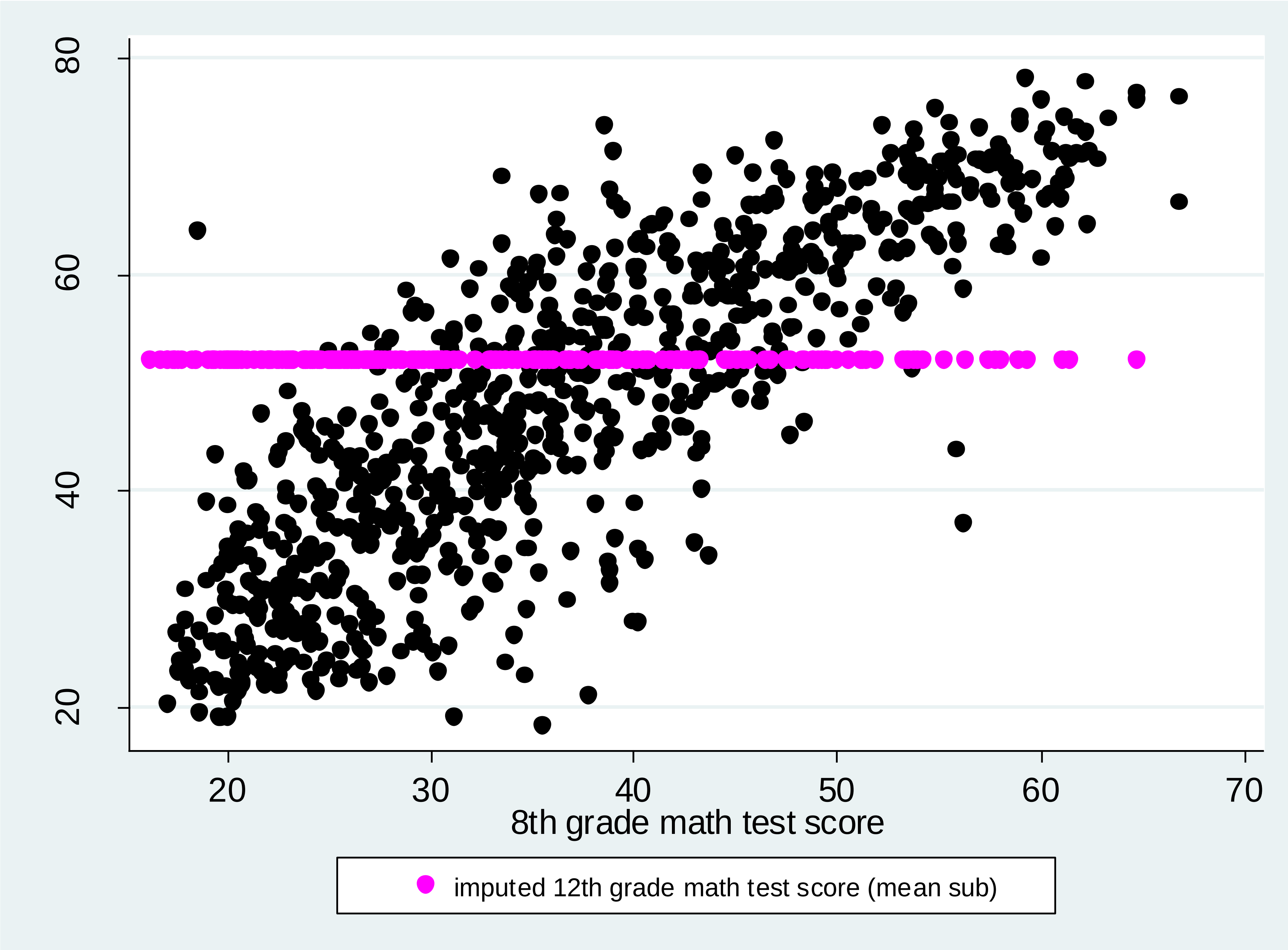
Gender	8^{th} grade math test score	12^{th} grade math score
F	45	.
M	.	99
F	55	86
F	85	88
F	80	75
.	81	82
F	75	80
M	95	.
M	86	90
F	70	75
F	85	.

Single imputation methods

- Mean/Mode substitution
- Dummy variable control
- Conditional mean substitution

Mean/Mode Substitution

- Replace missing value with sample mean or mode
- Run analyses as if all complete cases
- Advantages:
  - Can use complete case analysis methods
- Disadvantages:
    - Reduces variability
    - Weakens covariance and correlation estimates in the data (because ignores relationship between variables)



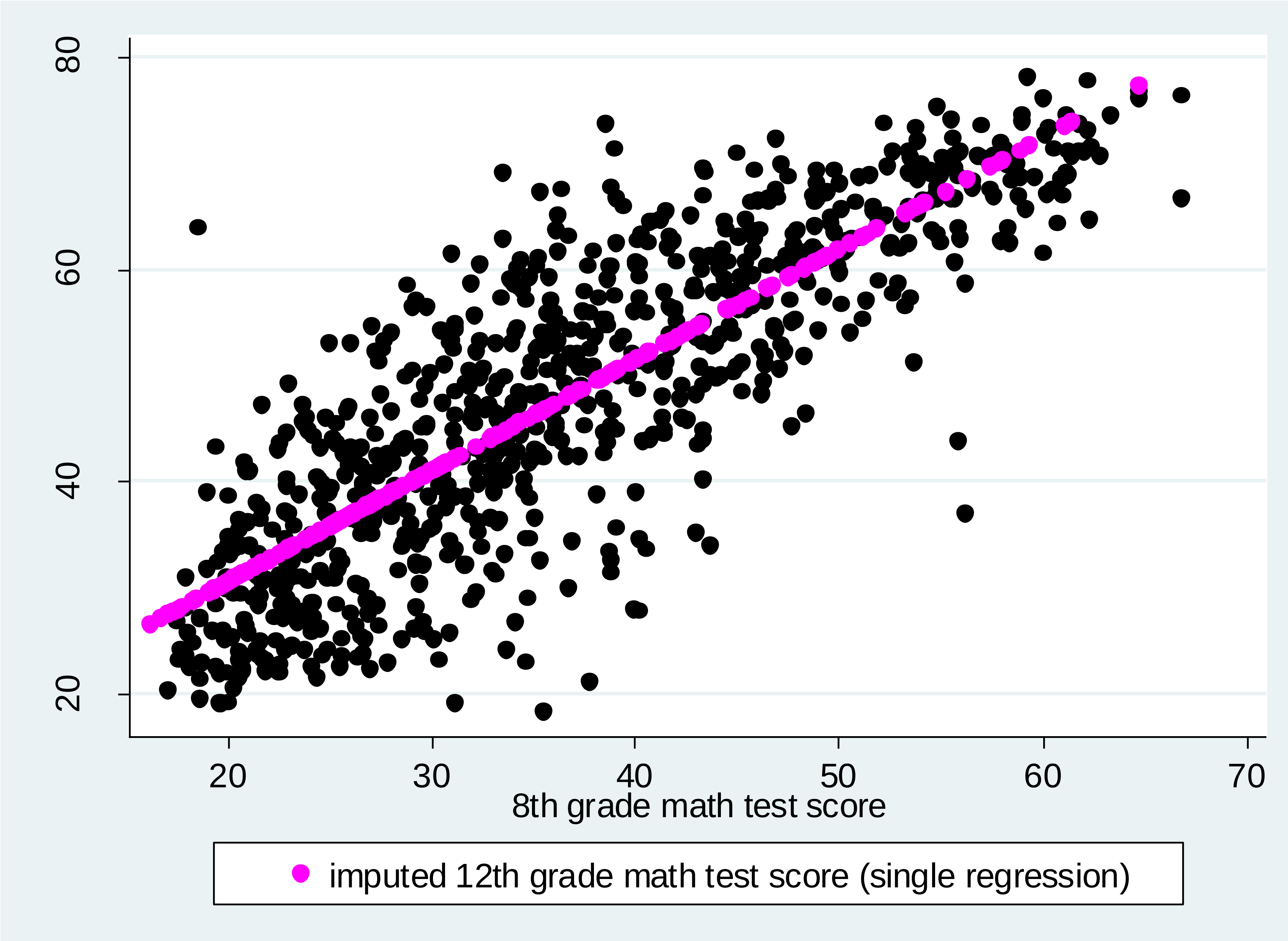
80
60
40
20
20
30
40
50
60
70
8th grade math test score
imputed 12th grade math test score (mean sub)

Dummy variable adjustment

- Create an indicator for missing value (1=value is missing for observation; 0=value is observed for observation)
- Impute missing values to a constant (such as the mean)
- Include missing indicator in regression
- Advantage:
  - Uses all available information about missing observation
- Disadvantage:
  - Results in biased estimates
  - Not theoretically driven
- NOTE: Results not biased if value is missing because of a legitimate skip

Regression Imputation

- Replaces missing values with predicted score from a regression equation.
  - Advantage:
    - Uses information from observed data
  - Disadvantages:
    - Overestimates model fit and correlation estimates
    - Weakens variance


80
60
40
20
20
30
40
50
60
70
8th grade math test score
imputed 12th grade math test score (single regression)

Model-based methods

- Maximum Likelihood
- Multiple imputation

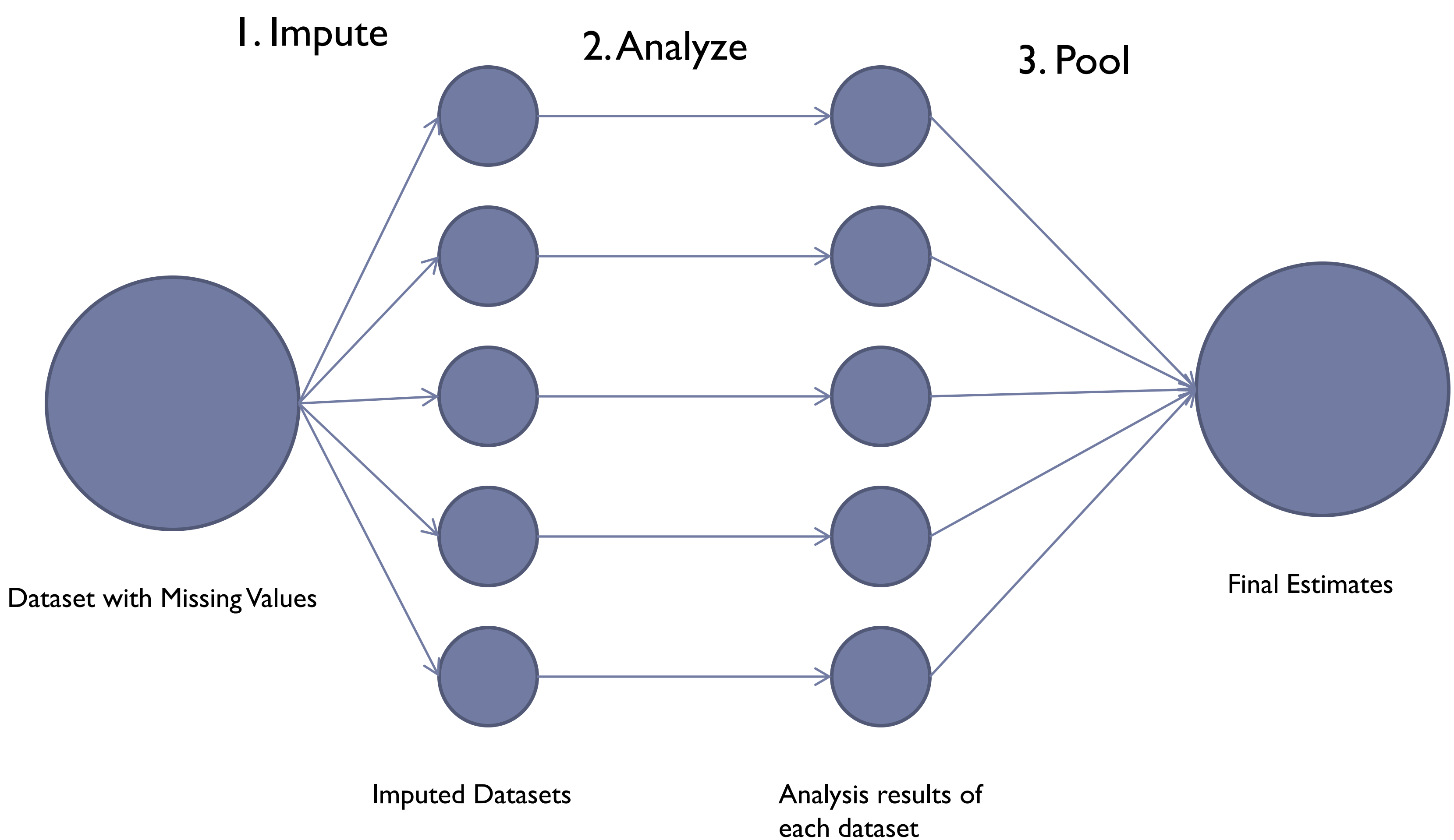
Model-based Methods: Maximum Likelihood Estimation

- Identifies the set of parameter values that produces the highest log-likelihood.
  - ML estimate: value that is most likely to have resulted in the observed data
- Conceptually, process the same with or without missing data
  - Advantages:
    - Uses full information (both complete cases and incomplete cases) to calculate log likelihood
    - Unbiased parameter estimates with MCAR/MAR data
  - Disadvantages
    - SEs biased downward—can be adjusted by using observed information matrix

Multiple Imputation

- 1. Impute: Data is ‘filled in’ with imputed values using specified regression model
  - This step is repeated *m* times, resulting in a separate dataset each time.
- 2. Analyze: Analyses performed within each dataset
- 3. Pool: Results pooled into one estimate
  - Advantages:
    - Variability more accurate with multiple imputations for each missing value
      - Considers variability due to sampling AND variability due to imputation
  - Disadvantages:
    - Cumbersome coding
    - Room for error when specifying models

Multiple Imputation Process



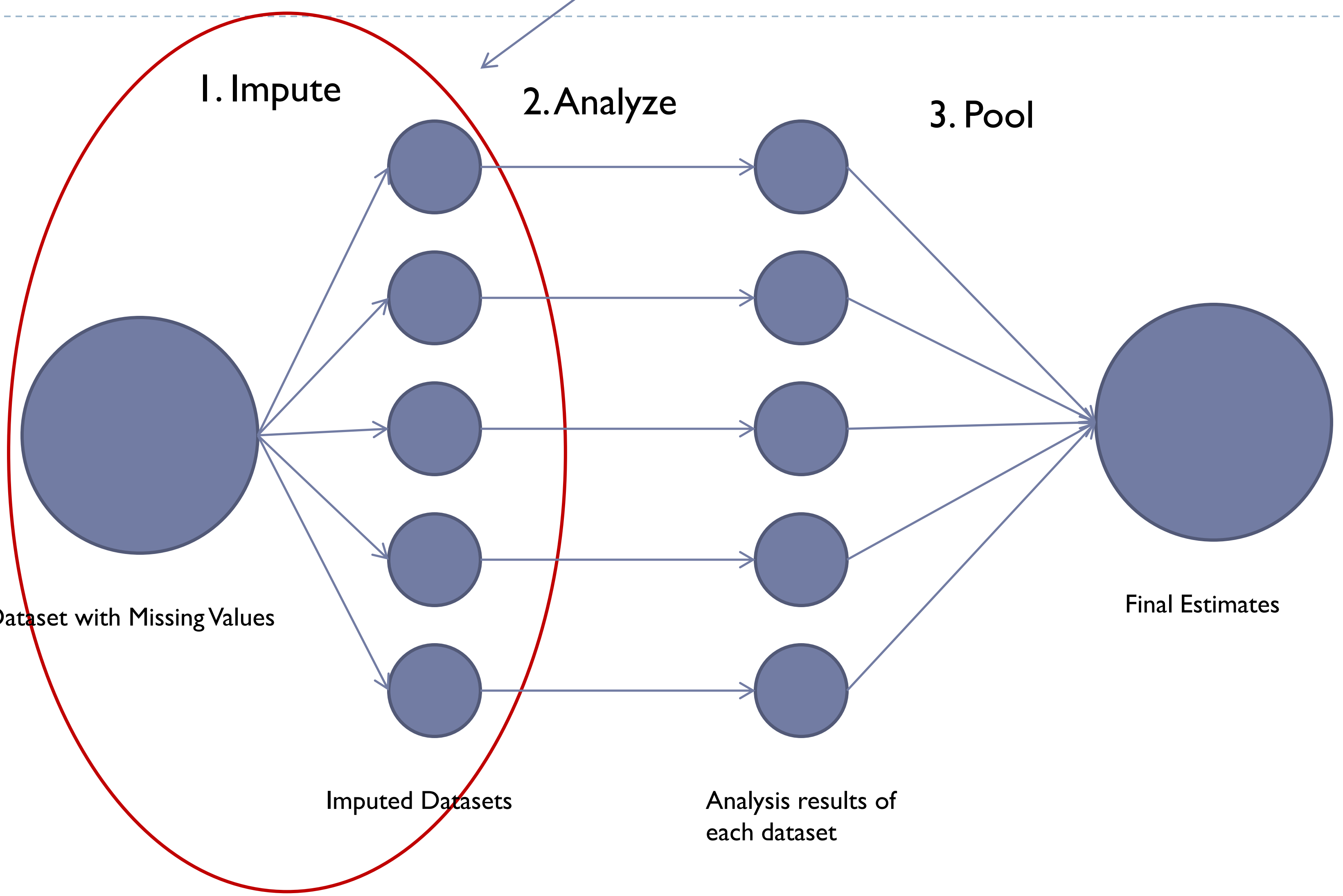
Multiple Imputation: Stata & SAS

- SAS:
  - Proc mi
- Stata:
  - ice (imputation using chained equations) & mim (analysis with multiply imputed dataset)
  - mi commands
    - mi set
    - mi register
    - mi impute
    - mi estimate
  - NOTE: the ice command is the only chained equation method until Stata12. Chained equations can be used as an option of mi impute since Stata12.

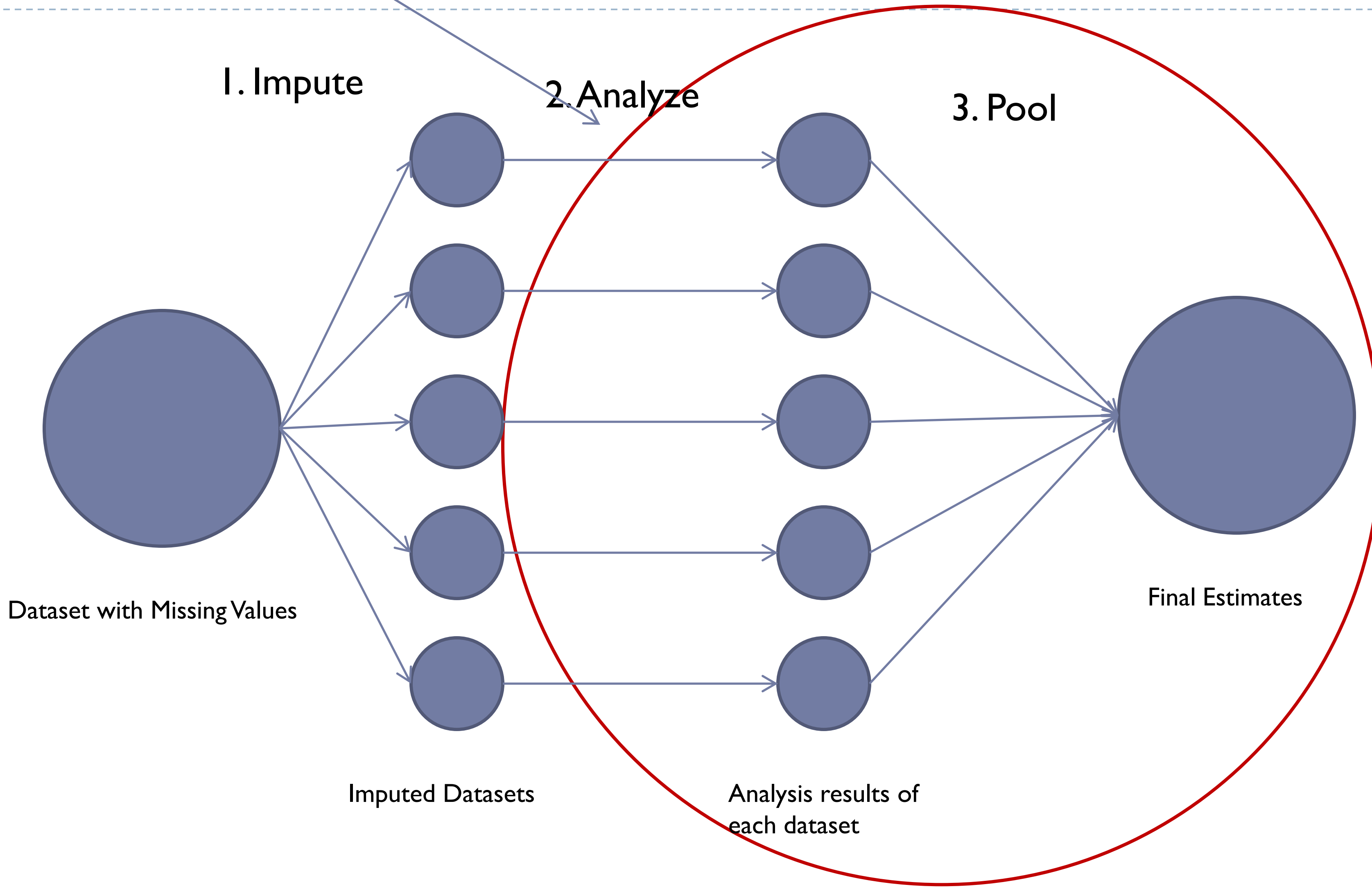
ice & mim

- ice: Imputation using chained equations
  - Series of equations predicting one variable at a time
  - Creates as many datasets as desired
- mim: prefix used before analysis that performs analyses across datasets and pools estimates

`ice` command


1. Impute
2. Analyze
3. Pool
Dataset with Missing Values
Imputed Datasets
Analysis results of each dataset
Final Estimates

`mim` command


1. Impute
2. Analyze
3. Pool
Dataset with Missing Values
Imputed Datasets
Analysis results of each dataset
Final Estimates

```
ice female lm latino black asian other F1PARED AGE1 intact bymirt ESL2 ALG2OH acgpa ac_engall
hardwtr Lksch MAE10 RAE10 hilep midw south public catholic colltype aceng_ESL Lksch_ESL, ///
saving(imputed2) m(5) cmd (Lksch:ologit)
```

```
   Variable | Command | Prediction equation
------------+---------+-------------------------------------------------------
     female |         | [No missing data in estimation sample]
         lm |         | [No missing data in estimation sample]
     latino |         | [No missing data in estimation sample]
      black |         | [No missing data in estimation sample]
     ALG2OH | logit   | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 acgpa ac_engall hardwtr Lksch MAE10 RAE10
            |         | hilep midw south public catholic colltype aceng_ESL
            |         | Lksch_ESL
      acgpa | regress | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 ALG2OH ac_engall hardwtr Lksch MAE10 RAE10
            |         | hilep midw south public catholic colltype aceng_ESL
            |         | Lksch_ESL
  ac_engall | regress | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 ALG2OH acgpa hardwtr Lksch MAE10 RAE10
            |         | hilep midw south public catholic colltype Lksch_ESL
    hardwtr | logit   | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 ALG2OH acgpa ac_engall Lksch MAE10 RAE10
            |         | hilep midw south public catholic colltype aceng_ESL
            |         | Lksch_ESL
      Lksch | ologit  | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 ALG2OH acgpa ac_engall hardwtr MAE10 RAE10
            |         | hilep midw south public catholic colltype aceng_ESL
      MAE10 | regress | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 ALG2OH acgpa ac_engall hardwtr Lksch RAE10
            |         | hilep midw south public catholic colltype aceng_ESL
            |         | Lksch_ESL
      RAE10 | regress | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 ALG2OH acgpa ac_engall hardwtr Lksch MAE10
            |         | hilep midw south public catholic colltype aceng_ESL
            |         | Lksch_ESL
      hilep | logit   | female lm latino black asian other F1PARED AGE1 intact
            |         | bymirt ESL2 ALG2OH acgpa ac_engall hardwtr Lksch MAE10
            |         | RAE10 midw south public catholic colltype aceng_ESL
            |         | Lksch_ESL
-------------------------------------------------------------------------------

Imputing ..........1..........2..........3..........4..........5
file imputed2.dta saved
```

```
mim, storebv: svy: mlogit colltype ESL2 lm female latino black asian other F1PARED lowinc
AGE1 intact bymirt ALG2OH acgpa Lksch, b(0)
```

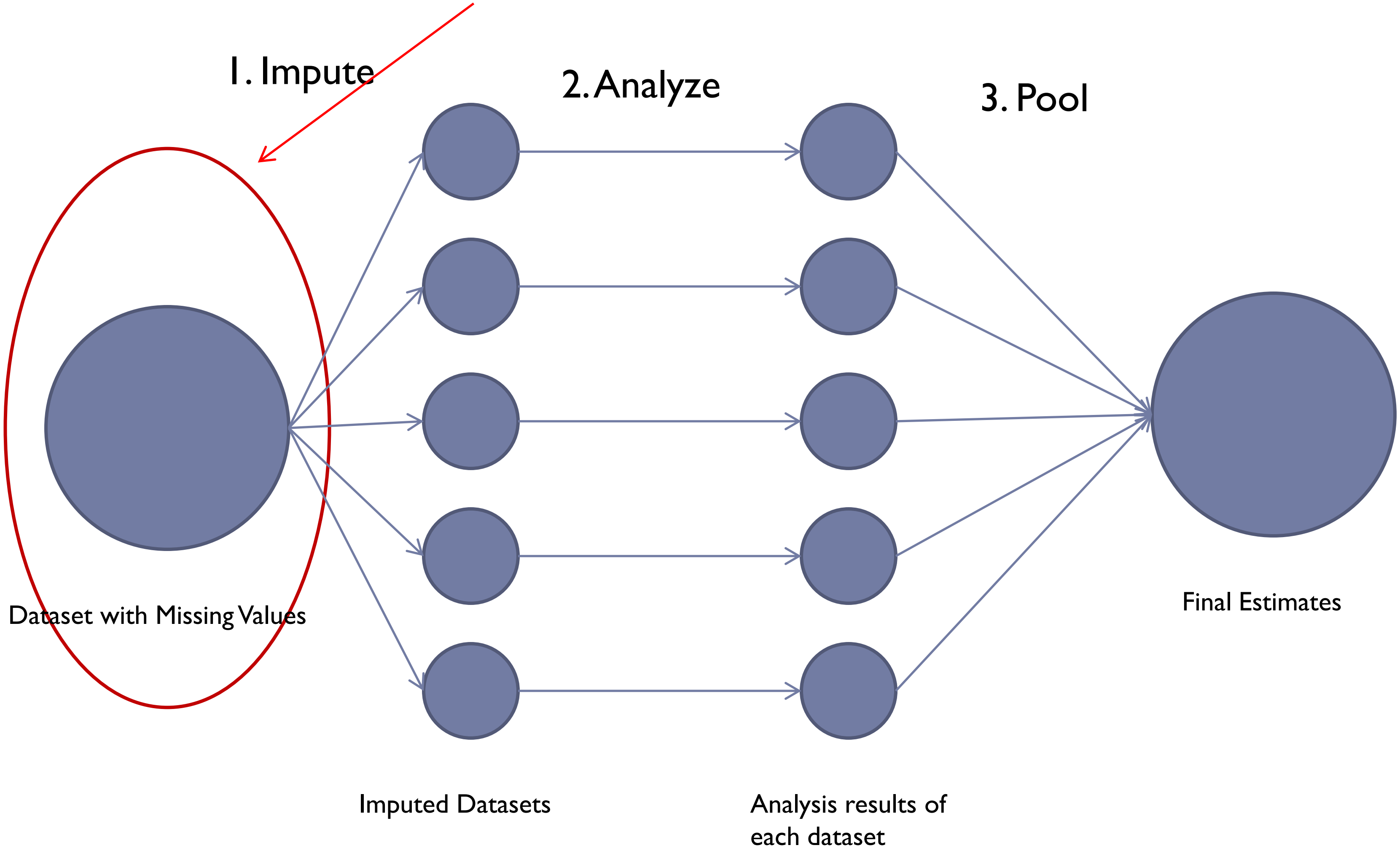
```
Multiple-imputation estimates (svy: mlogit)            Imputations =        5
Survey: Multinomial logistic regression                Minimum obs =    13394
                                                       Minimum dof =    511.9

------------------------------------------------------------------------------
    colltype |     Coef.  Std. Err.      t     P>|t|     [95% Conf. Int.]     FMI
-------------+----------------------------------------------------------------
1            |
        ESL2 |  -.375638   .172034   -2.18    0.029    -.713366 -.037909   0.000
          lm |   .448917   .132112    3.40    0.001     .189561  .708272   0.000
      female |   .243528   .073912    3.29    0.001     .098427  .388628   0.000
      latino |   .005748    .12592    0.05    0.964    -.241452  .252948   0.000
       black |   .133203   .120774    1.10    0.270    -.103895    .3703   0.001
       asian |   .342303   .172157    1.99    0.047     .004332  .680273   0.000
       other |  -.432693   .165435   -2.62    0.009    -.757467  -.10792   0.000
     F1PARED |   .170113   .033034    5.15    0.000     .105262  .234964   0.000
      lowinc |  -.256572   .104118   -2.46    0.014    -.460972 -.052171   0.000
        AGE1 |   -.40664   .086344   -4.71    0.000    -.576146 -.237134   0.000
      intact |   .177401   .069599    2.55    0.011     .040768  .314034   0.000
      bymirt |   .012549   .003725    3.37    0.001     .005238  .019861   0.001
      ALG2OH |   .483054   .081618    5.92    0.000     .322823  .643285   0.003
       acgpa |   .498286   .057879    8.61    0.000     .384662  .611911   0.001
       Lksch |   .068058   .059965    1.13    0.257    -.049733  .185848   0.043
       _cons |  -2.31716   .218751  -10.59    0.000    -2.74661  -1.8877   0.009
-------------+----------------------------------------------------------------
2            |
        ESL2 |  -.845765   .274438   -3.08    0.002    -1.38453 -.307001   0.000
          lm |   .197629   .148886    1.33    0.185    -.094659  .489916   0.001
      female |   .150927   .085302    1.77    0.077    -.016534  .318389   0.000
      latino |  -.041933   .150431   -0.28    0.781    -.337251  .253386   0.000
       black |   1.00681    .13483    7.47    0.000     .742115   1.2715   0.002
       asian |   .521137   .173992    3.00    0.003     .179564  .862711   0.000
       other |    .09246   .189309    0.49    0.625    -.279183  .464103   0.000
     F1PARED |   .454096    .03378   13.44    0.000     .387781  .520411   0.001
      lowinc |  -.379085   .119948   -3.16    0.002    -.614563 -.143608   0.000
        AGE1 |  -.394956   .089359   -4.42    0.000    -.570382 -.219531   0.001
      intact |   .279601   .083677    3.34    0.001      .11533  .443873   0.000
      bymirt |   .048036   .004558   10.54    0.000     .039089  .056984   0.001
      ALG2OH |   1.49035   .116042   12.84    0.000     1.26254  1.71816   0.004
       acgpa |   1.51343    .07672   19.73    0.000     1.36282  1.66404   0.001
       Lksch |   .236965   .070135    3.38    0.001     .099176  .374754   0.048
       _cons |  -7.84432   .292087  -26.86    0.000    -8.41775 -7.27089   0.008
```

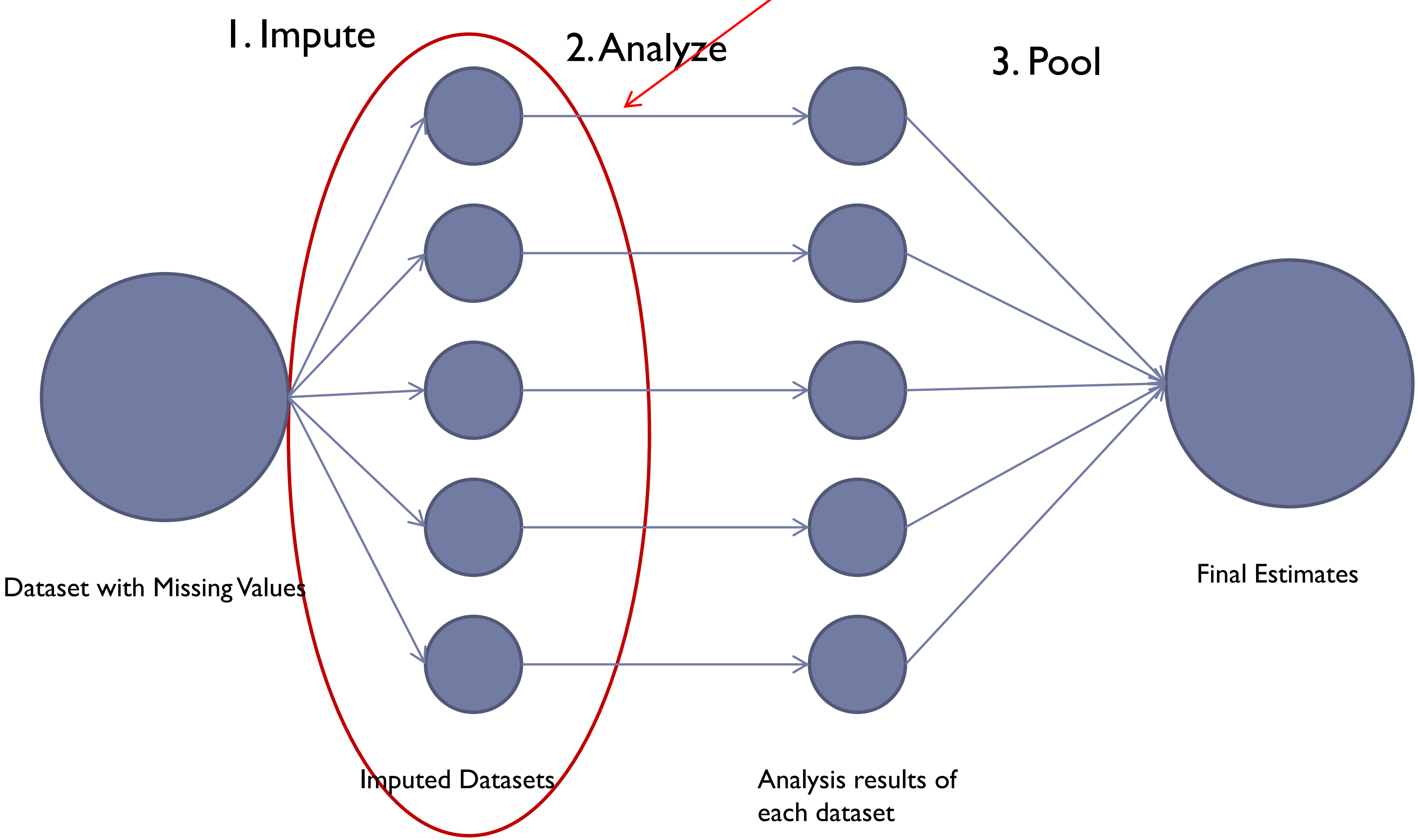
mi commands

- Included in Stata 11
- Includes univariate multiple imputation (impute only one variable)
- Multivariate imputation probably more useful for our data
- Specific order:
  - mi set
  - mi register
  - mi impute
  - mi estimate

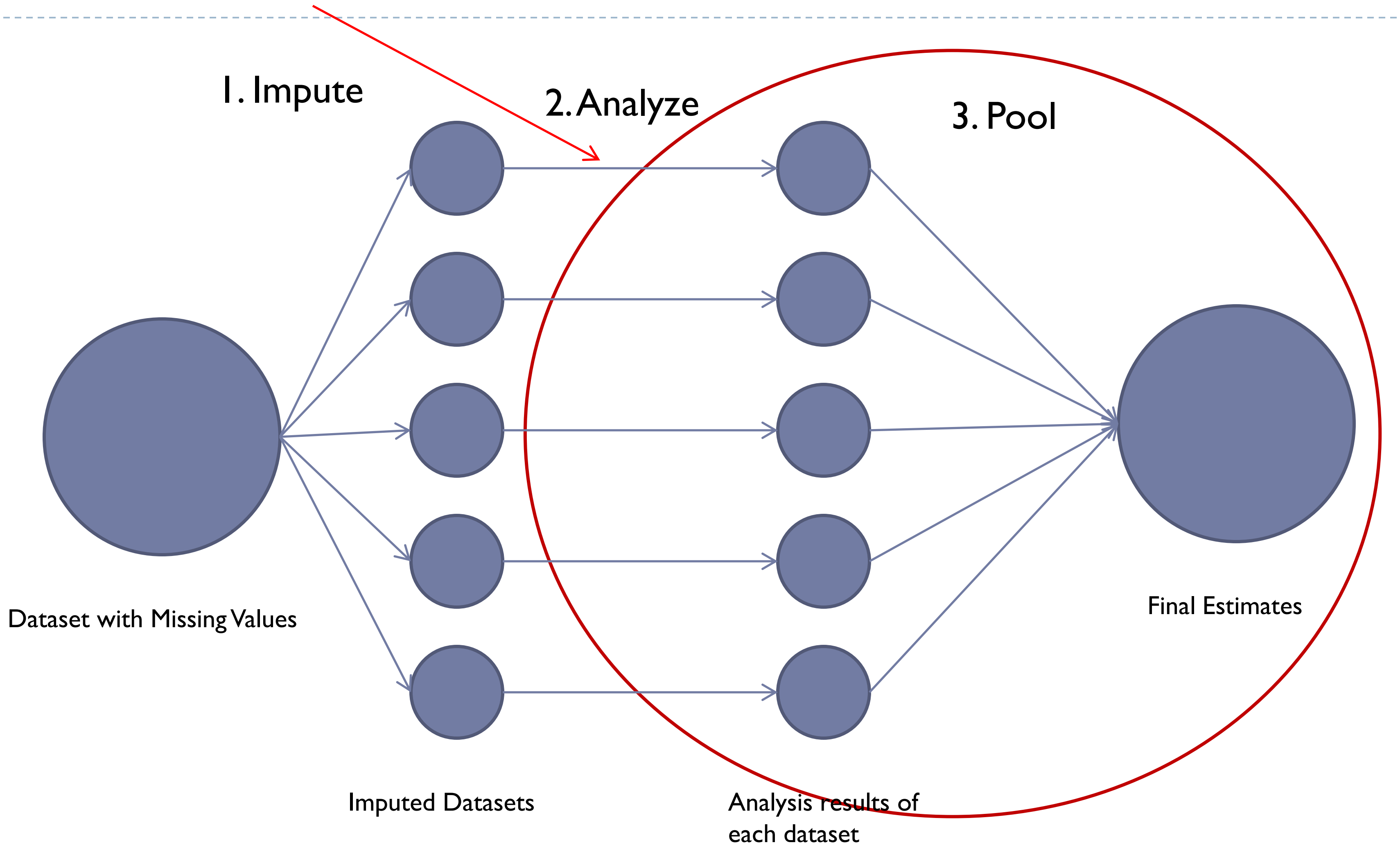
`mi set` and `mi register` commands



`mi impute` command



`mi estimate` command



```
*******set data to be multiply imputed (can set to 'wide' format also)
mi set flong

*******register variables as "imputed" (variables with missing data that you want imputed) or "regular"
mi register imputed readtest8 worked mathtest8
mi register regular sex race

*******describing data
mi describe

*******setting seed so results are replicable
set seed 8945

*******imputing using chained equations—using ols regression for predicting read and math test using mlogit to predict worked
mi impute chained (regress) readtest8 mathtest8 (mlogit) worked=sex i.race, add(10)

********check new imputed dataset
mi describe

*******estimating model using imputed values
mi estimate:regress mathtest12 mathtest8 sex race
```

```
. *set data to be multiply imputed
. mi set flong

. mi svyset
no survey characteristics are set

. *register variables as "imputed" (variables with missing data that you want imputed)
. mi register imputed readtest8 worked mathtest8
(165 m=0 obs. now marked as incomplete)

. mi register regular sex race


.
. mi describe

  Style:   flong
           last mi update 29mar2012 10:36:55, 0 seconds ago

  Obs.:    complete              955
           incomplete            165   (M = 0 imputations)
           ---------------------------
           total               1,120

  Vars.:   imputed:  3; readtest8(40) worked(132) mathtest8(41)

           passive:  0

           regular:  2; sex race

           system:   3; _mi_m _mi_id _mi_miss

          (there are 20 unregistered variables)
```

```
. *******setting seed so results are replicable
. set seed 8945

. *******imputing using chained equations
. mi impute chained (regress) readtest8 mathtest8 (mlogit) worked=sex i.race, add(10)

Conditional models:
         readtest8: regress readtest8 mathtest8 i.worked sex i.race
         mathtest8: regress mathtest8 readtest8 i.worked sex i.race
            worked: mlogit worked readtest8 mathtest8 sex i.race

Performing chained iterations ...

Multivariate imputation                     Imputations =       10
Chained equations                                 added =       10
Imputed: m=1 through m=10                       updated =        0

Initialization: monotone                     Iterations =      100
                                                burn-in =       10

         readtest8: linear regression
         mathtest8: linear regression
            worked: multinomial logistic regression

------------------------------------------------------------------
                   |               Observations per m
                   |----------------------------------------------
          Variable |   Complete   Incomplete   Imputed |     Total
-------------------+-----------------------------------+----------
         readtest8 |       1060           37        37 |      1097
         mathtest8 |       1060           37        37 |      1097
            worked |        958          139       139 |      1097
------------------------------------------------------------------
(complete + incomplete = total; imputed is the minimum across m
 of the number of filled-in observations.)
```

Dataset after imputation

```
. sum readtest8

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
   readtest8 |     12030    27.02419    8.862721  -4.311928   52.88457
```

```
. *******estimating model using imputed values
. mi estimate:regress mathtest12 mathtest8 sex race

Multiple-imputation estimates                 Imputations     =         10
Linear regression                             Number of obs   =        830
                                              Average RVI     =     0.1070
                                              Largest FMI     =     0.2241
                                              Complete DF     =        826
DF adjustment:   Small sample                 DF:     min     =     148.93
                                                      avg     =     410.45
                                                      max     =     704.25
Model F test:       Equal FMI                 F(   3,  515.9) =     525.22
Within VCE type:          OLS                 Prob > F        =     0.0000

------------------------------------------------------------------------------
  mathtest12 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   mathtest8 |   1.022907   .0276674    36.97   0.000      .968236    1.077579
         sex |   -2.05258   .5941458    -3.45   0.001    -3.219089   -.8860704
        race |   -.015127   .3232535    -0.05   0.963    -.6501539    .6198999
       _cons |   13.78052   1.717096     8.03   0.000     10.39951    17.16154
------------------------------------------------------------------------------
```

Notes and help with mi in stata

- LOTS of options
  - Can specify exactly how you want imputed
  - Can specify the model appropriately (ex. Using svy command)
  - mi impute mvn (multivariate normal regression) also useful
- Help mi is useful
- Also, UCLA has great website about ice and mi

General Tips

- Try a few methods: often if result in similar estimates, can put as a footnote to support method
- Some don’t impute dependent variable
  - But would still use to impute independent variables

References

- Allison, Paul D. 2001. Missing Data. *Sage University Papers Series on Quantitative Applications in the Social Sciences*. Thousand Oaks: Sage.
- Enders, Craig. 2010. Applied Missing Data Analysis. Guilford Press: New York.
- Little, Roderick J., Donald Rubin. 2002. Statistical Analysis with Missing Data. John Wiley & Sons, Inc: Hoboken.
- Schafer, Joseph L., John W. Graham. 2002. "Missing Data: Our View of the State of the Art." *Psychological Methods*.