Missing Data
Missing Data Methods in ML
Multiple Imputation

PSYC 943 (930): Fundamentals of Multivariate Modeling

Lecture 18: October 31, 2012

Today's Lecture

- The basics of missing data:
  - Types of missing data
- How NOT to handle missing data
  - Deletion methods (both pairwise and listwise)
  - Mean-substitution
  - Single Imputation
- How maximum likelihood works with missing data
- Multiple imputation for missing data
  - How imputation works
  - How to conduct analyses with missing data using imputation

Example Data #1

- To demonstrate some of the ideas of types of missing data, let's consider a situation where you have collected two variables:
  - IQ scores
  - Job performance

- Imagine you are an employer looking to hire employees for a job where IQ is important

IQ	Performance
78	9
84	13
84	10
85	8
87	7
91	7
92	9
94	9
94	11
96	7
99	7
105	10
105	11
106	15
108	10
112	10
113	12
115	14
118	16
134	12

Complete Data
From Enders (2010)

TYPES OF MISSING DATA

Our Notational Setup

- Let's let **D** denote our data matrix, which will include dependent (**Y**) and independent (**X**) variables

$$\mathbf{D} = \{\mathbf{X}, \mathbf{Y}\}$$

- **Problem:** some elements of $\mathbf{D}$ are missing

Missingness Indicator Variables

- We can construct an alternate matrix **M** consisting of indicators of missingness for each element in our data matrix **D**

  $M_{ij} = 0$ if the i^{th}observation's j^{th} variable is **not** missing

  $M_{ij} = 1$ if the i^{th}observation's j^{th} variable is missing

- Let $\boldsymbol{M}_{obs}$ and $\boldsymbol{M}_{mis}$ denote the observed and missing parts of $\boldsymbol{M}$

$$\boldsymbol{M} = \{\boldsymbol{M}_{obs}, \boldsymbol{M}_{mis}\}$$

Types of Missing Data

- A very rough typology of missing data puts missing observations into three categories:

1. Missing Completely At Random (MCAR)
2. Missing At Random (MAR)
3. Missing Not At Random (MNAR)

Missing Completely At Random (MCAR)

- Missing data are MCAR if the events that lead to missingness are independent of:
  - The observed variables

-and-

  - The unobserved parameters of interest

- Examples:
  - Planned missingness in survey research
    - Some large-scale tests are sampled using booklets
    - Students receive only a few of the total number of items
    - The items not received are treated as missing – but that is completely a function of sampling and no other mechanism

A (More) Formal MCAR Definition

- Our missing data indicators, $\boldsymbol{M}$ are **statistically independent** of our observed data $\boldsymbol{D}$

$$P(\boldsymbol{M}|\boldsymbol{D}) = P(\boldsymbol{M})$$

this comes from how independence works with pdfs

- Like saying a missing observation is due to pure randomness (i.e., flipping a coin)

Implications of MCAR

- Because the mechanism of missing is not due to anything other than chance, inclusion of MCAR in data will not bias your results
  - Can use methods based on listwise deletion, multiple imputation, or maximum likelihood

- Your effective sample size is lowered, though
  - Less power, less efficiency

IQ	Performance
78	-
84	13
84	-
85	8
87	7
91	7
92	9
94	9
94	11
96	-
99	7
105	10
105	11
106	15
108	10
112	-
113	12
115	14
118	16
134	-

MCAR Data

Missing data are dispersed randomly throughout data

Mean IQ of complete cases: 99.7
Mean IQ of incomplete cases: 100.8

Missing At Random (MAR)

- Data are MAR if the probability of missing depends **only** on some (or all) of the observed data

- $\boldsymbol{M}$ is independent of $\boldsymbol{D}_{mis}$

$$P(\boldsymbol{M}|\boldsymbol{D}) = P(\boldsymbol{M}|\boldsymbol{D}_{obs})$$

IQ	Perf	Indicator
78	-	1
84	-	1
84	-	1
85	-	1
87	-	1
91	7	0
92	9	0
94	9	0
94	11	0
96	7	0
99	7	0
105	10	0
105	11	0
106	15	0
108	10	0
112	10	0
113	12	0
115	14	0
118	16	0
134	12	0

MAR Data

Missing data are related to other data:

Any IQ less than 90 did not have a performance variable

Mean IQ of incomplete cases: 83.6
Mean IQ of complete cases: 105.5

Implications of MAR

- If data are missing at random, biased results could occur
- Inferences based on listwise deletion will be biased and inefficient
  - Fewer data points = more error in analysis
- Inferences based on maximum likelihood will be unbiased but inefficient
- We will focus on methods for MAR data today

Missing Not At Random (MNAR)

- Data are MNAR if the probability of missing data is related to values of the variable itself

$$P(\boldsymbol{M}|\boldsymbol{D}) = P(\boldsymbol{M}|\boldsymbol{D}_{obs}, \boldsymbol{D}_{mis})$$

- Often called non-ignorable missingness
  - Inferences based on listwise deletion or maximum likelihood will be biased and inefficient

- Need to provide statistical model for missing data simultaneously with estimation of original model

SURVIVING MISSING DATA: A BRIEF GUIDE

Using Statistical Methods with Missing Data

- Missing data can alter your analysis results dramatically depending upon:
  1. The type of missing data
  2. The type of analysis algorithm

- The choice of an algorithm and missing data method is important in avoiding issues due to missing data

The Worst Case Scenario: MNAR

- The worst case scenario is when data are MNAR: missing not at random
  - Non-ignorable missing

- You cannot easily get out of this mess
  - Instead you have to be clairvoyant

- Analyses algorithms must incorporate models for missing data
  - And these models must also be right

The Reality

- In most empirical studies, MNAR as a condition is an afterthought
- It is impossible to know definitively if data truly are MNAR
  - So data are treated as MAR or MCAR
- Hypothesis tests do exist for MCAR
  - Although they have some issues

The Best Case Scenario: MCAR

- Under MCAR, pretty much anything you do with your data will give you the "right" (unbiased) estimates of your model parameters

- MCAR is very unlikely to occur
  - In practice, MCAR is treated as equally unlikely as MNAR

The Middle Ground: MAR

- MAR is the common compromise used in most empirical research
  - Under MAR, maximum likelihood algorithms are unbiased

- Maximum likelihood is for many methods:
  - Linear mixed models in PROC MIXED
  - Models with “latent” random effects (CFA/SEM models) in Mplus

MISSING DATA IN MAXIMUM LIKELIHOOD

Missing Data with Maximum Likelihood

- Handling missing data in maximum likelihood is much more straightforward due to the calculation of the log-likelihood function
  - Each subject contributes a portion due to their observations

- If some of the data are missing, the log-likelihood function uses a reduced form of the MVN distribution
  - Capitalizing on the property of the MVN that subsets of variables from an MVN distribution are also MVN

- The total log-likelihood is then maximized
  - Missing data just are "skipped" – they do not contribute

Each Person's Contribution to the Log-Likelihood

- For a person p, the MVN log-likelihood can be written:

$$\log L_p = -\frac{V}{2}\log(2\pi) - \frac{1}{2}\log(|\boldsymbol{\Sigma_p}|) - \frac{(\boldsymbol{y}_p - \boldsymbol{\mu}_p)^T \boldsymbol{\Sigma}_p^{-1}(\boldsymbol{y}_p - \boldsymbol{\mu}_p)}{2}$$

- From our examples with missing data, subjects could either have all of their data…so their input into $\log L_p$ uses:

$$\boldsymbol{y}_p = \begin{bmatrix} y_{p,IQ} \\ y_{p,Perf} \end{bmatrix};$$

$$\boldsymbol{\mu}_p = \mathbf{X}_p\boldsymbol{\beta} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} \beta_0 + \beta_1 \\ \beta_0 \end{bmatrix} = \begin{bmatrix} \mu_{IQ} \\ \mu_{Perf} \end{bmatrix};$$

$$\boldsymbol{\Sigma}_p = \begin{bmatrix} \sigma_{IQ}^2 & \sigma_{IQ,Perf} \\ \sigma_{IQ,Perf} & \sigma_{Perf}^2 \end{bmatrix}$$

- …or could be missing the performance variable, yielding:

$$\boldsymbol{y}_p = [y_{p,IQ}]; \boldsymbol{\mu}_p = \mathbf{X}_p\boldsymbol{\beta} = [1 \quad 1]\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = [\beta_0 + \beta_1] = [\mu_{IQ}]; \boldsymbol{\Sigma}_p = [\sigma_{IQ}^2]$$

Evaluation of Missing Data in PROC MIXED (and pretty much all other packages)

- If the dependent variables are missing, PROC MIXED automatically skips those variables in the likelihood
  - The REPEATED statement specifies observations with the same subject ID – and uses the non-missing observations from that subject only

- If independent variables are missing, however, PROC MIXED uses listwise deletion
  - If you have missing IVs, this is a problem
  - You can sometimes phrase IVs as DVs, though

- SAS Syntax (identical to when you have complete data):

```
*EMPTY MODEL: MCAR Data;
PROC MIXED DATA=WORK.jobstackMCAR METHOD=ML COVTEST NOPROFILE ITDETAILS IC;
CLASS variable;
MODEL value = variable / S;
REPEATED / SUBJECT=ID TYPE=UN R=1,2 RCORR;
RUN;
```

Analysis of MCAR Data with PROC MIXED

- Covariance matrices from slide #4 (MIXED is closer to complete):

MCAR Data (Pairwise Deletion)		
IQ	115.6	19.4
Performance	19.4	8.0

Complete Data		
IQ	189.6	19.5
Performance	19.5	6.8

- Estimated $\mathbf{R}$ matrix from PROC MIXED:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr Z
UN(1,1)	ID	189.60	59.9557	3.16	0.0008
UN(2,1)	ID	31.7352	14.0984	2.25	0.0244
UN(2,2)	ID	10.0446	4.0984	2.45	0.0071

- Output for each observation (obs #1 = missing, obs #2 = complete):

Estimated R Matrix for Subject 1

Row	Col1
1	189.60

Estimated R Matrix for Subject 2

Row	Col1	Col2
1	189.60	31.7352
2	31.7352	10.0446

MCAR Analysis: Estimated Fixed Effects

- Estimated mean vectors:

Variable	MCAR Data (pairwise deletion)	Complete Data
IQ	93.73	100
Performance	10.6	10.35

- Estimated fixed effects:

Solution for Fixed Effects

Effect	variable	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept		10.6446	0.7623	19	13.96	<.0001
variable	IQ	89.3554	2.6244	19	34.05	<.0001
variable	Performance MCAR	0	.	.	.	.

- Means – IQ = 89.36+10.64 = 100; Performance = 10.64

Analysis of MAR Data with PROC MIXED

- Covariance matrices from slide #4 (MIXED is closer to complete):

MAR Data (Pairwise Deletion		
IQ	130.2	19.5
Performance	19.5	7.3

Complete Data		
IQ	189.6	19.5
Performance	19.5	6.8

- Estimated $\mathbf{R}$ matrix from PROC MIXED:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr Z
UN(1,1)	ID	189.60	59.9567	3.16	0.0008
UN(2,1)	ID	28.3696	12.6862	2.24	0.0253
UN(2,2)	ID	8.6176	3.3995	2.53	0.0056

- Output for each observation (obs #1 = missing, obs #10 = complete):

Estimated R Matrix for Subject 1

Row	Col1
1	189.60

Estimated R Matrix for Subject 10

Row	Col1	Col2
1	189.60	28.3696
2	28.3696	8.6176

MAR Analysis: Estimated Fixed Effects

- Estimated mean vectors:

Variable	MCAR Data (pairwise deletion)	Complete Data
IQ	105.4	100
Performance	10.7	10.35

- Estimated fixed effects:

Solution for Fixed Effects

Effect	variable	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept		9.8487	0.7098	19	13.88	<.0001
variable	IQ	90.1513	2.6734	19	33.72	<.0001
variable	Performance MAR	0	.	.	.	.

- Means – IQ = 90.15+9.85 = 100; Performance = 9.85

Additional Issues with Missing Data and Maximum Likelihood

- Given the structure of the missing data, the standard errors of the estimated parameters may be computed differently
  - Standard errors come from -1*inverse information matrix
    - Information matrix = matrix of second derivatives = hessian
- Several versions of this matrix exist
  - Some based on what is expected under the model
    - The default in SAS – good only for MCAR data
  - Some based on what is observed from the data
    - Empirical option in SAS – works for MAR data (only for fixed effects)
- Implication: some SEs may be biased if data are MAR
  - May lead to incorrect hypothesis test results
  - Correction needed for likelihood ratio/deviance test statistics
    - Not available in SAS; available for some models in Mplus

When ML Goes Bad…

- For linear models with missing **dependent variable(s)** PROC MIXED and almost every other stat package works great
  - ML "skips" over the missing DVs in the likelihood function, using only the data you have observed

- For linear models with missing **independent variable(s)**, PROC MIXED and almost every other stat package uses list-wise deletion
  - Gives biased parameter estimates under MAR

Options for MAR for Linear Models with Missing Independent Variables

1. **Use ML Estimators and hope for MCAR**

2. **Rephrase IVs as DVs**
   - In SAS: hard to do, but possible for some models
     - Dummy coding, correlated random effects
     - Rely on properties of how correlations/covariances are related to linear model coefficients β
   - In Mplus: much easier…looks more like a structural equation model
     - Predicted variables then function like DVs in MIXED

3. **Impute IVs (multiple times) and then use ML Estimators**
   - Not usually a great idea…but often the only option

ANOTHER EXAMPLE DATA SET

Today's Example Data #2

- Three variables were collected from a sample of 31 men in a course at NC State
  - **Oxygen**: oxygen intake, ml per kg body weight, per mintue
  - **Runtime**: time to run 1.5 miles in minutes
  - **Runpulse**: heart rate while running

- The research question: how does oxygen intake vary as a function of exertion (running time and running heart rate)

- The problem: some of the data are missing

Descriptive Statistics of Missing Data

- Descriptive statistics of our data:

The MEANS Procedure

Variable	Mean	Std Dev	N
Oxygen	47.1161786	5.4130470	28
RunTime	10.6882143	1.3798794	28
RunPulse	171.8636364	10.1432382	22

- Patterns of missing data:

The FREQ Procedure

MissingPattern	Frequency	Percent	Cumulative Frequency	Cumulative Percent
None Missing	21	67.74	21	67.74
Pulse Missing	4	12.90	25	80.65
Time and Pulse Missing	3	9.68	28	90.32
Oxygen Missing	1	3.23	29	93.55
Oxygen and Pulse Missing	2	6.45	31	100.00

Comparing Missing and Not Missing

OxygenMiss=Not Missing

The MEANS Procedure

Oxygen

Variable	Mean	Std Dev	N
Oxygen	47.1161786	5.4130470	28
RunTime	10.7020000	1.3943368	25
RunPulse	171.6666667	10.3505233	21

OxygenMiss=Missing

Variable	Mean	Std Dev	N
Oxygen	.	.	0
RunTime	10.5733333	1.5338296	3
RunPulse	176.0000000	.	1

RunTimeMiss=Not Missing

The MEANS Procedure

Running Time

Variable	Mean	Std Dev	N
Oxygen	46.4747200	5.0578561	25
RunTime	10.6882143	1.3798794	28
RunPulse	171.8636364	10.1432382	22

RunTimeMiss=Missing

Variable	Mean	Std Dev	N
Oxygen	52.4616667	6.3700017	3
RunTime	.	.	0
RunPulse	.	.	0

RunPulseMiss=Not Missing

The MEANS Procedure

Pulse Rate

Variable	Mean	Std Dev	N
Oxygen	46.3538095	5.4778395	21
RunTime	10.8613636	1.4576997	22
RunPulse	171.8636364	10.1432382	22

RunPulseMiss=Missing

Variable	Mean	Std Dev	N
Oxygen	49.4032857	4.8678064	7
RunTime	10.0533333	0.8612936	6
RunPulse	.	.	0

HOW NOT TO HANDLE MISSING DATA

Bad Ways to Handle Missing Data

- Dealing with missing data is important, as the mechanisms you choose can dramatically alter your results

- This point was not fully realized when the first methods for missing data were created
  - Each of the methods described in this section should ***never be used***
  - Given to show perspective – and to allow you to understand what happens if you were to choose each

Deletion Methods

- Deletion methods are just that: methods that handle missing data by deleting observations
  - Listwise deletion: delete the entire observation if any values are missing
  - Pairwise deletion: delete a pair of observations if either of the values are missing

- Assumptions: Data are MCAR

- Limitations:
  - Reduction in statistical power if MCAR
  - Biased estimates if MAR or MNAR

Listwise Deletion

- Listwise deletion discards ***all*** of the data from an observation if one or more variables are missing

- Most frequently used in statistical software packages that are not optimizing a likelihood function (need ML)

- In linear models:
  - SAS GLM list-wise deletes cases where **IVs** *or* **DVs** are missing

Listwise Deletion Example

- If you wanted to predict Oxygen from Running Time and Pulse Rate you could:
  - Start with one variable (running time):

Dependent Variable: Oxygen

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	442.6707707	442.6707707	59.44	<.0001
Error	23	171.2950243	7.4476098		
Corrected Total	24	613.9657950			

  - Then add the other (running time + pulse rate):

Dependent Variable: Oxygen

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	449.4733700	224.7366850	26.85	<.0001
Error	18	150.6611373	8.3700632		
Corrected Total	20	600.1345072			

- The nested-model comparison test cannot be formed
  - Degrees of freedom error changes as missing values are omitted

Pairwise Deletion

- Pairwise deletion discards a pair of observations if either one is missing
  - Different from listwise: uses more data (rest of data not thrown out)

- Assumes: MCAR

- Limitations:
  - Reduction in statistical power if MCAR
  - Biased estimates if MAR or MNAR

- Can be an issue when forming covariance/correlation matrices
  - May make them non-invertible, problem if used as input into statistical procedures

Pairwise Deletion Example

- Covariance Matrix from PROC CORR (see the different DF):

3 Variables: Oxygen RunTime RunPulse

Variances and Covariances
Covariance / Row Var Variance / Col Var Variance / DF

	Oxygen	RunTime	RunPulse
Oxygen	29.3010776	-5.9882853	-19.5021167
	29.3010776	25.5819081	30.0067254
	29.3010776	1.9441750	107.1333333
	27	24	20
RunTime	-5.9882853	1.9040671	3.6559091
	1.9441750	1.9040671	2.1248885
	25.5819081	1.9040671	102.8852814
	24	27	21
RunPulse	-19.5021167	3.6559091	102.8852814
	107.1333333	102.8852814	102.8852814
	30.0067254	2.1248885	102.8852814
	20	21	21

Single Imputation Methods

- **Single imputation** methods replace missing data with some type of value
  - **Single:** one value used
  - **Imputation:** replace missing data with value

- Upside: can use entire data set if missing values are replaced

- Downside: biased parameter estimates and standard errors (even if missing is MCAR)
  - Type-I error issues

- Still: never use these techniques

Unconditional Mean Imputation

- Unconditional mean imputation replaces the missing values of a variable with its estimated mean
  - Unconditional = mean value without any input from other variables
- Example: missing Oxygen = 47.1; missing RunTime = 10.7; missing RunPulse = 171.9

Before Single Imputation:

The MEANS Procedure

Variable	Mean	Std Dev	N
Oxygen	47.1161786	5.4130470	28
RunTime	10.6882143	1.3798794	28
RunPulse	171.8636364	10.1432382	22

After Single Imputation:

The MEANS Procedure

Variable	Mean	Std Dev	N
Oxygen	47.1146129	5.1352696	31
RunTime	10.6893548	1.3090733	31
RunPulse	171.8741935	8.4864585	31

- Notice: uniformly smaller standard deviations

Conditional Mean Imputation (Regression)

- Conditional mean imputation uses regression analyses to impute missing values
  - The missing values are imputed using the predicted values in each regression (conditional means)

- For our data we would form regressions for each outcome using the other variables
  - $OXYGEN = \beta_{01} + \beta_{11}*RUNTIME + \beta_{21}*PULSE$
  - $RUNTIME = \beta_{02} + \beta_{12}*OXYGEN + \beta_{22}*PULSE$
  - $PULSE = \beta_{03} + \beta_{13}*OXYGEN + \beta_{23}*RUNTIME$

- More accurate than unconditional mean imputation
  - But still provides biased parameters and SEs

Stochastic Conditional Mean Imputation

- Stochastic conditional mean imputation adds a random component to the imputation
  - Representing the error term in each regression equation
  - Assumes MAR rather than MCAR

- Again, uses regression analyses to impute data:
  - OXYGEN = $\beta_{01} + \beta_{11}$*RUNTIME + β_{21}*PULSE + **Error**
  - RUNTIME = $\beta_{02} + \beta_{12}$*OXYGEN + β_{22}*PULSE + **Error**
  - PULSE = $\beta_{03} + \beta_{13}$*OXYGEN + β_{23}*RUNTIME + **Error**

- **Error** is random: drawn from a normal distribution
  - Zero mean and variance equal to residual variance σ_e^2 for respective regression

Imputation by Proximity: Hot Deck Matching

- Hot deck matching uses real data – from other observations as its basis for imputing

- Observations are "matched" using similar scores on variables in the data set
  - Imputed values come directly from matched observations

- Upside: Helps to preserve univariate distributions; gives data in an appropriate range

- Downside: biased estimates (especially of regression coefficients), too-small standard errors

Scale Imputation by Averaging

- In psychometric tests, a common method of imputation has been to use a scale average rather than total score
  - Can re-scale to total score by taking # items * average score

- Problem: treating missing items this way is like using person mean
  - Reduces standard errors
  - Makes calculation of reliability biased

Longitudinal Imputation: Last Observation Carried Forward

- A commonly used imputation method in longitudinal data has been to treat observations that dropped out by carrying forward the last observation
  - More common in medical studies and clinical trials
- Assumes scores do not change after dropout – bad idea
  - Thought to be conservative
- Can exaggerate group differences
  - Limits standard errors that help detect group differences

Why Single Imputation Is Bad Science

- Overall, the methods described in this section are not useful for handling missing data

- If you use them you will likely get a statistical answer that is an artifact
  - Actual estimates you interpret (parameter estimates) will be biased (in either direction)
  - Standard errors will be too small
    - Leads to Type-I Errors

- Putting this together: you will likely end up making conclusions about your data that are wrong

WHAT TO DO WHEN ML WON'T GO: MULTIPLE IMPUTATION

Multiple Imputation

- Rather than using single imputation, a better method is to use multiple imputation
  - The multiply imputed values will end up adding variability to analyses – helping with biased parameter and SE estimates

- Multiple imputation is a mechanism by which you "fill in" your missing data with "plausible" values
  - End up with multiple data sets – need to run multiple analyses
  - Missing data are predicted using a statistical model using the observed data (the MAR assumption) for each observation

- MI is possible due to statistical assumptions
  - The most often used assumption is that the observed data are multivariate normal
  - We will focus on this today – and expand upon it on Friday

Multiple Imputation Steps

1. The missing data are filled in a number of times (say, *m* times) to generate *m* complete data sets

2. The m complete data sets are analyzed using standard statistical analyses

3. The results from the *m* complete data sets are combined to produce inferential results

Distributions: The Key to Multiple Imputation

- The key idea behind multiple imputation is that each missing value has a **distribution** of likely values
  - The distribution reflects the uncertainty about what the variable may have been

- Multiple imputation can be accomplished using variables outside an analysis
  - All contribute to multivariate normal distribution
  - Harder to justify why un-important variables omitted

- Single imputation, by any method, disregards the uncertainty in each missing data point
  - Results from singly imputed data sets may be biased or have higher Type-I errors

Multiple Imputation in SAS

- SAS has a pair of procedures for multiple imputation:
  - PROC MI: generates multiple complete data sets
  - PROC MIANALYZE: analyzes the results of statistical analyses with imputed data sets
- Most frequent assumption SAS uses is that data are multivariate normal
- Not MVN? Mplus provides imputation options

IMPUTATION PHASE

SAS PROC MI

- PROC MI uses a variety of methods depending on the type of missing data present

  - Monotone missing pattern: ordered missingness – if you order your variables sequentially, only the tail end of the variables collected is missing
    - Multiple methods exist for imputation

  - Arbitrary missing pattern: missing data follow no pattern
    - Most typical in data
    - Markov Chain Monte Carlo assuming MVN is used

Multivariate Normal Data

- The MVN distribution has several nice properties

- In SAS PROC MI, multiple imputation of arbitrary missing data takes advantage of the MVN properties

- Imagine we have *N* observations of *V* variables from a MVN:

$$\boldsymbol{Y}_{(N\ x\ V)} \sim N_V(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

- The property we will use is the conditional distribution of MVN variables
  - We will examine the conditional distribution of missing data given the data we have observed

Conditional Distributions of MVN Variables

- The conditional distribution of sets of variables from a MVN is also MVN
  - Used as the data-generating distribution in PROC MI

- If we were interested in the distribution of the first *q* variables, we partition three matrices:

  - The data: $[\boldsymbol{Y}_{(N\ x\ q)} \quad \boldsymbol{X}_{(N\ x\ V-q)}]$
  - The mean vector: $\begin{bmatrix} \boldsymbol{\mu}_{Y:(q\ x\ 1)} \\ \boldsymbol{\mu}_{X:(V-q\ x\ 1)} \end{bmatrix}$
  - The covariance matrix: $\begin{bmatrix} \boldsymbol{\Sigma}_{YY:(q\ x\ q)} & \boldsymbol{\Sigma}_{YX:(q\ x\ V-q)} \\ \boldsymbol{\Sigma}_{XY:(V-q\ x\ q)} & \boldsymbol{\Sigma}_{XX:(V-q\ x\ V-q)} \end{bmatrix}$

Conditional Distributions of MVN Variables

- The conditional distribution of $\boldsymbol{Y}$ given the values of $\boldsymbol{X} = \boldsymbol{x}$ is then:

$$\boldsymbol{Y}|\boldsymbol{X} \sim N_q(\boldsymbol{\mu}^*, \boldsymbol{\Sigma}^*)$$

Where (using our partitioned matrices):

$$\boldsymbol{\mu}^* = \boldsymbol{\mu}_Y + \boldsymbol{\Sigma}_{YX}\boldsymbol{\Sigma}_{\mathrm{XX}}^{-1}(\boldsymbol{x}' - \boldsymbol{\mu}_X)$$

And:

$$\boldsymbol{\Sigma}^* = \boldsymbol{\Sigma}_{YY} - \boldsymbol{\Sigma}_{YX}\boldsymbol{\Sigma}_{XX}^{-1}\boldsymbol{\Sigma}_{XY}$$

Example from our Data

- From estimates with missing data:

$$\bar{\boldsymbol{y}} = \begin{bmatrix} 47.1 \\ 10.7 \\ 171.9 \end{bmatrix}; \mathbf{S} = \begin{bmatrix} 29.3 & -6.0 & -19.5 \\ -6.0 & 1.9 & 3.7 \\ -19.5 & 3.7 & 102.9 \end{bmatrix}$$

- For observation #4 (missing oxygen): $\mathbf{x} = [11.96 \quad 176]$
  - We wish to impute the first observation (oxygen) conditional on the values of runtime and pulse

- Assuming MVN, we get the following sub-matrices:

$$\bar{\mathbf{x}}_Y = [47.1]; \bar{\mathbf{x}}_X = \begin{bmatrix} 10.7 \\ 171.9 \end{bmatrix}$$

$$\mathbf{S}_{YY} = [29.3]; \mathbf{S}_{YX} = [-6.0 \quad -19.5];$$

$$\mathbf{S}_{XY} = \begin{bmatrix} -6.0 \\ -19.5 \end{bmatrix}; \mathbf{S}_{XX} = \begin{bmatrix} 1.9 & 3.7 \\ 3.7 & 102.9 \end{bmatrix}; \mathbf{S}_{XX}^{-1} = \begin{bmatrix} .56 & -.02 \\ -.02 & .01 \end{bmatrix}$$

Imputation Distribution

- The imputed value for Oxygen for observation #4 is drawn from a $N_1(43.0, 9.8)$:

Mean:

$$\bar{\boldsymbol{y}}^* = \bar{\mathbf{x}}_Y + \mathbf{S}_{YX}\mathbf{S}_{XX}^{-1}(\mathbf{x}' - \bar{\mathbf{x}}_X) =$$

$$[47.1] + [-6.0 \quad -19.5]\begin{bmatrix} .56 & -.02 \\ -.02 & .01 \end{bmatrix}\left(\begin{bmatrix} 11.96 \\ 176 \end{bmatrix} - \begin{bmatrix} 10.7 \\ 171.9 \end{bmatrix}\right)$$

$$= 43.0$$

Variance:

$$\mathbf{S}^* = \mathbf{S}_{YY} - \mathbf{S}_{YX}\mathbf{S}_{XX}^{-1}\mathbf{S}_{XY}$$

$$= [29.3] - [-6.0 \quad -19.5]\begin{bmatrix} .56 & -.02 \\ -.02 & .01 \end{bmatrix}\begin{bmatrix} -6.0 \\ -19.5 \end{bmatrix}$$

$$= 9.8$$

Using the MVN for Missing Data

- If we consider our missing data to be $\boldsymbol{Y}$, we can then use the result from the last slide to generate imputed (plausible) values for our missing data

- Data generated from a MVN distribution is fairly common and "easy" to do computationally

- However….

The Problem: True μ and Σ are Unknown

- Problem: the true mean vector and covariance matrix for our data is unknown
  - We only have sample estimates
    - Sample estimates have sampling error
      - The mean vector has a MVN distribution
      - The sample covariance matrix has a (scaled) Wishart distribution
  - Missing data complicate the situation by providing even fewer observations to estimate either parameter

- The example from before used one estimate (but that is unlikely to be correct)
  - It used pairwise deletion

The PROC MI Solution

- PROC MI: use MCMC to estimate data and parameters simultaneously:

Step 0: Create starting value estimates for $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$: $(\boldsymbol{\mu}_{t-1=0}, \boldsymbol{\Sigma}_{t-1=0})$

Iterate *t* times through:

Step 1: Using $\boldsymbol{\mu}_{t-1}, \boldsymbol{\Sigma}_{t-1}$ generate the missing data from the conditional MVN (conditional on the observed values for each case)

Step 2: Using the imputed and observed data, draw a new $\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t$ from the MVN and Wishart distributions, respectively

The Process of Imputation

- The iterations take "a while" to reach a steady state – stable values for the distribution of $\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t$
  - The burn in period

- After this period, you can take sets of imputed data to be used in your multiple analyses
  - The sets should be taken with "enough" iterations in between so as to not be highly correlated
    - The thinning interval

Using PROC MI

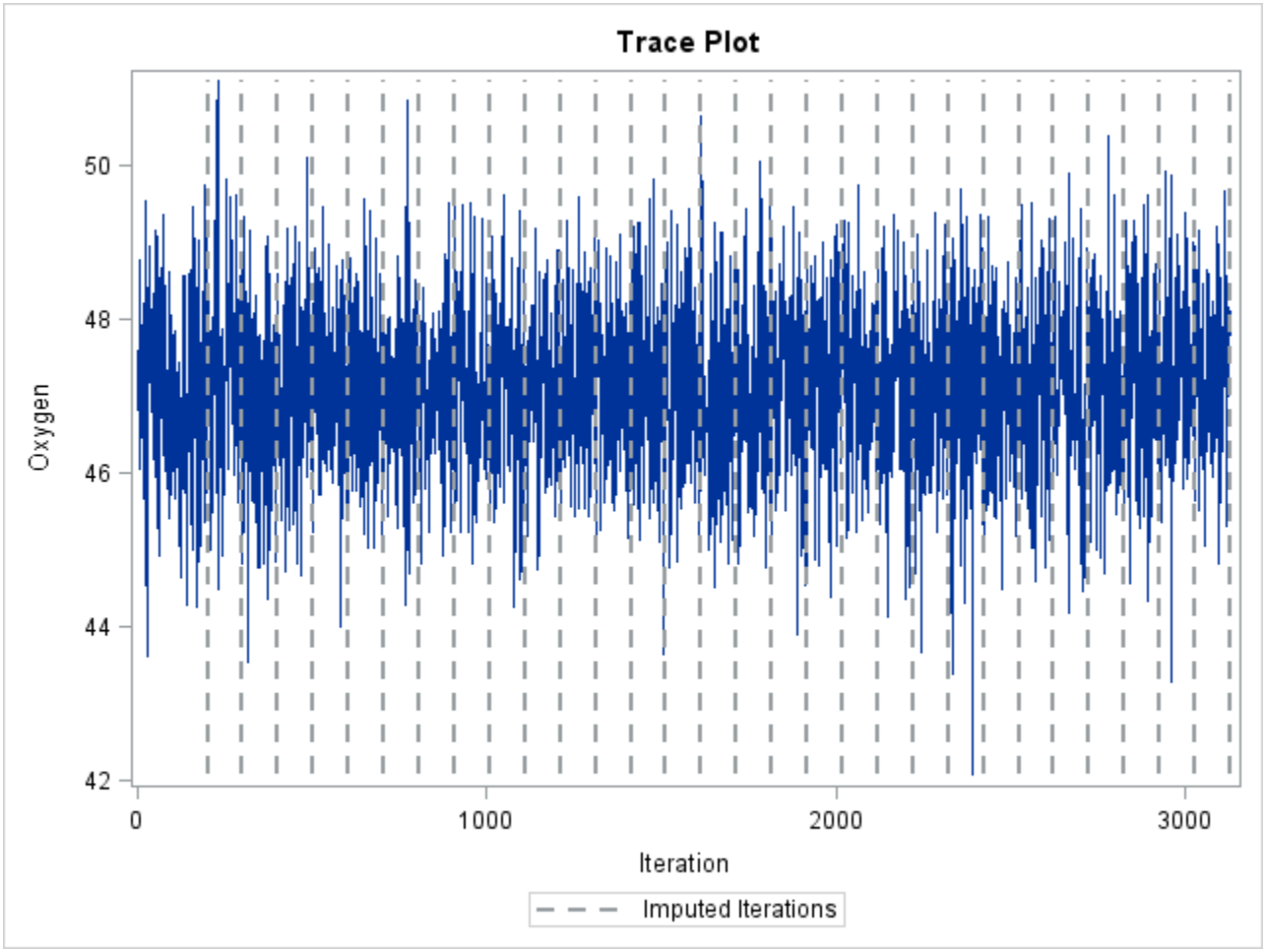
- PROC MI Syntax:

```
*IMPUTATION PHASE:;
*USING PROC MI TO IMPUTE DATA:;
PROC MI DATA=WORK.fitmiss OUT=WORK.fitimpute NIMPUTE=30 SEED=10292012;
MCMC CHAIN=SINGLE DISPLAYINIT INITIAL=EM(ITPRINT) PLOTS=ALL
     OUTITER=WORK.outiter OUTEST=WORK.outest;
VAR oxygen runtime runpulse;
RUN;
```

- More often than not, the output of MI does not have much useful information
  - Must assume convergence of mean vector and covariance matrix – but limited statistics to check convergence

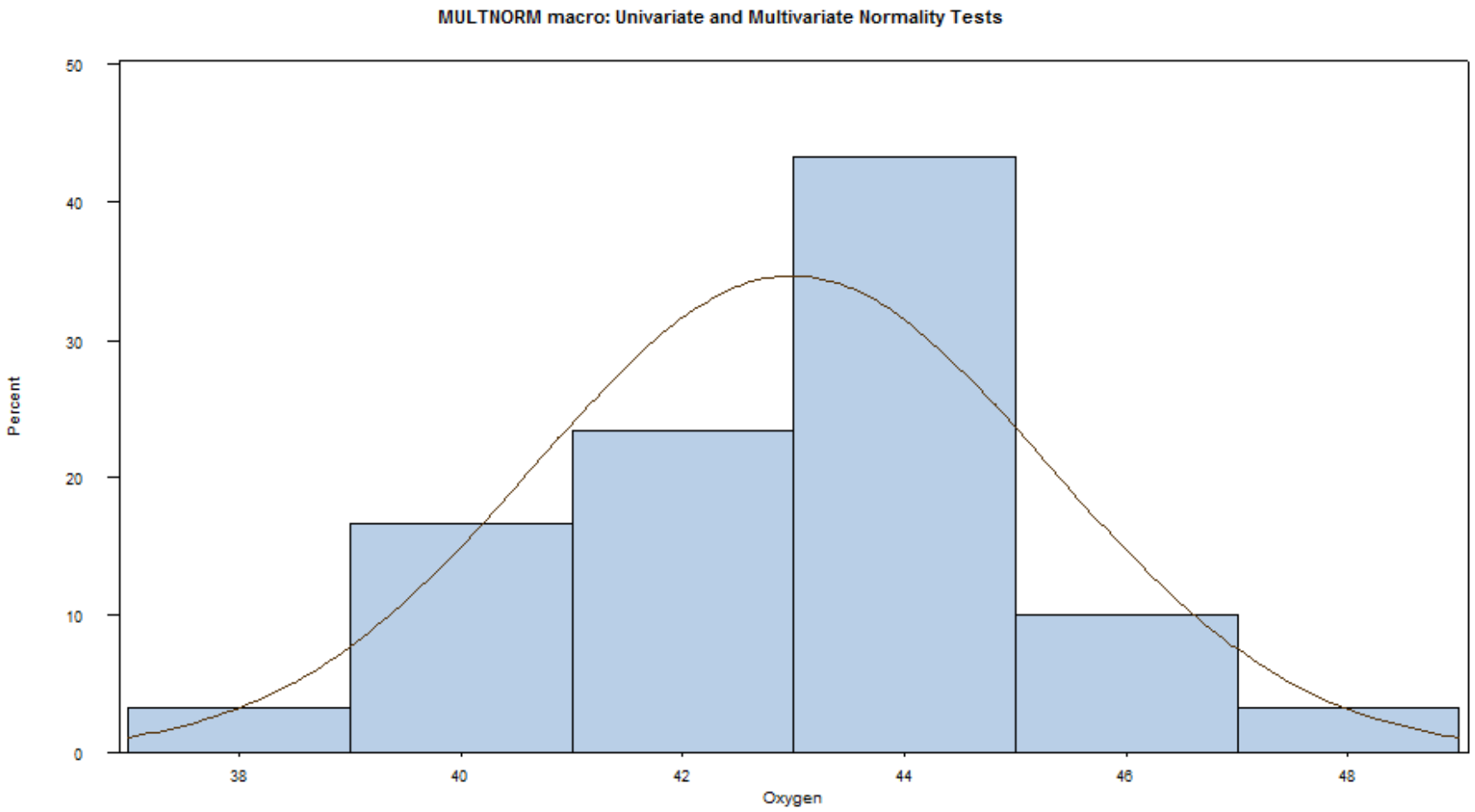
- Of interest is the new data set (WORK.fitimpute)
  - Here it contains 30 imputations for each missing variable
    - Need to run the regression 30 times – Analysis and Pooling Phase

MCMC Trace Plots – Use for Checking Convergence



Inspecting Imputed Values

- To demonstrate the imputed values, look at the histogram of the 30 values for observation 4:



Resulting Data Sets

- The new data sets are all stacked on top of each other
- Analyses now must add a line that says BY so each new data set has its own analysis

	Imputation Number	Oxygen	RunTime	RunPulse	MissingPattern
1	1	44.609	11.37	178	0
2	1	54.297	8.65	156	0
3	1	49.874	9.22	177.95495543	1
4	1	42.352679775	11.95	176	4
5	1	39.442	13.08	174	0
6	1	50.541	9.4485552222	177.07803459	3
7	1	44.754	11.12	176	0
8	1	51.855	10.33	166	0
9	1	40.836	10.95	168	0
10	1	46.774	10.25	166.09209796	1
11	1	39.407	12.63	174	0
12	1	45.441	9.63	164	0
13	1	45.118	11.08	179.26160327	1
14	1	45.79	10.47	186	0
15	1	48.673	9.4	186	0
16	1	47.467	10.5	170	0
17	1	45.313	10.07	185	0
18	1	59.571	7.704924026	172.89225626	3
19	1	44.811	11.63	176	0
20	1	44.2901159	10.85	177.48176509	5
21	1	60.055	8.63	170	0
22	1	37.388	14.03	186	0
23	1	47.273	9.7465552053	162.99703576	3
24	1	49.156	8.95	180	0
25	1	46.672	10	183.28206872	1
26	1	50.388	10.08	168	0
27	1	46.08	11.17	156	0
28	1	55.656883116	8.92	149.36487646	5
29	1	39.203	12.88	168	0
30	1	50.545	9.93	148	0
31	1	47.92	11.5	170	0
32	2	44.609	11.37	178	0
33	2	54.297	8.65	156	0

MULTIPLE IMPUTATION: ANALYSIS PHASE

Up Next: Multiple Analyses

- Once you run PROC MI, the next step is to use each of the imputed data sets in its own analysis
  - Called the analysis phase
  - For our example, that would be 30 times

- The multiple analyses are then compiled and processed into a single result
  - Yielding the answers to your analysis questions (estimates, SEs, and P-values)

- GOOD NEWS: SAS will automate all of this for you

Analysis Phase

- Analysis Phase: run the analysis on all imputed data sets

```
*ANALYSIS PHASE:;
PROC MIXED DATA=WORK.fitimpute METHOD=ML COVTEST NOPROFILE ITDETAILS IC ASYCOV;
BY _IMPUTATION_;
MODEL oxygen = runtime runpulse / SOLUTION COVB;
ODS OUTPUT SolutionF=WORK.FixedEffects CovB=WORK.CovMatrices;
RUN;
```

- Syntax runs for each data set (BY _IMPUTATION_)
- The ODS OUTPUT line saves information needed in the pooling phase:
  - Parameter estimates (to make parameter estimates)
    - SolutionF=WORK.fixedeffects
  - Asymptotic covariance matrix of the fixed effects $(\boldsymbol{X}^T\boldsymbol{V}^{-1}\boldsymbol{X})^{-1}$
    - CovB=WORK.CovMatrices

Saving Information from Other SAS PROCs

- Because of the various number of PROC types SAS implements, there are a variety of difference commands you must use if you are using Multiple Imputation in SAS

- The SAS User's Group document by Yuan posted on our website outlines the varying ways to do so
  - Although, some will not work without a reference to the SAS 9.3 manual

MULTIPLE IMPUTATION: POOLING PHASE

Pooling Parameters from Analyses of Imputed Data Sets

- In the pooling phase, the results are pooled and reported

- For parameter estimates, the pooling is straight forward
  - The estimated parameter is the average parameter value across all imputed data sets
    - For our example the average intercept, slope for runtime, and slope for runpulse are taken over the 30 imputed data sets and analyses

- For standard errors, pooling is more complicated
  - Have to worry about sources of variation:
    - Variation from sampling error that would have been present had the data not been missing
    - Variation from sampling error resulting from missing data

Pooling Standard Errors Across Imputation Analyses

- Standard error information comes from two sources of variation from imputation analyses (for m imputations)

- Within Imputation Variation:

$$V_W = \frac{1}{m}\sum_{i=1}^{m} SE_i^2$$

- Between Imputation Variation (here θ is an estimated parameter from an imputation analysis):

$$V_B = \frac{1}{m-1}\sum_{i=1}^{m}\left(\hat{\theta}_i - \bar{\theta}\right)^2$$

- Then, the total sampling variance is: $V_T = V_W + V_B + \frac{V_B}{M}$
- The subsequent (imputation pooled) SE is $SE = \sqrt{V_T}$

Pooling Phase in SAS: PROC MIANALYZE

- SAS PROC MIANALYZE conducts the pooling phase of imputations: no calculations are needed

```
*POOLING PHASE:;
PROC MIANALYZE PARMS=WORK.fixedeffects CovB(EFFECTVAR=ROWCOL)=Work.CovMatrices EDF=28;
MODELEFFECTS Intercept RunTime RunPulse;
RUN;
```

- The parameter data set, the asymptotic covariance matrix dataset, and the number of error degrees of freedom are all input

- The MODELEFFECTS line combs through the input data and conducts the pooling

- NOTE: different PROC lines have different input values. SEE:

http://support.sas.com/documentation/cdl/en/statug/63962/HTML/default/viewer.htm#mianalyze_toc.htm

PROC MIANALYZE OUTPUT

Variances:
See Next Slides

Variance Information

Parameter	Variance: Between	Within	Total	DF
Intercept	24.841980	67.878685	93.548731	18.112
RunTime	0.039703	0.117858	0.158884	18.599
RunPulse	0.000808	0.002397	0.003233	18.594

Variance Information

Parameter	Relative Increase in Variance	Fraction Missing Information	Relative Efficiency
Intercept	0.378175	0.278142	0.990814
RunTime	0.348097	0.261601	0.991355
RunPulse	0.348394	0.261768	0.991350

Parameter Estimates – With Hypothesis Test P-Values

Parameter Estimates

Parameter	Estimate	Std Error	95% Confidence Limits		DF
Intercept	92.129564	9.672059	71.81834	112.4408	18.112
RunTime	-3.055738	0.398603	-3.89124	-2.2202	18.599
RunPulse	-0.074091	0.056855	-0.19327	0.0451	18.594

Parameter Estimates

Parameter	Minimum	Maximum	Theta0	t for H0: Parameter=Theta0	Pr > |t|
Intercept	83.042973	101.702192	0	9.53	<.0001
RunTime	-3.409403	-2.709447	0	-7.67	<.0001
RunPulse	-0.132395	-0.003353	0	-1.30	0.2084

Additional Pooling Information

- The decomposition of imputation variance leads to two helpful diagnostic measures about the imputation:

- Fraction of Missing Information: $FMI = \frac{V_B + \frac{V_B}{m}}{V_T}$
  - Measure of influence of missing data on sampling variance
  - Example: intercept = 0.28; runtime = .26; runpulse = .26
  - ~27% of parameters variance attributable to missing data

- Relative Increase in Variance: $RIV = \frac{V_B + \frac{V_B}{m}}{V_W} = \frac{FMI}{1 - FMI}$
  - Another measure of influence of missing data on sampling variance
  - Example: intercept = 0.38; runtime = .35; runpulse = .35

ISSUES WITH IMPUTATION

Common Issues that can Hinder Imputation

- MCMC Convergence
  - Need “stable” mean vector/covariance matrix
- Non-normal data: counts, skewed distributions, categorical (ordinal or nominal) variables
  - Mplus is a good option
  - Some claim it doesn’t matter as much with many imputations
- Preservation of model effects
  - Imputation can strip out effects in data
    - Interactions are most difficult – form as auxiliary variable
- Imputation of multilevel data
  - Differing covariance matrices

Number of Imputations

- The number of imputations (m from the previous slides) is important: bigger is better
  - Basically, run as many as you can (100s)

- Take a look at the SEs for our parameters as I varied the number of imputations:

Parameter	$m = 1$	$m = 10$	$m = 30$	$m = 100$
Intercept	8.722	9.442	9.672	9.558
RunTime	0.366	0.386	0.399	0.389
RunPulse	0.053	0.053	0.057	0.056

WRAPPING UP

Wrapping Up

- Missing data are common in statistical analyses

- They are frequently neglected
  - MNAR: hard to model missing data and observed data simultaneously
  - MCAR: doesn't often happen
  - MAR: most missing imputation assumes MVN

- More often than not, ML is the best choice
  - Software is getting better at handling missing data
  - We will discuss how ML works next week