Handling missing data with MICE

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01/29/2020

Missing data

Missing data are observations that should be part of your data but aren't

ID	Y	X1	X2	X3
1	32	0	6	5
2	25	1	5	3
3	40	1	7	6
4	?	?	?	?
5	5	1	4	2
6	27	0	?	7

Methods for handling missing data

- There are several!
- R uses listwise deletion by default
  - Can lose power and/or bias results
- Multiple Imputation by Chained Equations (MICE)
  - Imputation = substituting missing data with estimated values

MICE Lab Demo

1) Run a simple linear regression using pairwise deletion, the default in R
2) Impute dataset’s missing vales using the mice package
3) Run a simple linear regression in the imputed data
4) Compare model estimates across missing data techniques

Load Libraries

````
---
title: "PSY 653 Module 1: Missing Data"
subtitle: "Jan 29, 2020"
output:
  html_document:
    df_print: paged
---

# Part 1: In class Demo

## Load Libraries
```{r,message=FALSE}
library(tidyverse)
library(mice)
library(olsrr)
```
````

Read in data

```
## Read in data
```{r,message=FALSE}
mice_data1 <- read_csv("mice_data1.csv")
```
```

This dataset has 2 simulated variables: X1 and X2

X1 has some missing values

X1	X2
1	3
2	0
3	3
1	0
2	0
3	4
NA	0
1	0
2	1
3	0
1	2
2	0

Use a Simple Linear Regression to regress X1 on X2

```
## Simple Linear regression model X1 ~ X2
Using pairwise deletion for missing data by default
```{r}
mod1 <- lm(X1 ~ X2, data = mice_data1)
ols_regress(mod1)
```
```

Simple linear regression output with pairwise deletion

Model Summary

R	0.026	RMSE	0.714
R-Squared	0.001	Coef. Var	39.353
Adj. R-Squared	-0.002	MSE	0.510
Pred R-Squared	-0.009	MAE	0.592

RMSE: Root Mean Square Error
MSE: Mean Square Error
MAE: Mean Absolute Error

ANOVA

	Sum of Squares	DF	Mean Square	F	Sig.
Regression	0.137	1	0.137	0.27	0.6039
Residual	204.939	402	0.510		
Total	205.077	403			

Parameter Estimates

model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
(Intercept)	1.828	0.044		41.152	0.000	1.741	1.916
X2	-0.011	0.022	-0.026	-0.519	0.604	-0.055	0.032

We interpret this output as usual

In write-up, would specify “missing data were handled using pairwise deletion”

Impute the data with mice

````
## Impute the dataset 5 times (using mice)
```{r}
imputed_data <- mice(mice_data1, m=5, maxit = 50, method = 'pmm', seed = 500)
```
````

- **mice_data1** = name of the dataset you are imputing
- **m** = # of imputations (# of imputed *versions* of the dataset you will create)
- **maxit** = number of iterations for each imputation (default is 5, generally do more)
- **method = pmm** = “Predictive Mean Matching”
- **seed** = specifying a # will allow you to get the same results each time

What the imputation process look like

MICE uses all of the other variables to predict each missing value

```
iter imp variable
 1    1   X1
 1    2   X1
 1    3   X1
 1    4   X1
 1    5   X1
 2    1   X1
 2    2   X1
 2    3   X1
 2    4   X1
 2    5   X1
 3    1   X1
 3    2   X1
```

Run the same simple linear regression of X1 on X2, but this time use the imputed dataset

```
## Regress X1 on X2 on imputed dataset using the "with" function
```{r, results= hide}
mod.imp <- with(imputed_data, exp= lm(X1 ~ X2))
summary(mod.imp)
```
```

- **mod.imp** = model name
- **with()** = tells R to run the analysis in all imputations of the data
- **exp** = an expression with a formula object
- **lm(X1 ~ X2)** = the model you want to run. In this case, a simple linear regression
- **summary()** = use to view model output

Simple linear regression output with MICE for *all imputations*

```
mod.imp <- with(imputed_data, exp= lm(X1 ~ X2))
summary(mod.imp)
```
```

| term <chr> | estimate <dbl> | std.error <dbl> | statistic <dbl> | p.value <dbl> |
|---|---|---|---|---|
| (Intercept) | 1.843998789 | 0.04306806 | 42.81592551 | 1.230265e-158 |
| X2 | -0.019184199 | 0.02092467 | -0.91682191 | 3.597405e-01 |
| (Intercept) | 1.829037385 | 0.04236086 | 43.17752920 | 6.251121e-160 |
| X2 | -0.001437869 | 0.02058108 | -0.06986363 | 9.443341e-01 |
| (Intercept) | 1.835000757 | 0.04178940 | 43.91067814 | 1.559009e-162 |
| X2 | -0.019259876 | 0.02030343 | -0.94860191 | 3.433462e-01 |
| (Intercept) | 1.832034206 | 0.04266410 | 42.94088903 | 4.385727e-159 |
| X2 | -0.020546390 | 0.02072841 | -0.99121896 | 3.221259e-01 |
| (Intercept) | 1.791168458 | 0.04269351 | 41.95411954 | 1.589717e-155 |
| X2 | 0.012751627 | 0.02074270 | 0.61475263 | 5.390373e-01 |

1-10 of 10 rows

Imputation 1 | Imputation 2 | Imputation 3 | Imputation 4 | Imputation 5
```

Pool model estimates from all the imputations

```
## Pool model estimates across imputed versions of the dataset
```{r}
combined_imp <- pool(mod.imp)
summary(combined_imp)
```
```

```
                 estimate  std.error  statistic       df p.value
(Intercept)  1.822457999 0.04641326 39.2658866 100.5742 0.00000
X2          -0.006076888 0.02123498 -0.2861734 289.4252 0.77495
```

- **mod.imp** = model name for SLR
- **pool()** = tells R to combine model estimates across each imputation
- **summary()** = use to view model output

Compare model results between the missing data techniques

Pairwise Deletion:

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.82821    0.04443  41.152   <2e-16 ***
X2          -0.01142    0.02200  -0.519    0.604
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Pooled across MICE datasets:

```
                estimate  std.error  statistic       df p.value
(Intercept)  1.822457999 0.04641326 39.2658866 100.5742 0.00000
X2          -0.006076888 0.02123498 -0.2861734 289.4252 0.77495
```

A few notes on the mice package

- The with() and pool() functions allow you to pool model estimates for many common analyses
- In general, you should examine missing data patterns before using mice
- Can take a lot of computational power and time to run in larger datasets
- Not currently compatible with machine learning and some multivariate analyses
    - Mplus has its own code for multiple imputation
- To read more on the mice package, view the vignette here:
    - https://cran.r-project.org/web/packages/mice/mice.pdf