Multiple Imputation for Multilevel Data

Multilevel Data

A unit of analysis is the what or whom being studied (e.g., observations, individuals, classrooms, groups, families, etc.)

Multilevel data structures have multiple units of analysis that are hierarchically nested

Lower-level units are nested within higher-level units

Some Terminology

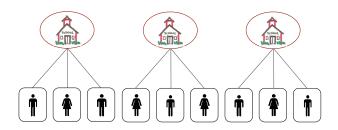
Observations at the lowest level of the data hierarchy are level-1 units

Observations at the second level of the hierarchy are level-2 units (or clusters)

e.g., Students at level-1 are nested within schools (clusters) at level-2, daily diary observations at level-1 are nested within individuals (clusters) at level-2

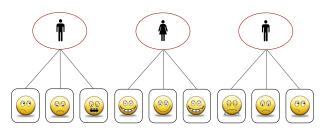
Multilevel Data Example 1

Sample comprised of multiple schools and several students in each school (i.e., students nested within schools)



Multilevel Data Example 2

Sample comprised of multiple individuals, each with several daily assessments of mood (i.e., observations nested within individuals)



Other Examples

Clients nested within therapists

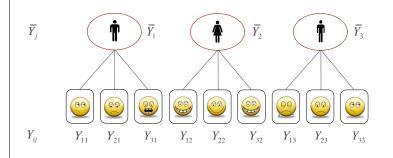
Twins nested within dyads

Individuals nested within families

Employees nested within workgroups

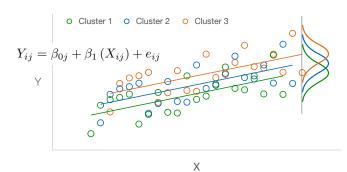
Mood Example

Mood scores vary across days within person, and average mood scores vary across persons



Random Intercept Model

A random intercept model is one where each cluster has unique intercepts (means) but the same slope



Level-2 Model and Reduced Form Model

Each cluster's intercept can be expressed as a mean intercept plus a residual

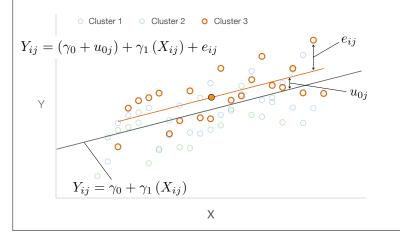
$$\beta_{0j} = \gamma_0 + u_{0j}$$

$$\beta_1 = \gamma_1$$

Substituting the right side of each equation into the level-1 model gives the reduced form model

$$Y_{ij} = (\gamma_0 + u_{0j}) + \gamma_1 (X_{ij}) + e_{ij}$$

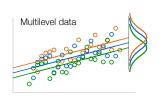
Random Intercept Model

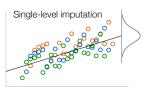


Single-Level Imputation

Standard imputation routines assume a common distribution for all clusters (same means and variance-covariance matrix)

Single-level imputation will introduce substantial bias under any mechanism





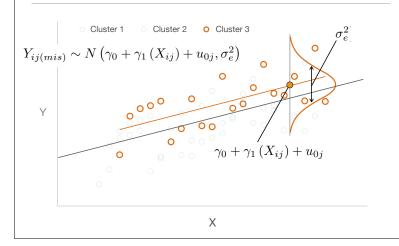
Multilevel Imputation

Multilevel imputation defines replacement values as a predicted score plus a normally distributed residual term

Each cluster has a unique regression line, so predicted scores account for between-cluster (level-2) differences

Within-cluster (level-1) variability defines the amount of random noise in the residuals

Random Intercept Imputation Model



Blimp Imputation Script for Random Intercepts

DATA: ~/desktop/examples/data.csv;

VARNAMES: cluster y x;

MISSING: -99;

MODEL: cluster ~ y x;

SEED: 90291; BURN: 1000; THIN: 1000; NIMPS: 20;

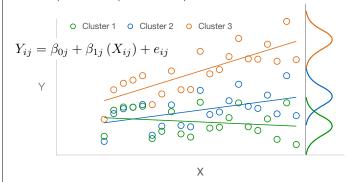
OUTFILE: ~/desktop/examples/imps.csv;

OPTIONS: stacked;

CHAINS: 2 processors 2;

Random Slope Model

A random slope model is one where each cluster has unique intercepts and slopes



Level-2 Model and Reduced Form Model

Each cluster's intercept and slope can be expressed as a mean intercept and mean slope plus a residual

$$\beta_{0j} = \gamma_0 + u_{0j}$$

$$\beta_{1j} = \gamma_1 + u_{1j}$$

Substituting the right side of each equation into the level-1 model gives the reduced form model

$$Y_{ij} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})(X_{ij}) + e_{ij}$$

Random Slope Model $Y_{ij} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})(X_{ij}) + e_{ij}$ $V_{ij} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})(X_{ij}) + e_{ij}$ $V_{ij} = \gamma_0 + \gamma_1(X_{ij})$

Blimp Imputation Script for Random Slopes

```
DATA: ~/desktop/examples/data.csv;

VARNAMES: cluster y x;

MISSING: -99;

MODEL: cluster ~ y:x;

OUTCOME: y;

SEED: 90291;

BURN: 1000;

THIN: 1000;

NIMPS: 20;

OUTFILE: ~/desktop/examples/imps.csv;

OPTIONS: stacked;

CHAINS: 2 processors 2;
```

Analysis Example

Analysis Example

Data from a math problem solving intervention with students nested in classrooms

50 classrooms with 25 students each are randomly assigned to an intervention or a control curriculum

Researchers collect a number of student-level variables (e.g., pre and post problem-solving scores, math self-efficacy) and school-level variables (percentage of minority students, intervention dummy code)

Analysis Model

The analysis is a linear growth curve model with a random slope for months since the start of the school year and a condition-by-time interaction effect

$$\begin{split} &Probsolve_{ij} = \left(\gamma_0 + u_{0j}\right) + \left(\gamma_1 + u_{1j}\right)\left(Months_{ij}\right) + \gamma_2\left(Efficacy_{ij}\right) \\ &+ \gamma_3\left(Stanmath_j\right) + \gamma_4\left(Condition_j\right) + \gamma_5\left(Months_{ij}\right)\left(Condition_j\right) + e_{ij} \end{split}$$

Diagnostic Output

Ex8.1.imp Blimp Diagnostic Script

```
DATA: ~/desktop/examples/probsolve.csv;

VARIABLES: school condition esolpercent student abilitygrp
female stanmath frlunch wave months probsolve efficacy;

ORDINAL: condition efficacy frlunch;

OUTCOME: probsolve;

MISSING: -99;

MODEL: student ~ probsolve:months efficacy stanmath condition months*condition frlunch;

NIMPS: 2;

BURN: 10000;

THIN: 1;

SEED: 90291;

OUTFILE: ~/desktop/examples/imp*.csv;

OPTIONS: separate psr;

CHAINS: 2 processors 2;
```

Ex8.2.imp Blimp Imputation Script (Mplus Format)

```
DATA: ~/desktop/examples/probsolve.csv;
VARIABLES: school condition esolpercent student abilitygrp
female stanmath frlunch wave months probsolve efficacy;
ORDINAL: condition efficacy frlunch;
OUTCOME: probsolve;
MISSING: -99;
MODEL: student ~ probsolve:months efficacy stanmath condition months*condition frlunch;
NIMPS: 20;
BURN: 5000;
THIN: 2500;
SEED: 90291;
OUTFILE: ~/desktop/examples/imp*.csv;
OPTIONS: separate;
CHAINS: 2 processors 2;
```

VARIABLE ORDER IN SAVED DATA: school condition esolpercent student abilitygrp female stanmath frlunch wave months probsolve efficacy

Ex8.3.inp Mplus Analysis Script

```
DATA:

file = implist.csv;

type = imputation;

VARIABLE:

names = school condition esolpercent student abilitygrp

female stanmath frlunch wave months probsolve

efficacy;

usevariables = probsolve months efficacy stanmath

condition;

cluster = student;

within = months efficacy;

between = stanmath condition;

ANALYSIS:

type = twolevel random;
```

Ex8.3.inp Mplus Analysis Script

```
MODEL:
%within%
ranslope | probsolve on months;
probsolve on efficacy;
%between%
probsolve on stanmath condition;
ranslope on condition;
probsolve with ranslope;
```

Mplus Analysis Output

MODEL RESULTS Two-Tailed Rate of Estimate S.E. Est./S.E. P-Value Missing Within Level PROBSOLVE ON EFFICACY 0.720 0.133 5.418 0.494 Residual Variances PROBSOLVE 62.549 1.760 35.539 0.000 0.321

Mplus Analysis Output

				Two-Tailed	Rate of	
	Estimate	S.E.	Est./S.E.	P-Value	Missing	
Between Level			,		· ·	
RANSLOPE ON						
CONDITION	0.631	0.111	5.688	0.000	0.258	
PROBSOLVE ON						
STANMATH	0.049	0.002	22.529	0.000	0.089	
CONDITION	-0.406	0.518	-0.784	0.433	0.157	
PROBSOLV WITH						
RANSLOPE	0.497	0.495	1.002	0.316	0.358	
Intercepts						
PROBSOLVE	73.424	1.150	63.822	0.000	0.116	
RANSLOPE	0.677	0.088	7.669	0.000	0.314	
Residual Variance	:S					
PROBSOLVE	18.075	2.901	6.230	0.000	0.350	
RANSLOPE	0.347	0.130	2.673	0.008	0.410	

Ex8.4.imp Blimp Imputation Script (R, SAS, SPSS, and Stata Format)

```
DATA: ~/desktop/examples/probsolve.csv;
VARIABLES: school condition esolpercent student abilitygrp
female stanmath frlunch wave months probsolve efficacy;
ORDINAL: condition efficacy frlunch;
OUTCOME: probsolve;
MISSING: -99;
MODEL: student ~ probsolve:months efficacy stanmath
condition months*condition frlunch;
NIMPS: 20;
BURN: 5000;
THIN: 2500;
SEED: 90291;
OUTFILE: ~/desktop/examples/imps.csv;
OPTIONS: stacked;
CHAINS: 2 processors 2;
```

Blimp Output

```
VARIABLE ORDER IN SAVED DATA:

imp# school condition esolpercent student abilitygrp
female stanmath frlunch wave months probsolve efficacy
```

Ex8.5.r R Analysis Script

```
# Required packages
library(mitml)
library(lme4)
# Read data
filepath <- "~/desktop/examples/imps.csv"
impdata <- read.csv(filepath, header = F)
names(impdata) <- c("imputation", "school", "condition",</pre>
  "esolpercent", "student", "abilitygrp", "female", "stanmath",
  "frlunch", "wave", "months", "probsolve", "efficacy")
impdata$conditionbytime <- impdata$months * impdata$condition</pre>
# Analyze data and pool estimates
implist <- as.mitml.list(split(impdata, impdata$imputation))</pre>
analysis <- with(implist, lmer(probsolve ~ months + efficacy +
 stanmath + condition + conditionbytime + (months|student), REML = F))
estimates <- testEstimates(analysis, var.comp = T, df.com = NULL)</pre>
estimates
```

R Analysis Output

Final parameter estimates and inferences obtained from 20 imputed data sets.

	Estimate	Std.Error	t.value	df	P(> t)	RIV	FMI
(Intercept)	73.423	1.120	65.564	1288.367	0.000	0.138	0.123
months	0.677	0.090	7.526	216.433	0.000	0.421	0.303
efficacy	0.720	0.132	5.459	79.432	0.000	0.957	0.501
stanmath	0.049	0.002	23.827	1961.783	0.000	0.109	0.099
condition	-0.406	0.520	-0.782	796.053	0.434	0.183	0.157
conditionbytime	0.631	0.112	5.651	304.107	0.000	0.333	0.255

Unadjusted hypothesis test as appropriate in larger samples.

Ex8.6.sps SPSS Analysis Script

data list free file = '/users/craig/desktop/examples/imps.csv'
/imputation_ school condition esolpercent student abilitygrp
female stanmath frlunch wave months probsolve efficacy.
exe.

- * Initiate pooling routines. sort cases by imputation_. split file layed by imputation_.
- * Analysis and pooling.
 mixed probsolve with months efficacy stanmath condition
 /print = solution testcov
 /fixed = intercept months efficacy stanmath condition
 months*condition
 /random = intercept months | subject(student) covtype(un).

SPSS Analysis Output

		Estimates o	f Fixed Eff	ects		
imputation_	Parameter	Estimate	Std. Error	df	t	Sig.
1.00	Intercept	73.060509	1.024685	1028.985	71.300	.000
	months	.702627	.076895	1017.335	9.138	.000
	efficacy	.796354	.094220	5076.361	8.452	.000
	stanmath	.049140	.001896	963.958	25.921	.000
20.00	Intercept	73.068045	1.054519	1025.566	69.290	.000
	months	.656013	.073626	1035.066	8.910	.000
	efficacy	.747865	.095300	5183.331	7.847	.000
	stanmath	.048990	.001959	961.319	25.012	.000
	condition	183669	.477103	956.877	385	.700
	months * condition	.655700	.094142	966.332	6.965	.000
ooled	Intercept	73.423899	1.121607		65.463	.000
	months	.677472	.090082		7.521	.000
	efficacy	.719974	.132043		5.453	.000
	stanmath	.048831	.002053		23.789	.000
	condition	406429	.520246		781	.435
	months * condition	.630883	.111729		5.647	.000

SPSS Analysis Output

	Estimat	es of Covar	iance Param	eters		
imputation_	Parameter	es or covar	Estimate	Std. Error	Wald Z	Sig.
1.00	Residual		62.236143	1.291955	48.172	.00
	Intercept + months [subject = student]	UN (1,1)	15.574233	2.313213	6.733	.00
		UN (2,1)	.661883	.401679	1.648	.09
		UN (2,2)	.434035	.105553	4.112	.00
		014 (2,2)	.131033	.103333	7.112	.0
20.00	Residual		63.251133	1.312133	48.205	.00
	Intercept + months	UN (1.1)	17.577185	2.425691	7.246	.00

20.00	Residual		63.251133	1.312133	48.205	.000
	Intercept + months	UN (1,1)	17.577185	2.425691	7.246	.000
	[subject = student]	UN (2,1)	.819120	.394488	2.076	.038
		UN (2,2)	.218377	.097110	2.249	.025
Pooled	Residual		62.556498	1.631058		.000
	Intercept + months	UN (1,1)	18.230427	2.977649		.000
	[subject = student]	UN (2,1)	.484011	.502966		.337
		UN (2,2)	.351111	.131212		.008

Ex8.7.do Stata Analysis Script

```
// Import and save original data
import delimited "~/desktop/examples/probsolve.csv"
rename (v1 - v12)(school condition esolpercent student abilitygrp female stanmath frlunch wave months probsolve efficacy)
generate imp = 0
generate id = student * 10000 + wave
// Recode missing values
foreach var of varlist school condition esolpercent student abilitygrp female stanmath
  frlunch wave months probsolve efficacy {
  replace 'var' = . if 'var'== -99
save original, replace
// Import and save imputed data clear
import delimited "~/desktop/examples/imps.csv"
rename (v1 - v13)(imp school condition esolpercent student abilitygrp female stanmath
  frlunch wave months probsolve efficacy)
generate id = student * 10000 + wave
save imputed, replace
```

Ex8.7.do Stata Analysis Script

```
// Append original and imputed data
use original, clear
append using imputed

// Convert to mi data
mi import flong, m(imp) id(id) imputed(school condition
esolpercent student abilitygrp female stanmath frlunch wave
months probsolve efficacy) clear

// Analyze data and pool results
mi estimate, cmdok: mixed probsolve months efficacy stanmath
condition c.months#c.condition || student: months,
covariance(un) var
```

Stata Analysis Output

Multiple-imputation es	timates		Imputat	ions	=		20	
Nixed-effects ML regre	ssion		Number	of obs	=	6,4	96	
Group variable: studen	nt			of groups	=	9	28	
			Obs per	group:				
				min				
						7		
				max			7	
				RVI				
				FMI				
)F adjustment: Large	: sample		DF:					
				avg				
=				max				
Model F test: Eq	ual FMI			1453.9)				
			Prob >	F	=	0.00	00	
probsolve	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]	
+								
	. 6774599							
	. 7202682							
	.0488297			0.000				
	4063836						. 6134959	
.months#c.condition								
	73.42347	1.110870	65.56	0.000	71.9	2648	75.62045	

Stata Analysis Output

Random-effects Parameters		Std. Err.	[95% Conf.	
tudent: Unstructured				
sd(months)	. 5799701	.1216618	. 3827207	. 878879
sd(_cons)	4.24296	. 3508909	3.604052	4.99513
		. 2984953	3708364	. 693063