

Models With Three or More Levels and Cross-Classified Models

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Introduction

A two level multilevel model imagines that *Level 1* units are nested in *Level 2* units. A three level multilevel model imagines that *Level 1* units are nested in *Level 2* units, which are in turn nested in *Level 3*. As more levels are added to the model (e.g. *Level 4*), we imagine all of these levels to be hierarchically nested.

A *cross classified* model imagines that the nesting is not hierarchical, but rather that there are two sets of clusters or nestings in which individuals may be nested.

Below, I describe the use of [Stata](#), [R](#), and [Julia](#) to estimate these models.

Three Or More Levels

The Data

I use the *longitudinal* data from *Multilevel Thinking* to which I have added an extra level of *United Nations Region* (Arel-Bundock, Enevoldsen, and Yetman 2018). This data thus requires a four level model.

The Equation

$$\text{outcome}_{itjk} = \beta_0 + \beta_1 \text{parental warmth}_{itjk} + \beta_2 \text{physical punishment}_{itjk} + \beta_3 \text{time}_{itjk} + \quad (1)$$

$$\beta_4 \text{identity}_{itjk} + \beta_5 \text{intervention}_{itjk} + \beta_6 \text{HDI}_{itjk} +$$

$$w_{0k} + u_{0j} + v_{0i} + e_{itjk}$$

Here we imagine w_{0k} (region), u_{0j} (country) and v_{0i} (family) are hierarchically nested effects.

Run The Models

Stata

Get The Data

```
use "fourlevel.dta", clear
```

Unconditional Model

```
mixed outcome || UNregion: || country: || family:
```

Performing EM optimization ...

Performing gradient-based optimization:

Iteration 0: Log likelihood = -29061.686

Iteration 1: Log likelihood = -29061.679

Iteration 2: Log likelihood = -29061.679

Computing standard errors ...

Mixed-effects ML regression

Number of obs = 9,000

Grouping information

Group variable		No. of groups	Observations per group		
			Minimum	Average	Maximum
UNregion		5	600	1,800.0	3,600
country		30	300	300.0	300
family		3,000	3	3.0	3

Wald chi2(0) = .

Log likelihood = -29061.679

Prob > chi2 = .

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
_cons	54.05906	.987367	54.75	0.000	52.12385	55.99426

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]	
UNregion: Identity					
	var(_cons)	4.172687	3.187885	.9334852	18.65194
country: Identity					
	var(_cons)	2.849348	.8710225	1.565093	5.187414
family: Identity					
	var(_cons)	11.72403	.57475	10.64997	12.90641
	var(Residual)	28.23424	.5154842	27.24177	29.26286

LR test vs. linear model: chi2(3) = 1843.44

Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

Conditional Model

```
mixed outcome t warmth physical_punishment i.identity i.intervention HDI ///  
|| UNregion: || country: || id:
```

Performing EM optimization ...

Performing gradient-based optimization:

Iteration 0: Log likelihood = -28503.082

Iteration 1: Log likelihood = -28503.039

Iteration 2: Log likelihood = -28503.039

Computing standard errors ...

Mixed-effects ML regression

Number of obs = 9,000

Grouping information

Group variable		No. of groups	Observations per group		
			Minimum	Average	Maximum
UNregion		5	600	1,800.0	3,600
country		30	300	300.0	300
id		3,000	3	3.0	3

Log likelihood = -28503.039

Wald chi2(6) = 1209.42

Prob > chi2 = 0.0000

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
t	.9433791	.0658667	14.32	0.000	.8142827	1.072476
warmth	.9140704	.0379156	24.11	0.000	.8397571	.9883837
physical_punishment	-1.008615	.0497772	-20.26	0.000	-1.106176	-.9110531
1.identity	-.1332133	.1516437	-0.88	0.380	-.4304294	.1640028
1.intervention	.8589263	.1519619	5.65	0.000	.5610865	1.156766
HDI	.0148561	.0196605	0.76	0.450	-.0236777	.0533899
_cons	50.16426	1.675219	29.94	0.000	46.88089	53.44763

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]	
UNregion: Identity					
	var(_cons)	4.722007	3.585939	1.065898	20.91884
country: Identity					
	var(_cons)	2.863495	.8656459	1.583342	5.178668
id: Identity					
	var(_cons)	8.421131	.4711947	7.546445	9.397199
	var(Residual)	26.02919	.4752587	25.11417	26.97755

LR test vs. linear model: chi2(3) = 1844.00

Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

R

Get The Data

```
library(haven)

df4 <- read_dta("fourlevel.dta")
```

Change Some Variables To Categorical

```
df4$identity <- factor(df4$identity)

df4$intervention <- factor(df4$intervention)
```

Unconditional Model

Caution

`lme4` does not directly provide p values in results, because of some disagreement over exactly how these p values should be calculated. Therefore, in this Appendix, I also call library `lmerTest` to provide p values for `lme4` results.

Tip

R prefers to use scientific notation when possible. I find that the use of scientific notation can be confusing in reading results. I turn off scientific notation by setting a penalty for its use: `options(scipen = 999)`.

```
library(lme4)

library(lmerTest)
```

Attaching package: 'lmerTest'

The following object is masked from 'package:lme4':

`lmer`

The following object is masked from 'package:stats':

step

```
options(scipen = 999)

fit4A <- lmer(outcome ~ (1 | UNregion/country/id),
              data = df4)

summary(fit4A)
```

Linear mixed model fit by REML. t-tests use Satterthwaite's method [lmerModLmerTest]

Formula: outcome ~ (1 | UNregion/country/id)

Data: df4

REML criterion at convergence: 58121.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.7850	-0.6064	-0.0047	0.6020	3.4399

Random effects:

Groups	Name	Variance	Std.Dev.
id:(country:UNregion)	(Intercept)	11.724	3.424
country:UNregion	(Intercept)	2.842	1.686
UNregion	(Intercept)	5.478	2.340
Residual		28.234	5.314

Number of obs: 9000, groups:

id:(country:UNregion), 3000; country:UNregion, 30; UNregion, 5

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	54.061	1.112	3.777	48.6	0.00000201 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Conditional Model

```
fit4B <- lmer(outcome ~ t + warmth + physical_punishment +
              identity + intervention + HDI +
```

```

      (1 | UNregion/country/id),
      data = df4)

summary(fit4B)

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]

Formula:

outcome ~ t + warmth + physical_punishment + identity + intervention +
HDI + (1 | UNregion/country/id)

Data: df4

REML criterion at convergence: 57026.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.6846	-0.6096	-0.0038	0.6138	3.6850

Random effects:

Groups	Name	Variance	Std.Dev.
id:(country:UNregion)	(Intercept)	8.438	2.905
country:UNregion	(Intercept)	2.979	1.726
UNregion	(Intercept)	6.178	2.486
Residual		26.036	5.103

Number of obs: 9000, groups:

id:(country:UNregion), 3000; country:UNregion, 30; UNregion, 5

Fixed effects:

	Estimate	Std. Error	df	t value
(Intercept)	50.11857	1.78086	15.79112	28.143
t	0.94338	0.06588	5998.37756	14.321
warmth	0.91406	0.03793	4745.28492	24.096
physical_punishment	-1.00876	0.04980	6483.46337	-20.257
identity1	-0.13324	0.15173	2969.00938	-0.878
intervention1	0.85872	0.15205	2971.85430	5.648
HDI	0.01560	0.02006	24.39852	0.778

Pr(>|t|)

(Intercept)	0.00000000000000641	***
t	< 0.0000000000000002	***
warmth	< 0.0000000000000002	***
physical_punishment	< 0.0000000000000002	***
identity1	0.380	


```
intervention1      0.00000001780521096 ***
HDI                0.444
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Correlation of Fixed Effects:

```
(Intr) t      warmth physc_ idntt1 intrv1
t          -0.073
warmth     -0.071 -0.002
physc1_pnsh -0.073 -0.007 -0.012
identity1   -0.040  0.000 -0.013 -0.003
interventn1 -0.045  0.000  0.039  0.019 -0.018
HDI         -0.738  0.000 -0.005  0.005 -0.001  0.001
```

Julia

Get The Data

```
using Tables, MixedModels, StatFiles, DataFrames, CategoricalArrays, DataFramesMeta

df4 = DataFrame(load("fourlevel.dta"))
```

Change Some Variables To Categorical

```
@transform!(df4, :country = categorical(:country))

@transform!(df4, :UNregion = categorical(:UNregion))

@transform!(df4, :identity = categorical(:identity))

@transform!(df4, :intervention = categorical(:intervention))
```

Unconditional Model

```
m4A = fit(MixedModel, @formula(outcome ~ t + warmth +
                                physical_punishment +
                                identity + intervention +
                                HDI +
                                (1 | UNregion) +
```

```
(1 | country) +  
(1 | id)), df4)
```

Linear mixed model fit by maximum likelihood

```
outcome ~ 1 + t + warmth + physical_punishment + identity + intervention + HDI + (1 | UNregion)  
logLik   -2 logLik      AIC      AICc      BIC  
-28503.0394  57006.0787  57028.0787  57028.1081  57106.2335
```

Variance components:

	Column	Variance	Std.Dev.
id	(Intercept)	8.42110	2.90191
country	(Intercept)	2.86347	1.69218
UNregion	(Intercept)	4.72082	2.17274
Residual		26.02921	5.10188

Number of obs: 9000; levels of grouping factors: 3000, 30, 5

Fixed-effects parameters:

	Coef.	Std. Error	z	Pr(> z)
(Intercept)	50.1643	1.67514	29.95	<1e-99
t	0.943379	0.0658668	14.32	<1e-45
warmth	0.91407	0.0379156	24.11	<1e-99
physical_punishment	-1.00861	0.0497772	-20.26	<1e-90
identity	-0.133213	0.151644	-0.88	0.3797
intervention	0.858927	0.151962	5.65	<1e-07
HDI	0.0148553	0.0196604	0.76	0.4499

Conditional Model

```
m4B = fit(MixedModel, @formula(outcome ~ t + warmth +  
                                physical_punishment +  
                                identity + intervention +  
                                HDI +  
                                (1 | UNregion) +  
                                (1 | country) +  
                                (1 | id)), df4)
```

Linear mixed model fit by maximum likelihood

```

outcome ~ 1 + t + warmth + physical_punishment + identity + intervention + HDI + (1 | UNregion)
logLik    -2 logLik      AIC      AICc      BIC
-28503.0394 57006.0787 57028.0787 57028.1081 57106.2335

```

Variance components:

	Column	Variance	Std.Dev.
id	(Intercept)	8.42110	2.90191
country	(Intercept)	2.86347	1.69218
UNregion	(Intercept)	4.72082	2.17274
Residual		26.02921	5.10188

Number of obs: 9000; levels of grouping factors: 3000, 30, 5

Fixed-effects parameters:

	Coef.	Std. Error	z	Pr(> z)
(Intercept)	50.1643	1.67514	29.95	<1e-99
t	0.943379	0.0658668	14.32	<1e-45
warmth	0.91407	0.0379156	24.11	<1e-99
physical_punishment	-1.00861	0.0497772	-20.26	<1e-90
identity	-0.133213	0.151644	-0.88	0.3797
intervention	0.858927	0.151962	5.65	<1e-07
HDI	0.0148553	0.0196604	0.76	0.4499

Interpretation

Cross-Classified Models

The Data

I use the *cross-sectional* data from *Multilevel Thinking* to which I have added an extra level of a hypothetical language.

The Equation

$$\text{outcome}_{itj} = \beta_0 + \beta_1 \text{parental warmth}_{itj} + \beta_2 \text{physical punishment}_{itj} + \beta_3 \text{time}_{itj} + \quad (2)$$

$$\beta_4 \text{identity}_{itj} + \beta_5 \text{intervention}_{itj} + \beta_6 \text{HDI}_{itj} +$$

$$u_{0j} + m_{0m} + e_{ijm}$$

Here u_{0j} (country) and m_{0m} (language) are not nested hierarchically, but are *cross classified*.

Run The Models

Stata

Get The Data

```
use "crossclassified.dta", clear
```

Unconditional Model

```
mixed outcome || _all: R.country || _all: R.language
```

Performing EM optimization ...

Performing gradient-based optimization:

Iteration 0: Log likelihood = -9835.8123

Iteration 1: Log likelihood = -9835.8111

Iteration 2: Log likelihood = -9835.8111

Computing standard errors ...

Mixed-effects ML regression

Group variable: _all

Number of obs = 3,000

Number of groups = 1

Obs per group:

min = 3,000

avg = 3,000.0

max = 3,000

Wald chi2(0) = .

Prob > chi2 = .

Log likelihood = -9835.8111

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
-----+-----						
_cons	52.43187	.3590214	146.04	0.000	51.7282	53.13554

Random-effects parameters	Estimate	Std. err.	[95% conf. interval]	
-----+-----				
_all: Identity				
var(R.country)	3.177791	.9244633	1.796798	5.620198
-----+-----				
_all: Identity				
var(R.language)	.9566314	.3284087	.4881235	1.87482
-----+-----				
var(Residual)	39.62877	1.045619	37.63148	41.73206

LR test vs. linear model: chi2(2) = 180.84			Prob > chi2 = 0.0000	

Note: LR test is conservative and provided only for reference.

Conditional Model

```
mixed outcome warmth physical_punishment i.identity i.intervention HDI || _all: R.country ||
```

Performing EM optimization ...

Performing gradient-based optimization:

Iteration 0: Log likelihood = -9663.2195

Iteration 1: Log likelihood = -9663.2194

Computing standard errors ...

Mixed-effects ML regression

Group variable: _all

Number of obs = 3,000

Number of groups = 1

Obs per group:

min = 3,000

avg = 3,000.0

max = 3,000

Wald chi2(5) = 367.04

Log likelihood = -9663.2194

Prob > chi2 = 0.0000

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]
-----+-----					

warmth	.8331461	.0579811	14.37	0.000	.7195052	.946787
physical_punishment	-.9979749	.080268	-12.43	0.000	-1.155297	-.8406525
1.identity	-.2922428	.2191421	-1.33	0.182	-.7217534	.1372678
1.intervention	.6097458	.2195139	2.78	0.005	.1795064	1.039985
HDI	-.0015879	.0204157	-0.08	0.938	-.0416021	.0384262
_cons	51.92255	1.411069	36.80	0.000	49.15691	54.6882

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]	
<hr/>					
_all: Identity					
var(R.country)		3.361218	.9603072	1.920024	5.884192
<hr/>					
_all: Identity					
var(R.language)		1.121946	.3269535	.6337502	1.986214
<hr/>					
var(Residual)		35.11959	.9263999	33.35002	36.98306
<hr/>					
LR test vs. linear model: chi2(2) = 227.02				Prob > chi2 = 0.0000	

Note: LR test is conservative and provided only for reference.

R

Get The Data

```
library(haven)

dfCC <- read_dta("crossclassified.dta")
```

Change Some Variables To Categorical

```
dfCC$identity <- factor(dfCC$identity)

dfCC$intervention <- factor(dfCC$intervention)
```

Unconditional Model

```
library(lme4)

library(lmerTest)

options(scipen = 999)

fitCC_A <- lmer(outcome ~
                (1 | country) +
                (1 | language),
                data = dfCC)

summary(fitCC_A)
```

Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]

Formula: outcome ~ (1 | country) + (1 | language)

Data: dfCC

REML criterion at convergence: 19671.8

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.3899	-0.6602	-0.0104	0.6798	3.6924

Random effects:

Groups	Name	Variance	Std.Dev.
language	(Intercept)	0.9604	0.980
country	(Intercept)	3.2919	1.814
Residual		39.6276	6.295

Number of obs: 3000, groups: language, 100; country, 30

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	52.4319	0.3643	33.4284	143.9	<0.0000000000000002 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Conditional Model

```
fitCC_B <- lmer(outcome ~ t + warmth + physical_punishment +
                identity + intervention + HDI +
```

```
(1 | country) +
(1 | language),
data = dfCC)
```

Error in model.frame.default(data = dfCC, drop.unused.levels = TRUE, formula = outcome ~ : i

```
summary(fitCC_B)
```

Error in h(simpleError(msg, call)): error in evaluating the argument 'object' in selecting a

Julia

Get The Data

```
using Tables, MixedModels, StatFiles, DataFrames, CategoricalArrays, DataFramesMeta

dfCC = DataFrame(load("crossclassified.dta"))
```

Change Some Variables To Categorical

```
@transform!(dfCC, :country = categorical(:country))

@transform!(dfCC, :language = categorical(:language))

@transform!(dfCC, :identity = categorical(:identity))

@transform!(dfCC, :intervention = categorical(:intervention))
```

Unconditional Model

```
mCCA = fit(MixedModel, @formula(outcome ~
                                (1 | country) +
                                (1 | language)), dfCC)
```



```
Linear mixed model fit by maximum likelihood
outcome ~ 1 + (1 | country) + (1 | language)
      logLik   -2 logLik       AIC       AICc       BIC
-9835.8111 19671.6222 19679.6222 19679.6356 19703.6477
```

Variance components:

	Column	Variance	Std.Dev.
language (Intercept)		0.956631	0.978075
country (Intercept)		3.177768	1.782629
Residual		39.628773	6.295139

Number of obs: 3000; levels of grouping factors: 100, 30

Fixed-effects parameters:

	Coef.	Std. Error	z	Pr(> z)
(Intercept)	52.4319	0.35902	146.04	<1e-99

Conditional Model

```
mCCA = fit(MixedModel, @formula(outcome ~ warmth +
                                physical_punishment +
                                identity + intervention +
                                HDI +
                                (1 | country) +
                                (1 | language)), dfCC)
```

```
Linear mixed model fit by maximum likelihood
outcome ~ 1 + warmth + physical_punishment + identity + intervention + HDI + (1 | country)
      logLik   -2 logLik       AIC       AICc       BIC
-9663.2194 19326.4388 19344.4388 19344.4990 19398.4962
```

Variance components:

	Column	Variance	Std.Dev.
language (Intercept)		1.12193	1.05921
country (Intercept)		3.36119	1.83335
Residual		35.11960	5.92618

Number of obs: 3000; levels of grouping factors: 100, 30

Fixed-effects parameters:

	Coef.	Std. Error	z	Pr(> z)
(Intercept)	51.9226	1.41106	36.80	<1e-99
warmth	0.833146	0.0579811	14.37	<1e-46
physical_punishment	-0.997975	0.080268	-12.43	<1e-34
identity	-0.292243	0.219142	-1.33	0.1823
intervention	0.609746	0.219514	2.78	0.0055
HDI	-0.00158794	0.0204156	-0.08	0.9380

Interpretation

Arel-Bundock, Vincent, Nils Enevoldsen, and CJ Yetman. 2018. “Countrycode: An r Package to Convert Country Names and Country Codes.” *Journal of Open Source Software* 3 (28): 848. <https://doi.org/10.21105/joss.00848>.