

# An Early Days Rough Draft Conversation About MAIHDA

Multilevel Analysis Of Individual Heterogeneity And Discriminatory Accuracy

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## 1 Inspirations

Conceptual inspiration comes from sources such as Cho et al. (2013), Cesaire (1956), Martín-Baró (1998), Montero & Sonn (2009), Antweiler (2016), Stage & Wells (2014), and Scharrer & Ramasubramanian (2021).

Substantively and practically, this handout depends **heavily** on the ideas, example code, and example data set in Evans et al. (2024).

## 2 The Basic Idea of Multilevel Modeling

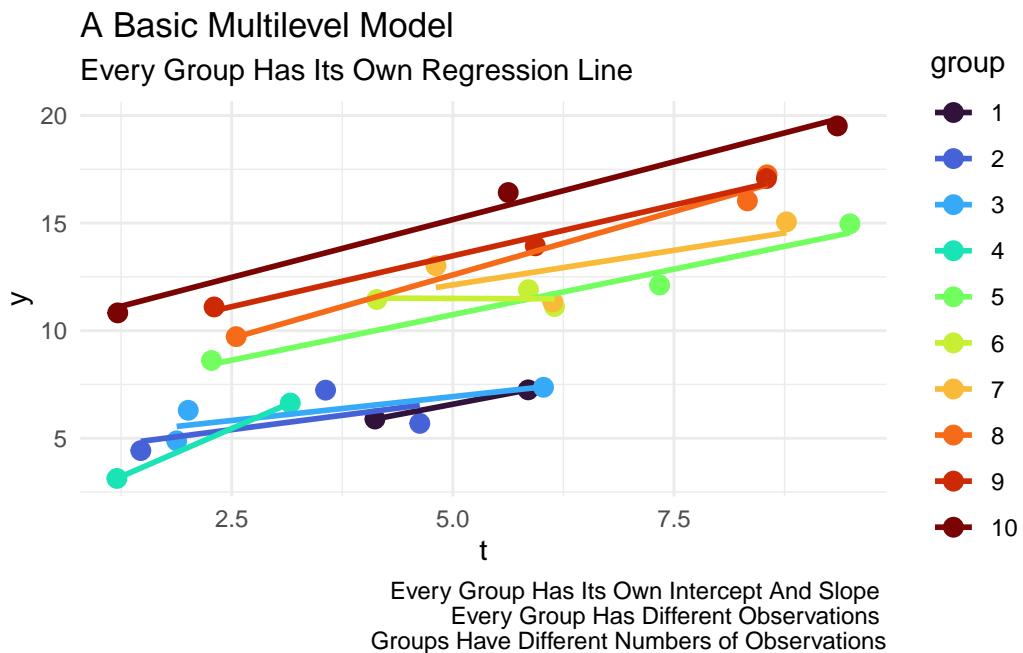


Figure 1: A Basic Multilevel Model

## 3 The Basic Idea Of MAIHDA

### 💡 Key Ideas

The key ideas are as follows:

1. A *traditional* approach would ask us to generate multiple interaction terms to explore interactions e.g.  $sex \times race \times education \times age$  as well as all of the lower level 2 and 3-way interactions. Upon first glance this seems unwieldy, though in a future discussion, we could talk about how some software (e.g. Stata) makes this approach less unwieldy than it might initially appear.
2. In contrast, **MAIHDA** uses combinations of variables to generate *strata* which are then treated as the levels in a multilevel model.

## 4 Get The Data

```
use "TutorialData.dta" // get the data  
  
describe // describe the data
```

Contains data from TutorialData.dta

Observations: 33,000

Variables: 7

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Variable name	Storage type	Display format	Value label	Variable label
HbA1c	float	%9.1f		HbA1c (mmol/mol)
diabetic	byte	%9.0g		
sex	byte	%12.0g	sexlabel	
race	byte	%12.0g	racelabel	
education	byte	%21.0g	educationlabel	
income	byte	%12.0g	incomelabel	
age	byte	%12.0g	agelabel	

Sorted by:

## 5 Generating The Strata

```
generate stratum = 10000*sex + 1000*race + 100*education + 10*income + 1*age
```

## 6 Empty or ANOVA Model

### 6.1 Model

```
mixed HbA1c || stratum: // ANOVA model
```

Performing EM optimization ...

Performing gradient-based optimization:

Iteration 0: Log likelihood = -121483.73

Iteration 1: Log likelihood = -121483.73

Computing standard errors ...

Mixed-effects ML regression

Group variable: stratum

Number of obs = 33,000

Number of groups = 384

Obs per group:

min = 1

avg = 85.9

max = 683

Wald chi2(0) = .

Prob > chi2 = .

Log likelihood = -121483.73

HbA1c		Coefficient	Std. err.	z	P> z	[95% conf. interval]
_cons		40.78932	.1760906	231.64	0.000	40.44419 41.13445

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]
stratum: Identity				
var(_cons)		9.33452	.8429295	7.820354 11.14186

LR test vs. linear model: chibar2(01) = 2228.00 Prob >= chibar2 = 0.0000

## 6.2 IntraClass Correlation Coefficient

 The ICC

The ICC answers the question: “How much clustering is there?”

```
estat icc // intraclass correlation coefficient
```

Intraclass correlation

Level	ICC	Std. err.	[95% conf. interval]
stratum	.0937219	.0077119	.0796605 .1099687

## 7 Full Model

```
mixed HbA1c i.sex i.race i.education i.income i.age || stratum:
```

Performing EM optimization ...

Performing gradient-based optimization:  
Iteration 0: Log likelihood = -121213.04  
Iteration 1: Log likelihood = -121213.02  
Iteration 2: Log likelihood = -121213.02

Computing standard errors ...

```
Mixed-effects ML regression                               Number of obs      = 33,000
Group variable: stratum                                Number of groups   =      384
                                                               Obs per group:
                                                               min =           1
                                                               avg =         85.9
                                                               max =        683
                                                               Wald chi2(12)    =  1344.70
Log likelihood = -121213.02                           Prob > chi2       =  0.0000
```

HbA1c	Coefficient	Std. err.	z	P> z	[95% conf. interval]
<hr/>					
sex					
Female					
Female	-.516474	.1575437	-3.28	0.001	-.8252541 -.207694
<hr/>					
race					
Black					
Black	4.44937	.1908202	23.32	0.000	4.07537 4.823371
Hispanic					
Hispanic	1.038471	.1939947	5.35	0.000	.6582485 1.418694
<hr/>					
education					
High school					
High school	-.5410972	.2378408	-2.28	0.023	-1.007257 -.0749378
Some coll..					
Some coll..	-.5476019	.2469721	-2.22	0.027	-1.031658 -.0635453
College p..					
College p..	-1.128424	.2441963	-4.62	0.000	-1.60704 -.649808
<hr/>					
income					
Low-mid					
Low-mid	.1807317	.2114433	0.85	0.393	-.2336895 .5951529
Mid-high					
Mid-high	-.3039793	.2188399	-1.39	0.165	-.7328975 .124939
High					
High	-1.327629	.252043	-5.27	0.000	-1.821624 -.8336339
<hr/>					
age					
30-44					
30-44	1.10363	.2312428	4.77	0.000	.6504026 1.556858
45-59					
45-59	1.808993	.2356534	7.68	0.000	1.347121 2.270865
60+					
60+	5.504486	.2405396	22.88	0.000	5.033037 5.975935
<hr/>					
_cons	38.03392	.2980168	127.62	0.000	37.44982 38.61802

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]
<hr/>				
stratum: Identity				
var(_cons)				
var(_cons)		.8002982	.1494763	.5549681 1.154079
<hr/>				
var(Residual)				
var(Residual)		90.2666	.7059543	88.8935 91.6609

LR test vs. linear model: chibar2(01) = 88.75                          Prob >= chibar2 = 0.0000

## 8 Discussion Questions

- Clarifying what we mean by intersectionality before moving to quantitative approaches

2. What MAIHDA adds beyond conventional interaction models. (Do interactions fail to capture these ideas? Are multiple interactions so hard to test?)
3. The role of multilevel modeling and partial pooling
4. MAIHDA in descriptive vs. causal contexts
5. Broader model evaluation and potential extensions of the method (CF testing multiple interactions and maximal models (<https://agrogan1.github.io/multilevel/Bayesian-and-frequentist-MLM/Bayesian-and-frequentist-MLM.html#maximal-models>))

## References

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