An Early Days Rough Draft Conversation About MAIHDA

Multilevel Analysis Of Individual Heterogeneity And Discriminatory Accuracy

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1 Inspirations

> "My conception of the universal is that of a universal enriched by all that is particular, a universal enriched by every particular: the deepening and coexistence of all particulars." (Cesaire, 1956)

Conceptual inspiration comes from sources such as Cho et al. (2013), Cesaire (1956), UNESCO (1997), 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

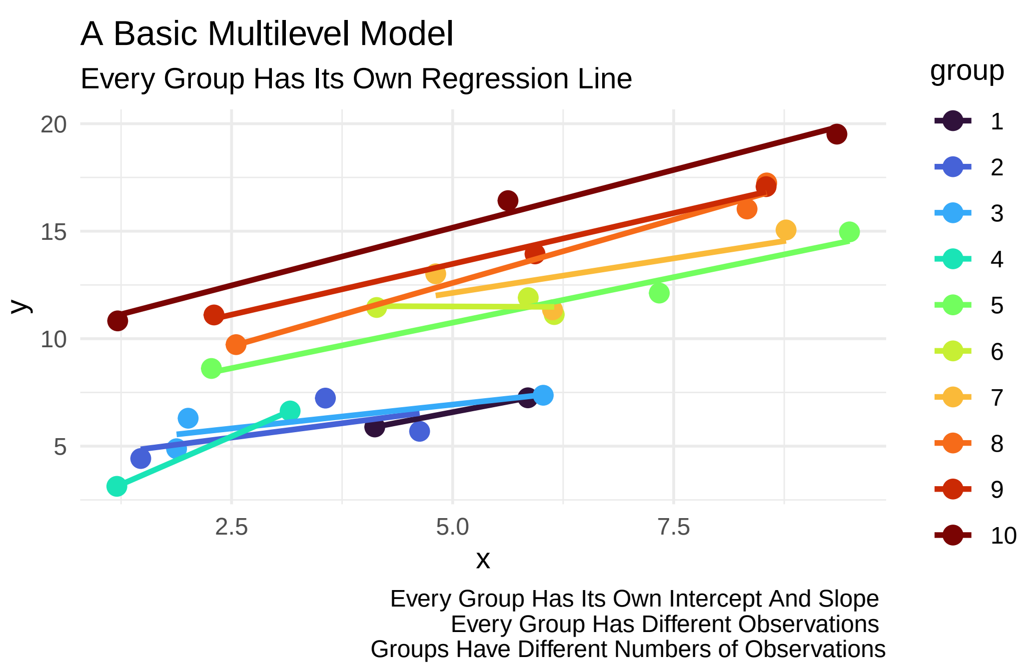

Figure 1: A Basic Multilevel Model

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

4.1 Stata

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

describe // describe the data
```

```
Contains data from TutorialData.dta
 Observations:        33,000
    Variables:             7                  12 Oct 2023 16:51
--------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    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:
```

4.2 R

```
library(haven) # read Stata

TutorialData <- read_dta("TutorialData.dta")
```

5 Generating The Strata

5.1 Stata

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

5.2 R

```
library(dplyr) # data wrangling

TutorialData <- TutorialData %>%
  mutate(stratum = 10000*sex +
           1000*race +
           100*education +
           10*income +
           1*age) # create stratum variable
```

6 Empty or ANOVA Model

6.1 Model

6.1.1 Stata

```
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                     Number of obs    = 33,000
Group variable: stratum                         Number of groups =    384
                                                Obs per group:
                                                             min =      1
                                                             avg =   85.9
                                                             max =    683
                                                Wald chi2(0)     =      .
Log likelihood = -121483.73                     Prob > chi2      =      .

------------------------------------------------------------------------------
       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
-----------------------------+------------------------------------------------
               var(Residual) |   90.26358   .7066668      88.88911    91.65931
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 2228.00       Prob >= chibar2 = 0.0000
```

6.1.2 R

```r
library(lme4)
```

```
Loading required package: Matrix
```

```r
fit1 <- lmer(HbA1c ~ (1 | stratum), data = TutorialData)

summary(fit1)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: HbA1c ~ (1 | stratum)
   Data: TutorialData

REML criterion at convergence: 242969.1

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7126 -0.6181 -0.0564  0.4822  6.5172

Random effects:
 Groups   Name        Variance Std.Dev.
 stratum  (Intercept)  9.366   3.060
 Residual             90.264   9.501
Number of obs: 33000, groups:  stratum, 384

Fixed effects:
            Estimate Std. Error t value
(Intercept)  40.7896     0.1763   231.3
```

6.2 IntraClass Correlation Coefficient

> **The ICC**
>
> The ICC answers the question: "How much clustering is there?"

6.2.1 Stata

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

```
Intraclass correlation

------------------------------------------------------------------------------
                       Level |        ICC   Std. err.     [95% conf. interval]
```

```
-----------------------------+------------------------------------------------
                     stratum |   .0937219   .0077119      .0796605    .1099687
------------------------------------------------------------------------------
```

6.2.2 R

```r
performance::icc(fit1) # ICC
```

```
# Intraclass Correlation Coefficient

    Adjusted ICC: 0.094
  Unadjusted ICC: 0.094
```

7 Full Model

> **One Perspective**
>
> The results indicate a balance of main effects of structural factors and intersectionality.

7.1 Stata

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

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
stratum: Identity            |
                  var(_cons) |   .8002982   .1494763      .5549681    1.154079
-----------------------------+------------------------------------------------
               var(Residual) |    90.2666   .7059543       88.8935     91.6609
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 88.75         Prob >= chibar2 = 0.0000
```

7.2 R

```
library(lme4)

TutorialData$sex <- factor(TutorialData$sex)
TutorialData$race <- factor(TutorialData$race)
TutorialData$education <- factor(TutorialData$education)
TutorialData$income <- factor(TutorialData$income)
TutorialData$age <- factor(TutorialData$age)

fit1 <- lmer(HbA1c ~ sex + race + education + income + age + (1 | stratum), data = TutorialDa

summary(fit1)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: HbA1c ~ sex + race + education + income + age + (1 | stratum)
   Data: TutorialData

REML criterion at convergence: 242446.4

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7402 -0.6212 -0.0553  0.4837  6.5708

Random effects:
 Groups   Name        Variance Std.Dev.
 stratum  (Intercept)  0.8844  0.9404
 Residual             90.2660  9.5008
Number of obs: 33000, groups:  stratum, 384

Fixed effects:
            Estimate Std. Error t value
(Intercept)  38.0335     0.3040 125.110
sex2         -0.5154     0.1612  -3.197
race2         4.4504     0.1951  22.816
race3         1.0364     0.1981   5.232
education2   -0.5480     0.2430  -2.256
education3   -0.5448     0.2519  -2.163
education4   -1.1337     0.2492  -4.550
income2       0.1790     0.2163   0.828
income3      -0.3006     0.2237  -1.344
income4      -1.3231     0.2573  -5.143
```

```
age2           1.1073     0.2362   4.688
age3           1.8094     0.2405   7.524
age4           5.5112     0.2456  22.442

Correlation matrix not shown by default, as p = 13 > 12.
Use print(x, correlation=TRUE)  or
    vcov(x)        if you need it
```

8 Discussion Questions

1. 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))

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