3-Step ML Auxiliary Variable Integration Using `MplusAutomation`

Adding Covariate and Distal Outcome Variables to Mixture Models

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What is included in this video tutorial?

> This `R` tutorial automates the 3-step ML auxiliary variable procedure using the `MplusAutomation` package (Hallquist & Wiley, 2018) to estimate models and extract relevant parameters. To learn more about auxiliary variable integration methods and why multi-step methods are necessary for producing un-biased estimates see Asparouhov & Muthén (2014).
>
> The motivation for this tutorial is that conducting the 3-step manually is highly error prone as it requires pulling logit values estimated in the step-1 model and adding them in the model statement of the step-2 model (i.e., lots of copying & pasting). In contrast, this approach is fully replicable and provides clear documentation which translates to more reliable research. Also, it saves time!

How to reference this tutorial:

Garber, A. C. (2021). 3-Step ML Auxiliary Variable Integration Using MplusAutomation. Retrieved from psyarxiv.com/phtxa

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Follow along! Link to `Github` repository:

https://github.com/immerse-ucsb/3step-ML-auto

Load packages

```
library(MplusAutomation) # Conduit between R & Mplus
library(glue)            # Pasting R code into strings
library(here)            # Location, location, location
library(tidyverse)       # Tidyness
```

Data Source: Civil Rights Data Collection (CRDC)

> The CRDC is a federally mandated school and district level data collection effort that occurs every other year. This public data is currently available for selected variables across 4 years (2011, 2013, 2015, 2017) and all US states. In the following tutorial six focal variables are utilized as indicators of the latent class model; three variables which report on harassment/bullying in schools based on disability, race, or sex, and three variables on full-time equivalent school staff employees (counselor, psychologist, law enforcement). For this example, we utilize a sample of schools from the state of Arizona reported in 2017.

Information about CRCD: https://www2.ed.gov/about/offices/list/ocr/data.html

Data access (`R`): https://github.com/UrbanInstitute/education-data-package-r

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Read in CSV data file from the `data` subfolder

```
data_3step <- read_csv(here("data", "crdc_aux_data.csv"))
```

“Manual 3-Step” ML Auxiliary Variable Integration Method

Step 1 - Estimate the unconditional model with all covariate & distal outcome variables mentioned in the `auxiliary` statement.

NOTE: In this example, Mplus input and output files are directed to the sub-folder `3step_mplus`. Due to the fact that adding auxiliary variables is conducted after enumeration, generally other sub-folders will exist in the top-most `Rproject` folder such as `enum_mplus`, `data`, and `figures`.

```
m_step1  <- mplusObject(
  TITLE = "Step1  (MANUAL 3-STEP ML APPROACH)",
  VARIABLE =
   "categorical = report_dis report_race report_sex counselors_fte psych_fte law_fte;

    usevar = report_dis report_race report_sex counselors_fte psych_fte law_fte;

    classes = c(3);

    !!! All auxiliary variables to be considered in the final model should be listed here !!!
    auxiliary =
    lunch_program read_test math_test;",

  ANALYSIS =
   "estimator = mlr;
    type = mixture;
    starts = 500 100;

    !!! to replicate class order use, `optseed = 887580;` !!!",

  SAVEDATA =
   "!!! This saved dataset will contain class probabilities and modal assignment columns !!!
    File=3step_savedata.dat;
    Save=cprob;
    Missflag= 999;",

  PLOT =
    "type = plot3;
    series = report_dis report_race report_sex counselors_fte psych_fte law_fte(*);",

  usevariables = colnames(data_3step),
  rdata = data_3step)

m_step1_fit <- mplusModeler(m_step1,
                 dataout=here("3step_mplus", "Step1_3step.dat"),
                 modelout=here("3step_mplus", "Step1_3step.inp") ,
                 check=TRUE, run = TRUE, hashfilename = FALSE)
```

Step 2 - Extract logits & saved data from the step 1 unconditional model.

Extract logits for the classification probabilities for the most likely latent class

```
logit_cprobs <- as.data.frame(m_step1_fit[["results"]]
                                          [["class_counts"]]
                                          [["logitProbs.mostLikely"]])
```

Extract saved data from the step 1 model `mplusObject` named "m_step1_fit"

```
savedata <- as.data.frame(m_step1_fit[["results"]]
                                      [["savedata"]])
```

Rename the column in savedata for "C" and change to "N"

```
colnames(savedata)[colnames(savedata)=="C"] <- "N"
```

Step 2 (part 2) - Estimate the unconditional model with logits from step 2.

This model is estimated to check that the class proportions are approximately the same as in step 1.

```
m_step2  <- mplusObject(
  TITLE = "Step2  (MANUAL 3-STEP ML APPROACH)",

  VARIABLE =
 "nominal=N;
  USEVAR = n;
  missing are all (999);
  classes = c(3); ",

  ANALYSIS =
 "estimator = mlr;
  type = mixture;
  starts = 0;",

  MODEL =
    glue(
 "%C#1%
  [n#1@{logit_cprobs[1,1]}];
  [n#2@{logit_cprobs[1,2]}];

  %C#2%
  [n#1@{logit_cprobs[2,1]}];
  [n#2@{logit_cprobs[2,2]}];

  %C#3%
  [n#1@{logit_cprobs[3,1]}];
  [n#2@{logit_cprobs[3,2]}];"),

  usevariables = colnames(savedata),
```

```
  rdata = savedata)

m_step2_fit <- mplusModeler(m_step2,
                 dataout=here("3step_mplus", "Step2_3step.dat"),
                 modelout=here("3step_mplus", "Step2_3step.inp"),
                 check=TRUE, run = TRUE, hashfilename = FALSE)
```

Step 3 - Add covariates & distal outcomes to the model.

Estimate the final SEM Model - Moderation Example

Specification details:

- This example contains two distal outcomes (`read_test` & `math_test`) and one binary covariate (`lunch_program`).
- Under each class-specific statement (e.g., `%C#1%`) the distal outcomes are mentioned to estimate the intercept parameters.
- Moderation is specified by mentioning the `"outcome ON covariate;"` syntax under each of the class-specific statements.
- Note that the binary covariate is centered so that reported distal means (intercepts) are estimated at the weighted average of `lunch_program`.

```
m_step3  <- mplusObject(
  TITLE = "Step3  (MANUAL 3-STEP ML APPROACH)",

  VARIABLE =
 "nominal = N;
  usevar = n;
  missing are all (999);

  usevar = lunch_pr read_tes math_tes;
  classes = c(3); ",

  DEFINE =
 "Center lunch_pr (Grandmean);",

  ANALYSIS =
 "estimator = mlr;
  type = mixture;
  starts = 0;",

  MODEL =
  glue(
 "!!! OUTCOMES = read_tes math_tes !!!
  !!! MODERATOR = lunch_pr !!!
```

```
 %OVERALL%
 read_tes on lunch_pr;
 read_tes;

 math_tes on lunch_pr;
 math_tes;

 %C#1%
 [n#1@{logit_cprobs[1,1]}];
 [n#2@{logit_cprobs[1,2]}];

 [read_tes](m01);
 read_tes;                    !!! estimate conditional intercept !!!
 read_tes on lunch_pr (s01);    !!! estimate conditional regression !!!

 [math_tes] (m1);
 math_tes;
 math_tes on lunch_pr (s1);

 %C#2%
 [n#1@{logit_cprobs[2,1]}];
 [n#2@{logit_cprobs[2,2]}];

 [read_tes](m02);
 read_tes;
 read_tes on lunch_pr (s02);

 [math_tes] (m2);
 math_tes;
 math_tes on lunch_pr (s2);

 %C#3%
 [n#1@{logit_cprobs[3,1]}];
 [n#2@{logit_cprobs[3,2]}];

 [read_tes](m03);
 read_tes;
 read_tes on lunch_pr (s03);

 [math_tes] (m3);
 math_tes;
 math_tes on lunch_pr (s3);"),

 MODELCONSTRAINT =
"New (diff12 diff13
 diff23 slope12 slope13
 slope23 ndiff12 ndiff13
 ndiff23 nslope12 nslope13
 nslope23);

 diff12 = m1-m2;   ndiff12 = m01-m02;
 diff13 = m1-m3;   ndiff13 = m01-m03;
 diff23 = m2-m3;   ndiff23 = m02-m03;
```

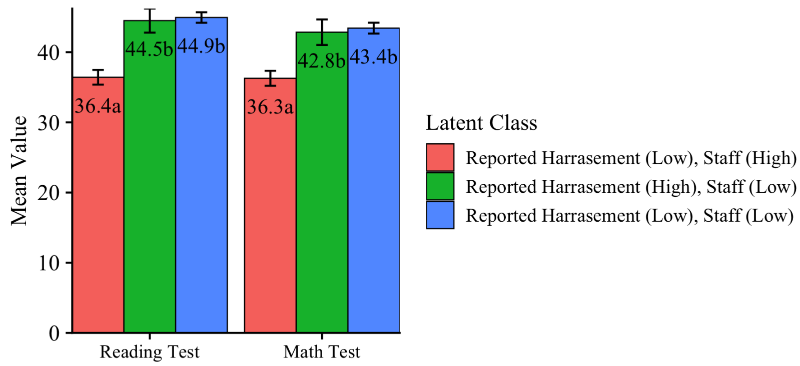
```
  slope12 = s1-s2;  nslope12 = s01-s02;
  slope13 = s1-s3;  nslope13 = s01-s03;
  slope23 = s2-s3;  nslope23 = s02-s03;",

  MODELTEST =
  ## NOTE: Only a single Wald test can be conducted per model run. Therefore,
  ## this example requires running separate models for each omnibus test (e.g.,
  ## 4 models; 2 outcomes and 2 slope coefficients). This can be done by
  ## commenting out all but one test and then estimating multiple versions of the model.

 "!m01=m02;    !!! Distal outcome omnibus Wald test for `read_tes` !!!
  !m02=m03;

  !s01=s02;   !!! Slope difference omnibus Wald test for `read_tes on lunch_pr` !!!
  !s02=s03;

  m1=m2;       !!! Distal outcome omnibus Wald test for `math_tes` !!!
  m2=m3;

  !s1=s2;      !!! Slope difference omnibus Wald test `math_tes on lunch_pr` !!!
  !s2=s3;



 ",

  usevariables = colnames(savedata),
  rdata = savedata)

m_step3_fit <- mplusModeler(m_step3,
                 dataout=here("3step_mplus", "Step3_3step.dat"),
                 modelout=here("3step_mplus", "Step3_3step.inp"),
                 check=TRUE, run = TRUE, hashfilename = FALSE)
```

End of 3-Step Procedure

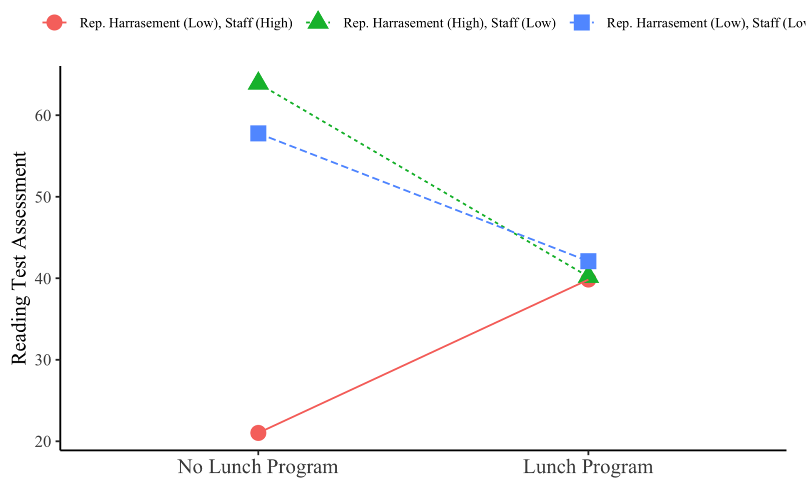
Visualize results:

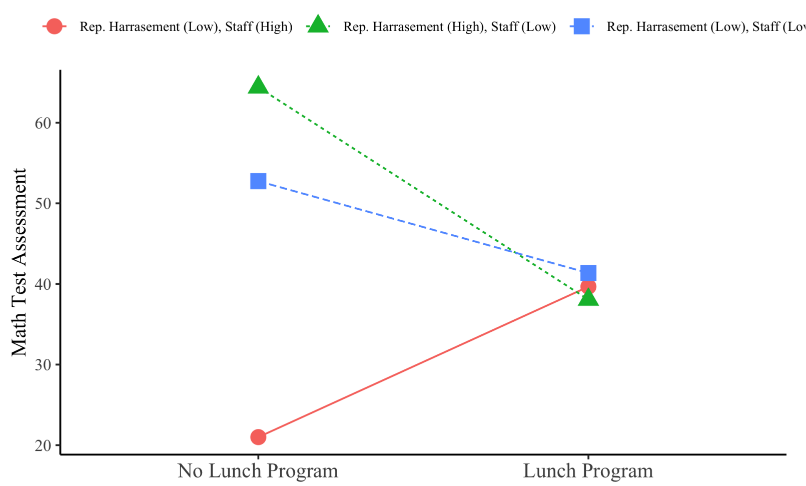
> NOTE: The next video in this series will include a detailed tutorial on how to interpret auxiliary variable output (i.e. distal outcomes & covariates) in the context of moderation. This tutorial will also cover `R` code to generate figures for visualizing the results.

Distal outcome mean differences



Latent class moderates effect of school `Lunch Program` (X) on `Reading` & `Mathassessments` (Ys)





References

Asparouhov, T., & Muthén, B. O. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. Structural Equation Modeling, 21, 329–341. http://dx.doi.org/10.1080/10705511.2014.915181

Hallquist, M. N., & Wiley, J. F. (2018). MplusAutomation: An R Package for Facilitating Large-Scale Latent Variable Analyses in Mplus. Structural equation modeling: a multidisciplinary journal, 25(4), 621-638.

Müller, Kirill. (2017). Here: A Simpler Way to Find Your Files. https://CRAN.R-project.org/package=here.

Muthén, B. O., Muthén, L. K., & Asparouhov, T. (2017). Regression and mediation analysis using Mplus. Los Angeles, CA: Muthén & Muthén.

Muthén, L.K. and Muthén, B.O. (1998-2017). Mplus User's Guide. Eighth Edition. Los Angeles, CA: Muthén & Muthén

US Department of Education Office for Civil Rights. (2014). Civil rights data collection data snapshot: School discipline. Issue brief no. 1.

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/

Wickham et al., (2019). Welcome to the tidyverse. Journal of Open Source Software, 4(43), 1686, https://doi.org/10.21105/joss.01686