A Quick Latent Class Analysis (LCA) from Start to Finish in MplusAutomation

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Adam Garber

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What is included in this video tutorial?

A demonstration of the speed at which an LCA analysis can be estimated and summarized using the Tidy MplusAutomation method.

Tutorial Outline

- 0. Download scripts & data from Github repository
- 1. Introduction to data example & LCA indicator variables
- 2. Load packages
- 3. Read in data to R
- 4. Enumeration: Estimate LCA models with 1-6 classes
- 5. Create model fit table
- 6. Plot information criteria (elbow plot)
- 7. Compare conditional item probability plots
- 8. Plot final model in publication format (e.g., Class-3 model)

0. Github repository (everything you need to replicate analysis):

Link: https://github.com/immerse-ucsb/quick-lca-mplusauto

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1. 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

Latent Class Indicator Variables

report_dis = Number of students harassed or bullied on the basis of disability

report_race = Number of students harassed or bullied on the basis of race, color, national origin

report_sex = Number of students harassed or bullied on the basis of sex

counselors_fte = Number of full time equivalent counselors hired as school staff

psych_fte = Number of full time equivalent psychologists hired as school staff

law_fte = Number of full time equivalent law enforcement officers hired as school staff

2. Load packages

```
library(MplusAutomation); library(glue) # estimation
library(tidyverse); library(here); # tidyness
library(gt); library(reshape2); library(cowplot) # tables & figures
```

3. Read in CSV data file from the data subfolder

```
bully_data <- read_csv(here("data", "crdc_lca_data.csv"))</pre>
```

4. Enumeration

```
lca_k1_6 <- lapply(1:6, function(k) {</pre>
  lca_enum <- mplusObject(</pre>
    TITLE = glue("Class {k}"),
    VARIABLE = glue(
    "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(\{k\}); "),
  ANALYSIS =
   "estimator = mlr;
   type = mixture;
    starts = 500 100;
    processors = 10;",
  OUTPUT = "tech11 tech14;",
  PLOT =
    "type = plot3;
     series = report_dis report_race report_sex counselors_fte psych_fte law_fte(*);",
  usevariables = colnames(bully_data),
  rdata = bully_data)
lca_enum_fit <- mplusModeler(lca_enum,</pre>
                             dataout=glue(here("mplus_lca", "lca.dat")),
                             modelout=glue(here("mplus_lca", "c{k}_lca.inp")) ,
                             check=TRUE, run = TRUE, hashfilename = FALSE)
})
```

Always check your model!

- In the RStudio window pane on the bottom-rightunder the files tab click on the mplus_lca folder
- Click on one of the Mplus output files (.out) to check if the model estimated or if there are any error messages

5. Generate Model Fit Summary Table

- This syntax can be used to compare model fit from the series of LCA models generated during enumeration
- The code produces a table that is approximately in APA format.

Read in model fit statistics using readModels() and mixtureSummaryTable() functions

Calculate relevant fit indices for summary table

```
allFit <- enum_summary %>%
  mutate(aBIC = -2*LL+Parameters*log((Observations+2)/24)) %>%
  mutate(CIAC = -2*LL+Parameters*(log(Observations)+1)) %>%
  mutate(AWE = -2*LL+2*Parameters*(log(Observations)+1.5)) %>%
  mutate(SIC = -.5*BIC) %>%
  mutate(expSIC = exp(SIC - max(SIC))) %>%
  mutate(expSIC = exp(SIC-lead(SIC))) %>%
  mutate(BF = exp(SIC-lead(SIC))) %>%
  mutate(cmPk = expSIC/sum(expSIC)) %>%
  dplyr::select(1:5,9:10,6:7,13,14) %>%
  arrange(Parameters)
```

Generate the fit summary table

```
allFit %>%
  mutate(Title = str_remove(Title, " LCA Enumeration ")) %>%
  gt() %>%
  tab_header(
    title = md("**Model Fit Summary Table**"), subtitle = md(" ")) %>%
  cols_label(
    Title = "Classes",
    Parameters = md("Par"),
    LL = md("*LL*"),
    T11_VLMR_PValue = "VLMR",
```

```
BLRT_PValue = "BLRT",
 BF = md("BF"),
  cmPk = md("*cmPk*")) \%>\%
tab footnote(
 footnote = md(
  "*Note.* Par = parameters; *LL* = log likelihood;
   BIC = bayesian information criterion;
   aBIC = sample size adjusted BIC; CAIC = consistent Akaike information criterion;
   AWE = approximate weight of evidence criterion;
   BLRT = bootstrapped likelihood ratio test p-value;
   VLMR = Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test p-value;
    cmPk = approximate correct model probability."),
 locations = cells_title()) %>%
tab_options(column_labels.font.weight = "bold") %>%
fmt_number(10,decimals = 2,
           drop_trailing_zeros=TRUE,
           suffixing = TRUE) %>%
fmt_number(c(3:9,11),
           decimals = 0) %>%
fmt_missing(1:11,
            missing text = "--") %>%
fmt(c(8:9,11),
 fns = function(x)
  ifelse(x<0.001, "<.001",
         scales::number(x, accuracy = 0.01))) %>%
fmt(10, fns = function(x)
 ifelse(x>100, ">100",
         scales::number(x, accuracy = .1)))
```

6. Plot Information Criteria

allFit %>% dplyr::select(2:7) %>%
 rowid_to_column() %>%
 pivot_longer(`BIC`:`AWE`,
 names_to = "Index",
 values_to = "ic_value") %>%
 mutate(Index = factor(Index,
 levels = c("AWE","CIAC","BIC","aBIC"))) %>%
 ggplot(aes(x = rowid, y = ic_value,
 color = Index, shape = Index,
 group = Index, lty = Index)) +
 geom_point(size = 2.0) + geom_line(size = .8) +
 scale_x_continuous(breaks = 1:6) +
 labs(x = "Number of Classes", y = "Information Criteria Value") +
 theme_cowplot() + theme(legend.title = element_blank(), legend.position = "top")

7. Compare Conditional Item Probability Plots

8. Plot Final Model - Conditional Item Probability Plot

This syntax creates a function called plot_lca_function that requires 7 arguments (inputs):

- model_name: name of Mplus model object (e.g., model_step1)
- item_num: the number of items in LCA measurement model (e.g., 5)
- class_num: the number of classes (k) in LCA model (e.g., 3)
- item_labels: the item labels for x-axis (e.g., c("Enjoy", "Useful", "Logical", "Job", "Adult"))
- class_labels: the class label names (e.g., c("Adaptive Coping", "Externalizing Behavior", "No Coping"))
- class_legend_order = change the order that class names are listed in the plot legend (e.g., c(2,1,3))
- plot_title: include the title of the plot here (e.g., "LCA Posterior Probability Plot")

Read in plot data from Mplus output file c3_lca.out

```
model_c3 <- readModels(here("mplus_lca", "c3_lca.out"), quiet = TRUE)</pre>
```

Load plot_lca_function into R environment

```
plot lca function <- function(model name, item num, class num, item labels,
                               class_labels,class_legend_order,plot_title){
mplus_model <- as.data.frame(model_name$gh5$means_and_variances_data$estimated_probs$values)
plot_data <- mplus_model[seq(2, 2*item_num, 2),]</pre>
c_size <- as.data.frame(model_name$class_counts$modelEstimated$proportion)</pre>
colnames(c_size) <- paste0("cs")</pre>
c_size <- c_size %>% mutate(cs = round(cs*100, 2))
colnames(plot_data) <- paste0(class_labels, glue(" ({c_size[1:class_num,]}%)"))</pre>
plot_data <- plot_data %>% relocate(class_legend_order)
plot_data <- cbind(Var = paste0("U", 1:item_num), plot_data)</pre>
plot data$Var <- factor(plot data$Var,</pre>
               labels = item_labels)
plot_data$Var <- fct_inorder(plot_data$Var)</pre>
pd_long_data <- melt(plot_data, id.vars = "Var")</pre>
p <- pd_long_data %>%
  ggplot(aes(x = as.integer(Var), y = value,
  shape = variable, colour = variable, lty = variable)) +
  geom_point(size = 4) + geom_line() +
  scale_x_continuous("", breaks = 1:item_num,
                      labels = function(x) str_wrap(plot_data$Var, width = 13)) +
  labs(title = plot_title, y = "Probability") +
  theme_cowplot() +
  theme(legend.title = element_blank(),
        legend.position = "top",
        axis.text.x = element_text(size=8))
return(p)
```

Run C3 Plot

```
plot_lca_function(
  model_name = model_c3,
  item_num = 6,
  class_num = 3,
  item_labels = c("harassment: disability","harassment: race","harassment: sex",
```

References

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