

Multivariate: Latent class / profile analysis

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1 Goals

1.1 Goals

1.1.1 Goals of this lecture

- Latent class / profile analysis (LCA / LPA)
 - **Dimension reduction:** reduce number of variables
- A large set of (potentially correlated) observed variables
 - **Discrete** classes or profiles
 - Different **patterns** of responses

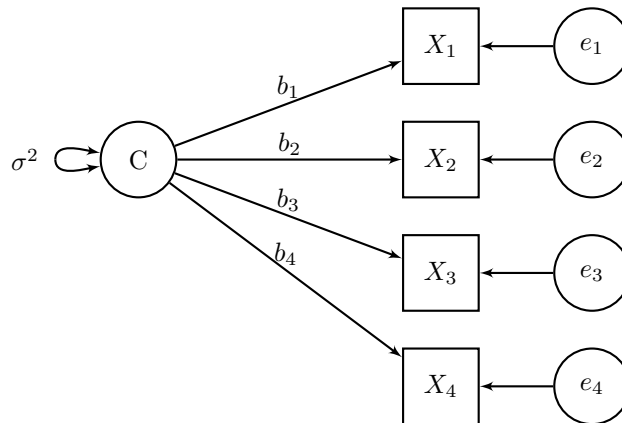
2 Latent class analysis

2.1 Latent class analysis

2.1.1 Latent class analysis

- Latent variable technique that **classifies** people into *previously unknown subgroups* based on their responses to a set of variables
 - Latent class = unknown / unobserved subgroups
 - LCA = only categorical variables; LPA = otherwise
- Groups of people have different *patterns of responses*
 - *Not a single value on a single variable*
 - e.g., people in *group 1* are **high on items 1-3**, **low on items 4-6** and people in *group 2* are **low on items 1-2** and **high on items 3-6**

2.1.2 What it looks like



- Latent class (C) is **categorical**: Typically nominal, not ordinal
- X_1 through X_4 are **indicators** of the latent class
- Note that the latent variable **causes** the indicator values

2.1.3 LCA is...

1. Data reduction
Large number of items \rightarrow smaller number of classes

2. Mixture model
Population is a “mixture” of subgroups, LCA “unmixes” them
3. Person-oriented approach
How do **people** have different *patterns*, rather than how are the **variables** related to one another for all *people*

2.1.4 LCA is similar to...

4. Factor analysis / measurement model
Very similar, but latent factor is continuous while **latent class is categorical**

2.1.5 Selecting the number of classes

- We have some number of patterns (classes)?
 - How do we decide how many?
- Similar to exploratory factor analysis (EFA) methods
 - Run several models with different numbers of classes
 - Compare these models in terms of **model fit** and **theory**
 - Choose the model that has the **best fit** and **makes the most sense**

2.1.6 Model fit for LCA

- **Chi-square test**
 - Problematic for large samples, do not rely on it
- **Likelihood ratio test** (also bootstrap LR test)
 - Same as previous LR tests, compare two models
- **AIC and BIC**
 - Smaller is better, not a measure of absolute fit
- **Entropy** - certainty of classification
 - Ranges from 0 to 1, closer to 1 is better

- Predicted vs observed means / probabilities
 - Mean for each item within each class - do they match?

2.1.7 Model fit for LCA

- BIC and LR test are best for **choosing the number of classes**
- AIC and entropy are bad for choosing the correct number of classes
 - You can *report* AIC and entropy – they tell you about the model – but **don't use them to decide on the number of classes**

2.2 LCA example 1

2.2.1 Mplus example 7.9 (modified)

4 continuous indicators, 2 classes

DATA:

FILE IS ex7.9.dat;

VARIABLE:

NAMES ARE y1-y4 x;

USEVARIABLES ARE y1-y4;

CLASSES = c (2);

ANALYSIS:

TYPE = MIXTURE;

PLOT:

TYPE=PLOT3;

SERIES = y1(1) y2(2) y3(3) y4(4);

2.2.2 Model-implied response pattern

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Latent Class 1				

Means				
Y1	-1.056	0.070	-15.030	0.000
Y2	-1.088	0.067	-16.255	0.000
Y3	-0.943	0.063	-15.050	0.000
Y4	-1.093	0.074	-14.688	0.000

...

Latent Class 2

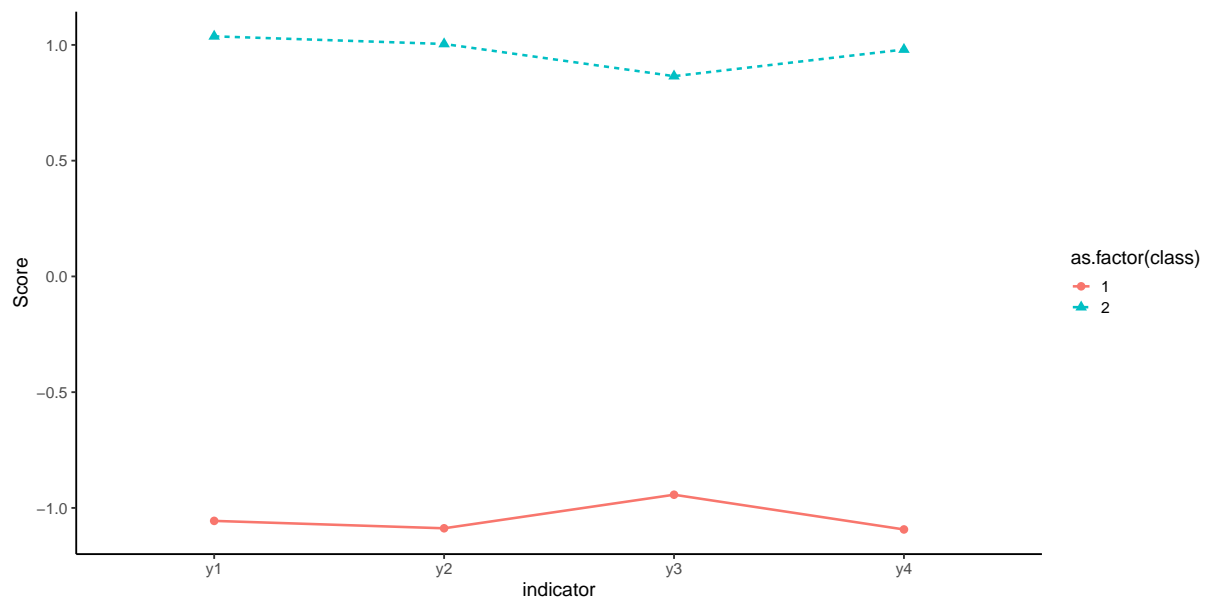
Means				
Y1	1.037	0.070	14.762	0.000
Y2	1.004	0.064	15.682	0.000
Y3	0.865	0.068	12.763	0.000
Y4	0.980	0.060	16.321	0.000

...

2.2.3 Model-implied response pattern

GRAPH → VIEW GRAPHS → ESTIMATED MEANS (Windows only)

2.2.4 Model-implied response pattern



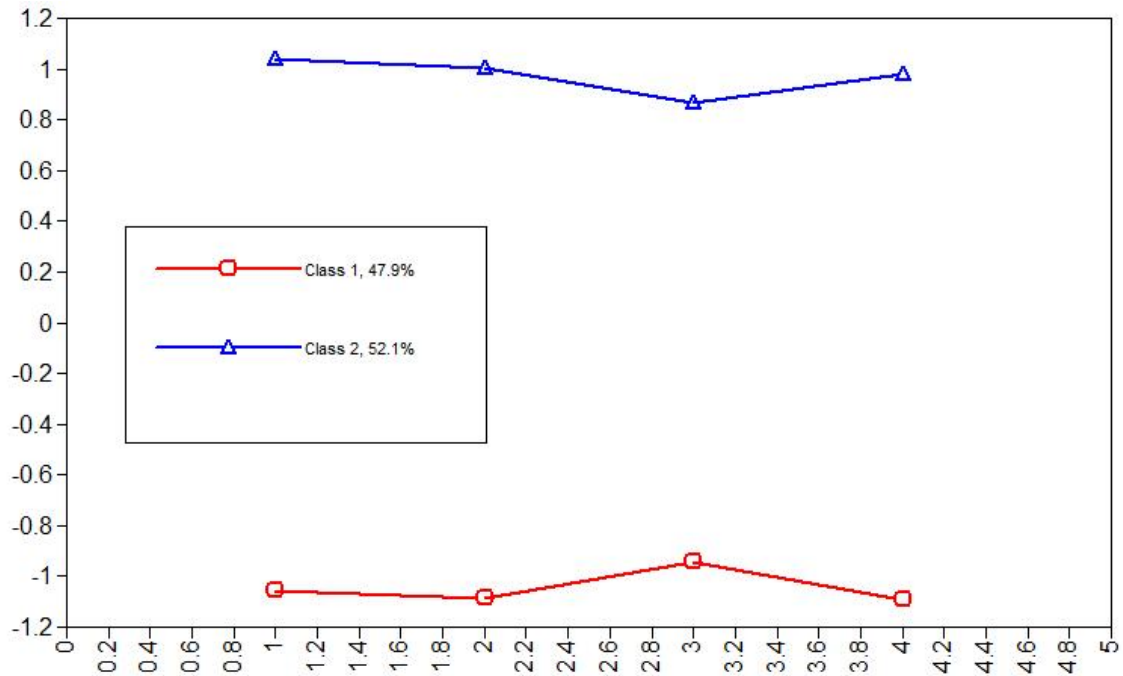


Figure 1: Response pattern

2.3 LCA example 2

2.3.1 Another example: Video game preferences

- Quaiser-Pohl, C., Geiser, C., & Lehmann, W. (2006). The relationship between computer-game preference, gender, and mental-rotation ability. *Personality and Individual differences*, 40(3), 609-619.
 - Classify people into types of video game players
 - 8 binary indicators (0 = never or rarely, 1 = often or very often)
 - 3 class solution

2.3.2 Indicators

- How often do you play the following types of computer games?
 1. Adventure
 2. Action
 3. Sport
 4. Fantasy role playing

5. Logic
6. Skill training
7. Simulation
8. Driving simulation

2.3.3 Mplus syntax

```
DATA: FILE = computer_games.dat;

VARIABLE: NAMES = gender c1-c8;
          USEVARIABLES = c1-c8;
          CATEGORICAL = c1-c8;
          CLASSES = L(3);

ANALYSIS: TYPE = MIXTURE;

PLOT:     TYPE = PLOT3;
          SERIES = c1(1) c2(2) c3(3) c4(4)
                  c5(5) c6(6) c7(7) c8(8);

SAVEDATA: FILE = computer_games_3_classes.dat;
          SAVE = CPROBABILITIES;
```

2.3.4 Model-implied response pattern

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Latent Class 1				
Thresholds				
C1\$1	0.555	0.144	3.852	0.000
C2\$1	-0.591	0.191	-3.101	0.002
C3\$1	-0.097	0.163	-0.593	0.553
C4\$1	0.463	0.143	3.244	0.001
C5\$1	1.154	0.247	4.680	0.000
C6\$1	1.542	0.291	5.290	0.000
C7\$1	-0.628	0.152	-4.134	0.000
C8\$1	-0.576	0.159	-3.633	0.000

Latent Class 2

Thresholds

C1\$1	1.398	0.506	2.761	0.006
C2\$1	1.920	0.706	2.717	0.007
C3\$1	1.675	0.423	3.961	0.000
C4\$1	1.489	0.523	2.850	0.004
C5\$1	-0.981	0.406	-2.413	0.016
C6\$1	-1.480	0.654	-2.263	0.024
C7\$1	0.187	0.357	0.524	0.600
C8\$1	0.685	0.334	2.052	0.040

Latent Class 3

Thresholds

C1\$1	4.582	0.780	5.872	0.000
C2\$1	4.334	0.804	5.388	0.000
C3\$1	2.723	0.322	8.455	0.000
C4\$1	4.583	0.927	4.947	0.000
C5\$1	2.216	0.300	7.391	0.000
C6\$1	2.166	0.366	5.924	0.000
C7\$1	2.873	0.326	8.817	0.000
C8\$1	2.845	0.410	6.937	0.000

...

RESULTS IN PROBABILITY SCALE

Latent Class 1

C1				
Category 1	0.635	0.033	19.021	0.000
Category 2	0.365	0.033	10.915	0.000
C2				
Category 1	0.356	0.044	8.152	0.000
Category 2	0.644	0.044	14.721	0.000
C3				
Category 1	0.476	0.041	11.727	0.000
Category 2	0.524	0.041	12.916	0.000
C4				
Category 1	0.614	0.034	18.144	0.000
Category 2	0.386	0.034	11.423	0.000

C5					
	Category 1	0.760	0.045	16.915	0.000
	Category 2	0.240	0.045	5.332	0.000
C6					
	Category 1	0.824	0.042	19.465	0.000
	Category 2	0.176	0.042	4.165	0.000
C7					
	Category 1	0.348	0.034	10.094	0.000
	Category 2	0.652	0.034	18.917	0.000
C8					
	Category 1	0.360	0.037	9.847	0.000
	Category 2	0.640	0.037	17.521	0.000
Latent Class 2					
C1					
	Category 1	0.802	0.080	9.967	0.000
	Category 2	0.198	0.080	2.463	0.014
C2					
	Category 1	0.872	0.079	11.068	0.000
	Category 2	0.128	0.079	1.623	0.105
C3					
	Category 1	0.842	0.056	14.991	0.000
	Category 2	0.158	0.056	2.808	0.005
C4					
	Category 1	0.816	0.078	10.399	0.000
	Category 2	0.184	0.078	2.345	0.019
C5					
	Category 1	0.273	0.081	3.383	0.001
	Category 2	0.727	0.081	9.020	0.000
C6					
	Category 1	0.185	0.099	1.877	0.060
	Category 2	0.815	0.099	8.247	0.000
C7					
	Category 1	0.547	0.088	6.179	0.000
	Category 2	0.453	0.088	5.125	0.000
C8					
	Category 1	0.665	0.074	8.941	0.000
	Category 2	0.335	0.074	4.508	0.000

Latent Class 3

C1

	Category 1	0.990	0.008	126.531	0.000
	Category 2	0.010	0.008	1.295	0.195
C2					
	Category 1	0.987	0.010	96.062	0.000
	Category 2	0.013	0.010	1.259	0.208
C3					
	Category 1	0.938	0.019	50.383	0.000
	Category 2	0.062	0.019	3.309	0.001
C4					
	Category 1	0.990	0.009	106.680	0.000
	Category 2	0.010	0.009	1.090	0.276
C5					
	Category 1	0.902	0.027	33.919	0.000
	Category 2	0.098	0.027	3.699	0.000
C6					
	Category 1	0.897	0.034	26.596	0.000
	Category 2	0.103	0.034	3.049	0.002
C7					
	Category 1	0.947	0.017	57.362	0.000
	Category 2	0.053	0.017	3.242	0.001
C8					
	Category 1	0.945	0.021	44.386	0.000
	Category 2	0.055	0.021	2.580	0.010

2.3.5 Model-implied response pattern

GRAPH → VIEW GRAPHS → ESTIMATED PROBABILITIES (Windows only)

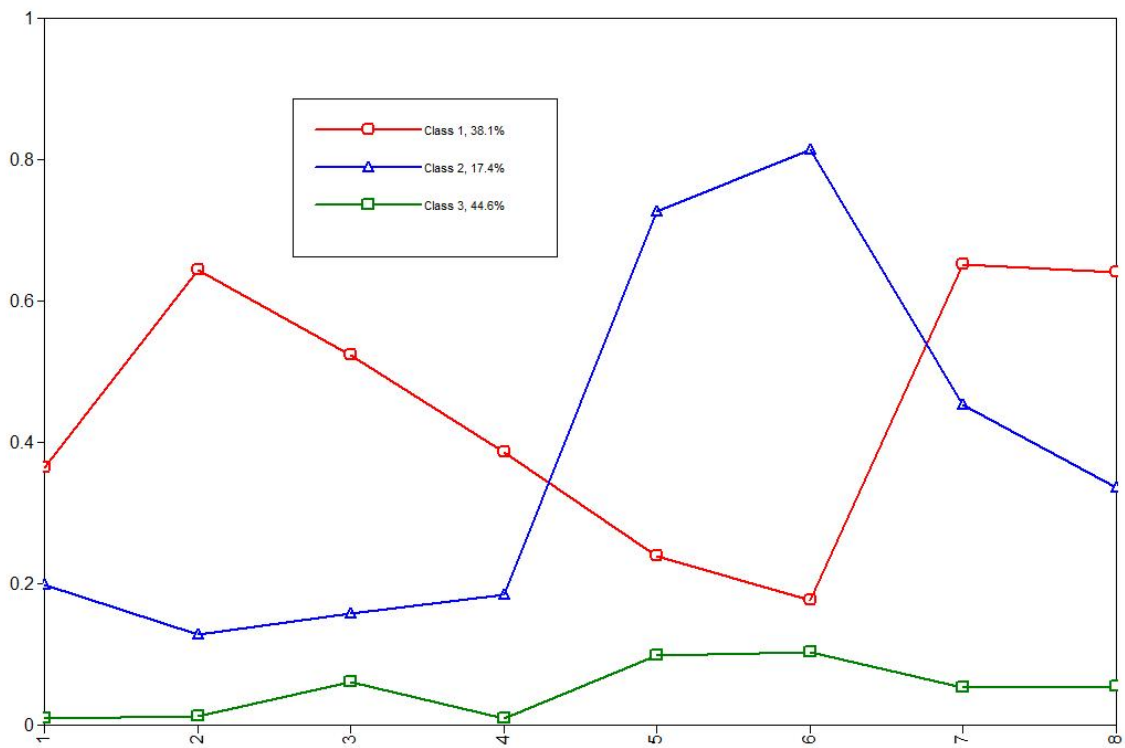
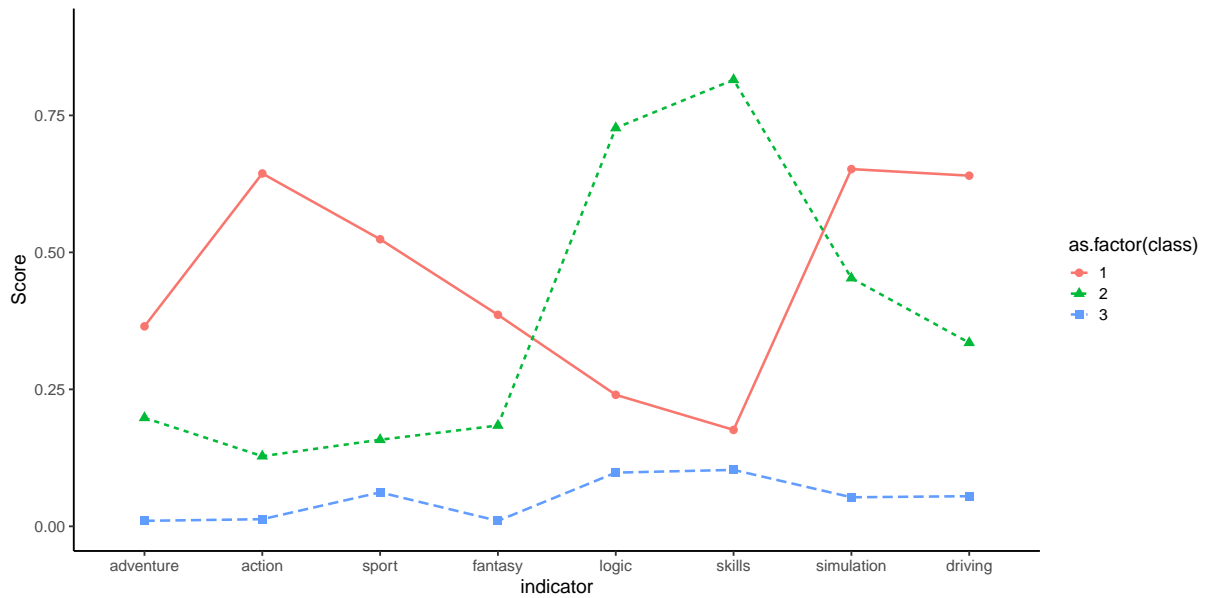
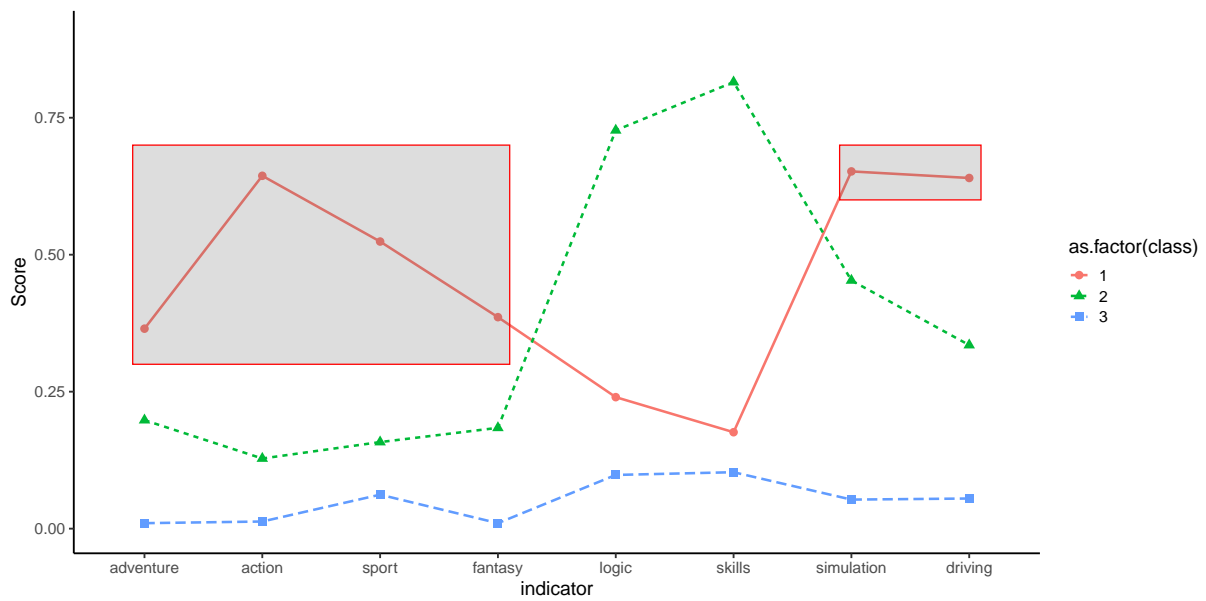


Figure 2: Three class binary

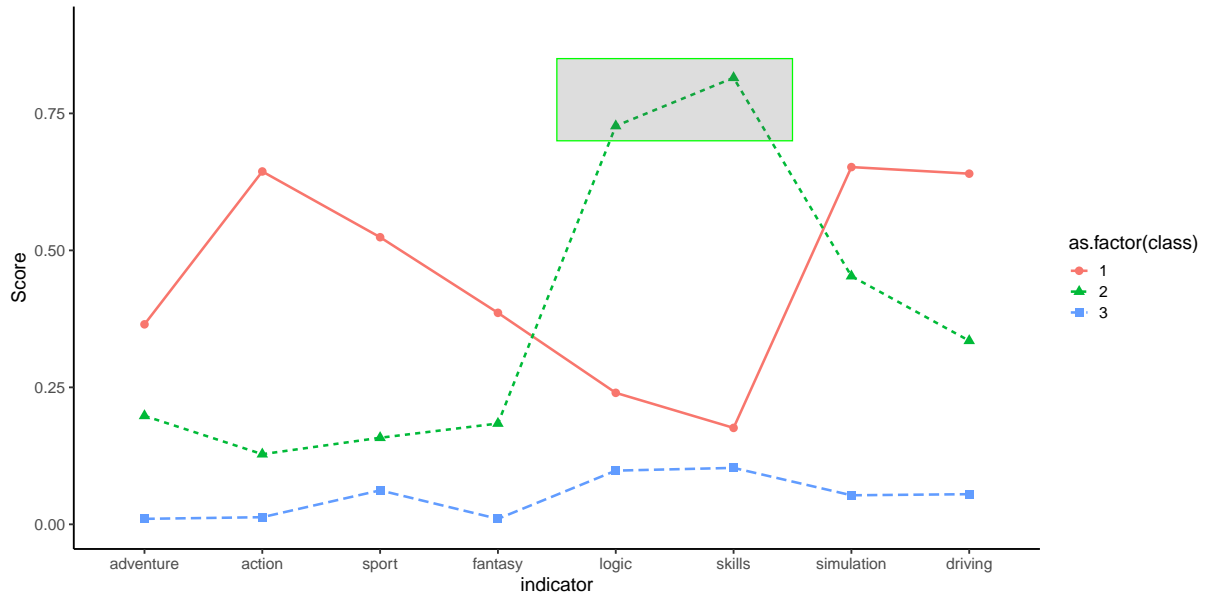
2.3.6 Model-implied response pattern



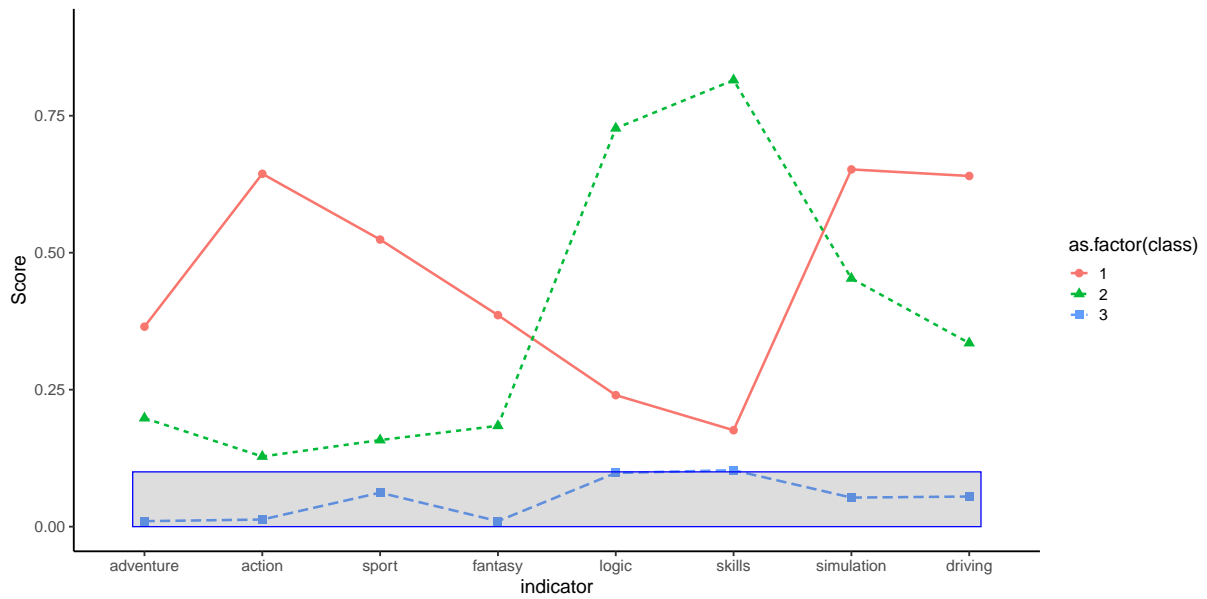
2.3.7 Model-implied response pattern



2.3.8 Model-implied response pattern



2.3.9 Model-implied response pattern



2.4 LPA example 3

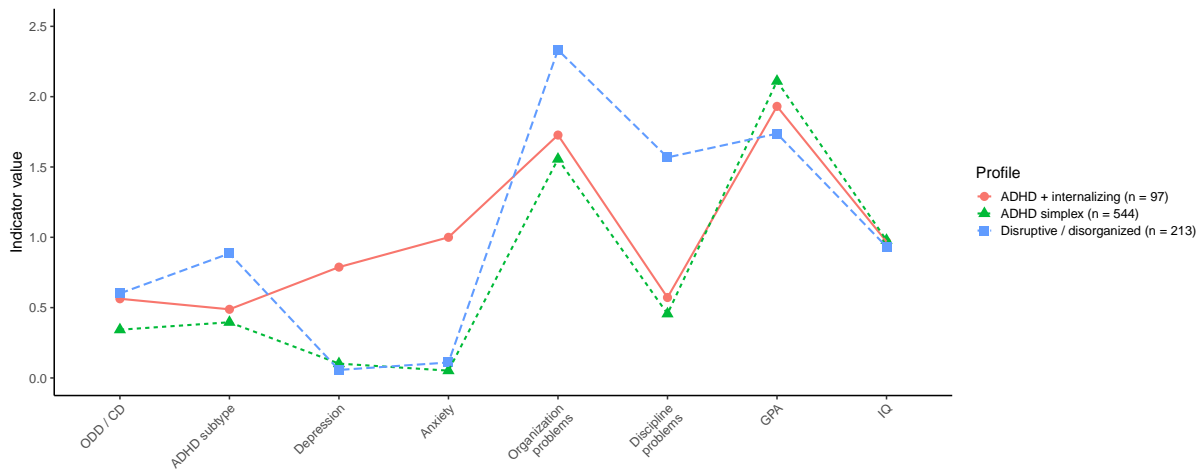
2.4.1 Another example: ADHD subtypes

- Coxe, S., Sibley, M. H., & Becker, S. P. (2021). Presenting problem profiles for adolescents with ADHD: differences by sex, age, race, and family adversity. *Child and Adolescent Mental Health*, 26(3), 228-237.
 - Characterize adolescents seeking treatment for ADHD
 - 8 indicators (next slide)
 - 3 class solution

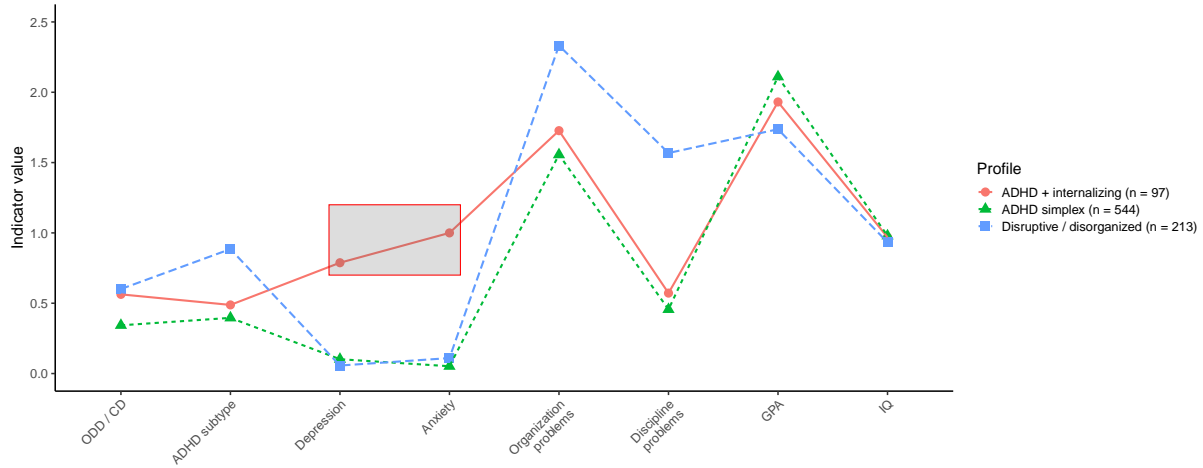
2.4.2 Indicators

- **Opposition-defiant disorder / conduct disorder:** Binary
- **ADHD combined subtype** (inattention and hyperactivity): Binary
- **Depression diagnosis:** Binary
- **Anxiety diagnosis:** Binary
- **Organization problems:** 0 to 3 (higher is worse, continuous)
- **Discipline problems:** 0 to 3 (higher is worse, continuous)
- **GPA:** 0 to 4 (higher is better)
- **IQ:** divided by 100 (population mean = 1.0, population SD = 0.15)

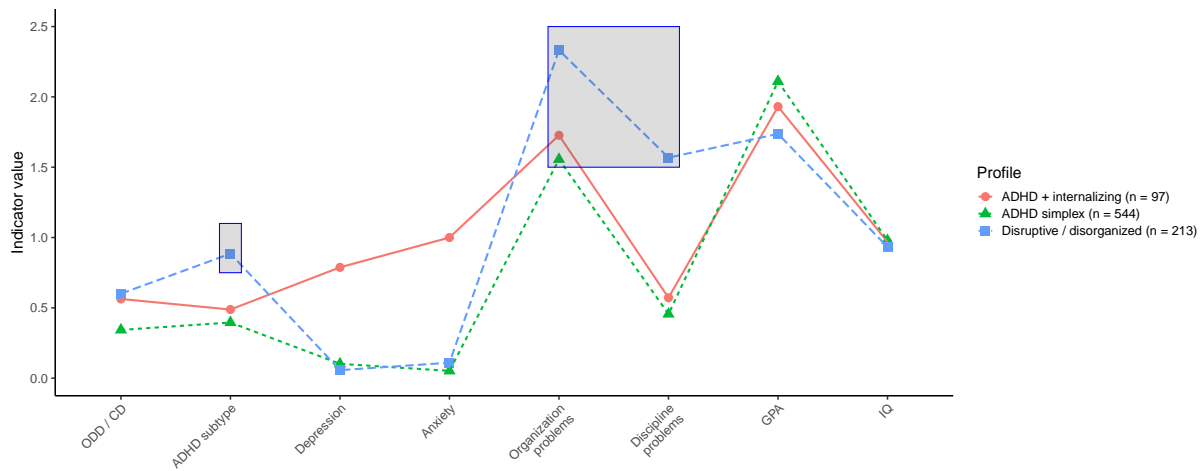
2.4.3 Model-implied response pattern



2.4.4 Model-implied response pattern



2.4.5 Model-implied response pattern



3 Conclusion

3.1 Summary of this week

3.1.1 Summary of this week

- Latent class / profile analysis
 - Latent or unknown groups

- Discrete groups
 - * Generally not just high, medium, low
 - * Patterns of responses
- Conceptually similar to factor analysis
 - Only with a discrete factor

3.2 Summary of this section

3.2.1 Summary of this section

- There are a lot of ways to **reduce the dimension** of your data
- Which one you use depends on (among other things)
 - What you think about measurement error
 - Which way the causal arrow is pointing
 - Whether the reduced dimension is continuous or categorical