

Latent Class Analysis

- Jouko Miettunen, PhD
- Department of Psychiatry
- University of Oulu
- phone: +358-8-3156923
- e-mail: jouko.miettunen@oulu.fi

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Topics of this presentation

- Introduction
- Related methods
- Applications
- Statistical issues
- Software
- Examples
- References

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Introduction (1)

Latent Class Analysis

- Specific statistical modelling method developed to group subjects according to selected characteristics
 - ◆ Classifies subjects to groups
 - ◆ Identifies characteristics that indicate groups

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Related methods (1)

Cluster analysis

- Based on distances between observations not on modelling

Fuzzy clustering

- "Grades of membership"
- Do not give characteristics for groups

Structural equation modelling and factor analyses

- Investigate variables not subjects
 - ◆ used to classify questionnaire items into subsets
 - ◆ models can include also confounders

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Related methods (2)

Several names are used to label LCA as a cluster analysis method

- mixture likelihood approach to clustering
- model-based clustering
- mixture-model clustering
- Bayesian classification
- unsupervised learning
- latent class cluster analysis

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Applications (1)

- PubMed found 159 and PsycINFO 211 articles (December 2004)
- Several in psychiatry and psychology
 - ◆ already 1982 in schizophrenia
- Categories of people
 - ◆ who are smokers or alcoholists
 - ◆ with eating disorders
 - ◆ with breast cancer

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Applications (2)

- Diagnostic validity / syndromes
 - ◆ ADHD
 - ◆ Hypochondriasis
 - ◆ psychosis
 - ◆ etc.
- Genetic studies
 - ◆ Alzheimer disease, etc.

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Statistical issues (1)

- Model based clustering method
 - ◆ E.g. maximum likelihood methods
 - ◆ Most packages use EM algorithm or some modification
- All observed variables (e.g., symptoms) should be statistically independent (roughly, uncorrelated) within each latent class

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Statistical issues (2)

- Problem of "local maxima," where the computer program, trying to find best-fitting values for quantities such as the population base rates of the latent classes, instead converges on values that are not best-fitting
- Many programs use multiple sets of starting values

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Statistical issues (3)

Model comparisons

- Information Criteria
 - ◆ Akaike's IC
 - ◆ Bayesian IC
 - ◆ CAIC
- Likelihood-ratio tests
- Entropy based measures
 - ◆ indicate how well the indicators predict class membership

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Software (1)

Mplus

- Integrates random effect, factor, and latent class analysis in both cross-sectional and longitudinal settings and for both single-level and multi-level data.
- Latent class analysis
 - ◆ unique features for covariates and complex sample data
- www.statmodel.com

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Software (2)

Stata package: GLLAMM

- Generalized Linear Latent And Mixed Models
- Can be used for
 - ◆ generalised linear mixed models
 - ◆ multilevel factor models
 - ◆ latent trait models
 - ◆ multilevel structural equation models
 - ◆ latent class models
- <http://www.gllamm.org/>

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Software (3)

- R package: LCA 1.1
- A library of 15 programs and utility functions for performing exploratory latent class analysis on binary data.
- Reference:
 - ◆ Waller N. An R package for exploratory latent class analysis. Applied Psychological Measurement. Vol 28(2), Mar 2004, pp. 141-142

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Software (4)

- Latent GOLD
- <http://www.latentGOLD.com/>
- <http://www.statisticalinnovations.com>
- Reference:
 - ◆ Vermunt JK & Magidson J. Applications of Latent Class Analysis: An introduction to the technique and the Latent GOLD software. (http://www.gla.ac.uk/External/RSS/RS_Scomp/vermunt.pdf)
- LEM (older free LCA software)

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Example: Anti-Social Behavior

- National Longitudinal Survey of Youth (NLSY)
- Respondent ages between 16 and 23
- Background information: age, gender and ethnicity
- N=7,326

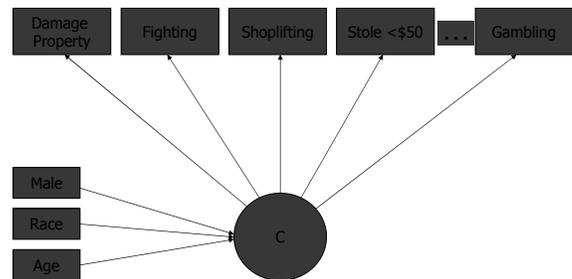
17 antisocial dichotomously scored behavior items:

- | | |
|----------------------|--------------------------|
| ■ Damaged property | ■ Use Marijuana |
| ■ Fighting | ■ Use other drug |
| ■ Shoplifting | ■ Sold Marijuana |
| ■ Stole <\$50 | ■ Sold hard drugs |
| ■ Stole >\$50 | ■ 'Con' somebody |
| ■ Use of force | ■ Stole an Automobile |
| ■ Seriously threaten | ■ Broken into a building |
| ■ Intent to injure | ■ Held stolen goods |
| | ■ Gambling Operation |

Reference:
<http://www.ats.ucla.edu/stat/mplus/seminars/lca/default.htm>

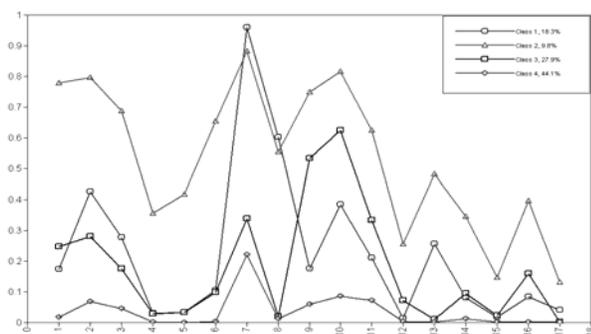
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Model for Anti-Social Behavior



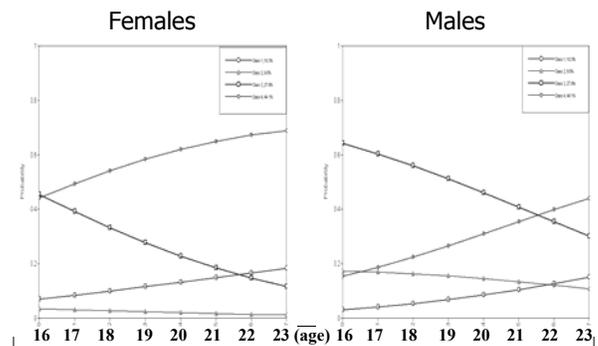
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Anti-Social Behavior probabilities



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Relationship between class probabilities and age by gender



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Results: Anti-Social Behavior

- Summary of four classes:
 - ◆ Property Offense Class (9.8%)
 - ◆ Substance Involvement Class (18.3%)
 - ◆ Person Offenses Class (27.9%)
 - ◆ Normative Class (44.1%)
- Classification Table:

		Columns: Latent class			
		1	2	3	4
Rows: Average latent class probability for most likely latent class membership	1	0.854	0.031	0.070	0.040
	2	0.041	0.917	0.040	0
	3	0.058	0.021	0.820	0.100
	4	0.038	0	0.080	0.880

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Example: Temperament

Northern Finland 1966 Birth Cohort

- Women who were living in the provinces of Oulu and Lapland and were due to deliver during 1966 (12,058 live births)
- Data from the 31 year follow-up
 - ◆ Temperament and Character Inventory (TCI)

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Variables for analyses

- Temperament and Character Inventory
 - ◆ True/False items (temperament part)
 - Novelty Seeking (40 items)
 - Harm Avoidance (35 items)
 - Reward Dependence (24 items)
 - Persistence (8 items)
 - ◆ covariates
 - educational level 1997
 - basic, secondary, tertiary
 - gender
- N = 4850

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Temperament Example I

- Mplus 3.01 program
- LCA with 4 categories
- No covariates
- No intercorrelations between temperament variables

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Mplus input

MPLUS INPUT INSTRUCTIONS

```

title: Mplus example on TCI variables - four factors
data: file is c:\tc\mplus.dat;
variable: names IDKT TCIP TCINS TCICHA TCICRD SUKUP TUT97LK;
missing = all (99);
usev are TCIP TCINS TCICHA TCICRD;
classes = c(4);
analysis: type = mixture; starts = 20 2;
model:
  %overall%
  %c#1%
  %c#2%
  %c#3%
  %c#4%
output: tech1 tech8 tech11;
savedata: file is tcicout.sav; save = cprobabilities;
plot: type=plot3;
series tcic tcins tcicrd tcip(*);

```

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Mplus output (1)

Output: TESTS OF MODEL FIT

INFORMATION CRITERIA

Akaike (AIC)	107150.024
Bayesian (BIC)	107299.218
Sample-Size Adjusted BIC	107226.133
(n* = (n + 2) / 24)	
Entropy	0.579

LUONG-LO-MENDELL-RUBIN LIKELIHOOD RATIO TEST FOR 3 (H0) VERSUS 4 CLASSES

H0 Loglikelihood Value	-53675.803
2 Times the Loglikelihood Difference	247.582
Difference in the Number of Parameters	5
Mean	-10.709
Standard Deviation	35.960
P-Value	0.0000

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Mplus output (2)

CLASSIFICATION OF INDIVIDUALS BASED ON
THEIR MOST LIKELY LATENT CLASS
MEMBERSHIP

Latent Classes	Class Counts and Proportions	
1	714	0.14722
2	1358	0.28000
3	482	0.09938
4	2296	0.47340

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Mplus output (3)

Average Latent Class Probabilities for Most
Likely Latent Class Membership (Row) by
Latent Class (Column)

	1	2	3	4
1	0.730	0.002	0.059	0.209
2	0.003	0.807	0.063	0.128
3	0.070	0.134	0.696	0.100
4	0.116	0.090	0.035	0.759

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Mplus output (4)

MEANS FOR LATENT CLASSES

	1	2	3	4
NOVELTY SEEKING (NS)	17.300	21.554	15.414	22.059
HARM AVOIDANCE (HA)	20.309	9.109	18.766	13.583
REWARD DEPENDENCE (RD)	13.358	14.599	14.066	15.543
PERSISTENCE (P)	2.750	5.949	5.690	3.458

Class characteristics (subjective):

Class 1: LOW P, HIGH HA
Class 2: HIGH P, LOW HA, HIGH NS
Class 3: LOW NS, HIGH HA, HIGH P
Class 4: LOW P, HIGH NS

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Temperament Example II

- Mplus 3.01 program
- LCA with 4 categories
- Intercorrelations
- Covariates

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Mplus input

MPLUS INPUT INSTRUCTIONS, MODEL PART

```
model:
%overall%
  tcip with tciha;
  tciha with tcins;
  tcird with tcins;
  c#1 c#2 c#3 on SUKUP TUT97LK;
%c#1%
%c#2%
%c#3%
%c#4%
```

with = "correlated with"
on = "regression on"
- last class is reference class

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Mplus output

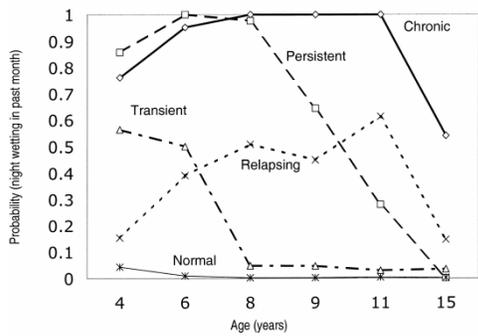
MODEL FIT

Akaike (AIC)	105992.455
Bayesian (BIC)	106258.412
Sample-Size Adjusted BIC	106128.128
Entropy	0.618

Latent Classes	Class Counts	Proportions
1	460	0.09485
2	761	0.15691
3	1763	0.36351
4	1866	0.38474

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Example: Nighttime wetting



Croudace et al. Developmental typology of trajectories to nighttime bladder control: Epidemiologic application of longitudinal latent class analysis. (2003)

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References (1)

- Muthén B & Muthén M. Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcohol Clin Exp Res*, 24, 882-91, 2000.
- Croudace TJ, Järvelin MR, Wadsworth ME & Jones PB. Developmental typology of trajectories to nighttime bladder control: Epidemiologic application of longitudinal latent class analysis. *American Journal of Epidemiology* 157(9), 834-42, 2003.
- Rindskopf D & Rindskopf W. The value of latent class analysis in medical diagnosis. *Statistics in Medicine*, 5, 21-7, 1986.

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References (2)

- Skrondal A & Rabe-Hesketh S. *Generalized Latent Variable Modeling: Multilevel, Longitudinal and Structural Equation Models*. Chapman & Hall/CRC, 2004.
- Hagenaars JA & McCutcheon AL. *Applied latent class analysis*. Cambridge, UK: Cambridge University Press, 2002.
- More references and examples, e.g. in
 - ◆ www.statmodel.com

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