

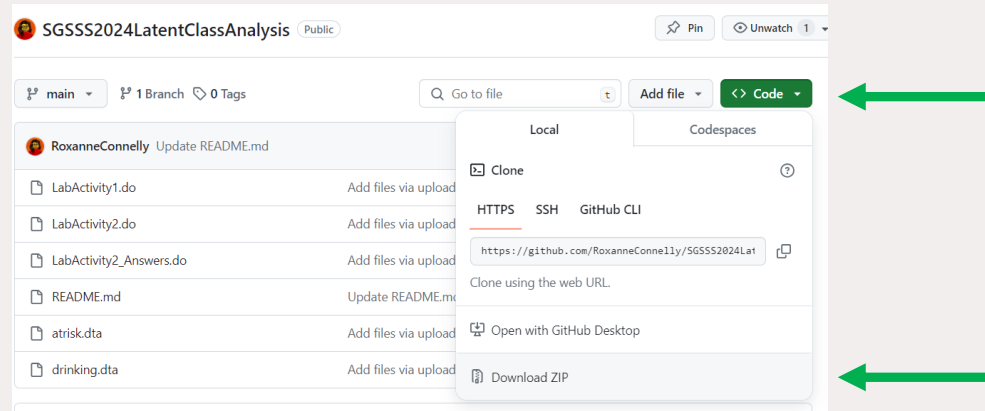
# Latent Class Analysis

June 2024

Dr Roxanne Connelly

Materials are available here:

<https://github.com/RoxanneConnelly/SGSSS2024LatentClassAnalysis>



Lecture Slides: **lectureslides.pdf**

# Workshop Aims

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This workshop will provide you with:

1. An introduction to what latent class analysis is and how it is used in the social sciences;
2. An introduction to how to carry out a latent class analysis and how to interpret the results.

# Timetable

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1000 – 1100	Talk 1
1100 – 1130	Lab Activities
1130 – 1200	Talk 2
1200 – 1230	Lab Activities
1230 – 1300	Final Advice and Questions

# Latent Class Analysis

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June 2024

Dr Roxanne Connelly

## Talk 1

# Operationalising Social Science Concepts

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Operationalisation is the process of turning abstract concepts into measurable observations

Many concepts in the social sciences cannot be observed or measured directly

Authoritarianism  
Social Exclusion  
Cultural Capital  
Sexism  
Economic Development

Neoliberalism  
Racial Prejudice  
Social Capital  
Anomie  
Social Class

# Operationalising Social Science Concepts

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Religiosity

‘The quality or state of being religious’

# Latent Class Analysis

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# Latent Class Analysis

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- Latent class analysis is a method used to extract meaningful groups (i.e. latent classes) from data.
- The concept of latent classes was first introduced by Paul Lazarsfeld (1950) and the implementation of the method was substantially developed by Leo Goodman (1974).

Lazarsfeld, P. F. (1950). The logical and mathematical foundation of latent structure analysis & the interpretation and mathematical foundation of latent structure analysis. In S. A. Stouffer, L. Guttman, E. A. Suchman, P. F. Lazarsfeld, S. A. Star, J. A. Clausen (Eds.), *Measurement and prediction* (pp. 362–472). Princeton, NJ: Princeton University Press.

Goodman, L. A. (1974). The analysis of systems of qualitative variables when some of the variables are unobservable: Part I—A modified latent structure approach. *American Journal of Sociology*, 79, 1179–1259.

Magidson, J., Vermunt, J. K., & Madura, J. P., (2020). Latent Class Analysis, In P. Atkinson, S. Delamont, A. Cernat, J.W. Sakshaug, & R.A. Williams (Eds.), *Sage Research Methods Foundations*. Sage.



# Latent Class Analysis

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- Covariation in the observed variables (i.e. manifest variables) is theorised to be due to the latent variable.
- The latent variable ‘explains’ the relationship between the observed variables.

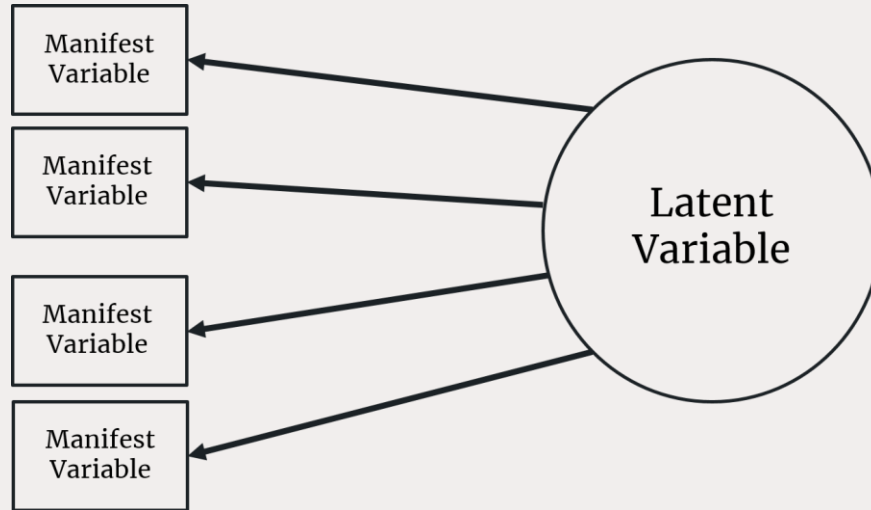
Lazarsfeld, P. F. (1950). The logical and mathematical foundation of latent structure analysis & the interpretation and mathematical foundation of latent structure analysis. In S. A. Stouffer, L. Guttman, E. A. Suchman, P. F. Lazarsfeld, S. A. Star, J. A. Clausen (Eds.), *Measurement and prediction* (pp. 362–472). Princeton, NJ: Princeton University Press.

Goodman, L. A. (1974). The analysis of systems of qualitative variables when some of the variables are unobservable: Part I—A modified latent structure approach. *American Journal of Sociology*, 79, 1179–1259.

# Latent Class Analysis

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Latent class analysis (LCA) is a statistical procedure used to identify **qualitatively different** subgroups.



# Latent Class Analysis

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Using latent class analysis we can fit a statistical model to try to determine which individuals are likely to belong to each latent class group based on the patterns in the manifest variables.

# Example Applications

# Cultural Consumption

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- Chan, T. W., & Goldthorpe, J. H. (2007). **Social stratification and cultural consumption: The visual arts in England.** Poetics, 35(2), 168–190.
- The aim was to examine the relationship between social stratification and cultural consumption. Specifically the consumption of the ‘visual arts’.
- This analysis used the Arts in England Survey.

# Cultural Consumption

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Table 1

Percentage of respondents who have visited various visual arts events or establishments in the past 12 months

Event involving video or electronic art	7.7
Cultural festival	11.0
Craft exhibition	18.5
Exhibition or collection of art, photography or sculpture	21.0
Museum or art gallery	38.7

Chan, T. W., & Goldthorpe, J. H. (2007). Social stratification and cultural consumption: The visual arts in England. *Poetics*, 35(2), 168-190.

# Cultural Consumption

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Potential patterns of response:

- 5 manifest variables
- 2 possible outcomes (yes/no)

Video / EA	Cultural Festival	Craft Exhib.	Art / Photo	Museum / Gallery
Yes	Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes	No
Yes	Yes	Yes	No	Yes
Yes	Yes	Yes	No	No
Yes	Yes	No	Yes	Yes
Yes	Yes	No	Yes	No
Yes	Yes	No	No	Yes
Yes	Yes	No	No	No

Chan, T. W., & Goldthorpe, J. H. (2007). Social stratification and cultural consumption: The visual arts in England. *Poetics*, 35(2), 168-190.

# Cultural Consumption

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Latent Class 1: Inactives

Latent Class 2: Paucivores

Latent Class 3: Omnivores

Table 3

Estimated relative sizes of latent classes and conditional probabilities of different forms of visual arts consumption under a three-class model

	1	2	3
Relative size (%)	58.6	34.4	7.0
Event involving video or electronic art	0.092	0.252	0.632
Cultural festival	0.040	0.120	0.644
Craft exhibition	0.035	0.067	0.478
Exhibition or collection of art, photography or sculpture	0.004	0.416	0.922
Museum or art gallery	0.071	0.809	0.966



# Cultural Consumption

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Latent Class 1: Inactives

Latent Class 2: Paucivores

Latent Class 3: Omnivores

Latent group membership is more strongly differentiated by social status than by social class or by income.

Education is the most important determinant of latent group membership.

# Caregiver Coping Strategies

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- Lin, I. F., & Wu, H. S. (2014). **Patterns of coping among family caregivers of frail older adults.** Research on aging, 36(5), 603-624.
- Previous studies have extensively examined the coping strategies of caregivers, but they have not considered the possibility that distinct groups of caregivers may use different coping strategies.
- This analysis used the National Long Term Care Survey.

**Table 1.** Percentages of Family Caregivers Who Said How They Coped.

	%
Emotion-focused coping	
Talk with friends or relatives	77.39
Pray or meditate	71.82
Watch TV	71.49
Read	67.15
Spend time alone	61.08
Spend time on exercise or hobbies	55.80
Eat	44.33
Take medication to calm	14.61
Drink alcohol	13.22
Smoke	12.52
Problem-focused coping	
Obtain assistive devices such as wheelchairs or walkers for care recipient	58.16
Use services for personal or nursing care at care recipient's home	29.72
Make modifications in care recipient's home	28.56
Use services to help with housework at care recipient's home	18.90
Use services delivering meals to care recipient's home	11.04
Use transportation services for care recipient	10.80
Use respite or caregiver support services	10.80
Request information on financial help for care recipient	10.59
N	1,552

**Table 3.** Three Latent Class Model ( $N = 1,552$ ).

	Latent Class		
	Unpatterned Coping	Emotional Coping	Hybrid Coping
Probability of membership	.20	.46	.33
Conditional probability of a Yes response			
Emotion-focused coping			
Talk with friends or relatives	.22	.91	.92
Pray or meditate	.22	.85	.85
Watch TV	.08	.90	.86
Read	.04	.86	.81
Spend time alone	.14	.72	.75
Spend time on exercise or hobbies	.07	.67	.70
Eat	.05	.50	.61
Take medication to calm	.02	.13	.24
Drink alcohol	.01	.15	.18
Smoke	.03	.16	.14
Problem-focused coping			
Obtain assistive devices	.45	.41	.89
Use personal or nursing care	.21	.08	.63
Make home modifications	.16	.15	.55
Use services to help with housework	.14	.08	.36
Use meal deliver services	.05	.04	.24
Use outside services for transportation	.07	.04	.22
Use respite or caregiver support services	.04	.02	.27
Request information on financial help	.03	.07	.20

# A Bourdieusian Social Class Measure

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- Connelly, R., Gayle, V., & Playford, C. (2021). **Social class inequalities in educational attainment: measuring social class using capitals, assets and resources.** Contemporary Social Science, 16(3), 280–293.
- Is it possible to create a social class measure based on indicators of capitals, assets and resources using existing social survey data resources?
- This analysis used the United Kingdom Household Longitudinal Study (UKHLS, Understanding Society).

**Table 3.** Prior probabilities for the six latent class solution.

Ascribed label	'Elite'	'The established middle class'	'The socially engaged middle class'	'The culturally engaged middle class'	'The traditional working class'	'The precariat'
% Allocated to Latent Class	–	31	–	11	35	19
<i>Prior Probabilities</i>						
<i>Economic Capital</i>						
Equivalised Net Monthly Household Income (mean)	7298.64	1559.42	1568.76	1494.50	1232.39	1348.61
Own Home	1.00	0.91	0.86	0.95	0.75	0.52
<i>Social Capital</i>						
Number of Friends (mean)	6.14	5.16	25.03	7.45	4.91	3.96
Active in Trade Union	0.15	0.09	0.05	0.09	0.02	0.06
Active in Professional Organisation	0.68	0.16	0.37	0.37	0.04	0.00
<i>Highbrow Cultural Capital</i>						
Classical Music Concerts	0.57	0.23	0.23	0.34	0.03	0.00
Historic Buildings	0.42	0.86	0.61	0.95	0.12	0.13
Museums / Galleries	0.85	0.84	0.78	0.98	0.21	0.29
Plays/Theatre/Pantomime	1.00	0.88	0.80	0.77	0.33	0.20
Ballet Performance	0.14	0.13	0.23	0.14	0.00	0.00
<i>Emerging Cultural Capital</i>						
Social Media	0.58	0.64	0.42	0.88	0.83	0.28
Regularly use the Internet	1.00	0.92	1.00	1.00	1.00	0.24
Gym/Fitness Classes	0.60	0.45	0.55	0.93	0.44	0.22
Rock/Pop/Jazz Concert	0.82	0.59	0.58	0.69	0.22	0.10
Cycle	0.42	0.46	0.43	0.99	0.28	0.12
Racquet Sports	0.13	0.24	0.66	0.66	0.09	0.06
Golf	0.27	0.19	0.19	0.28	0.07	0.03

Note: – indicates that the values in the cell have been suppressed for statistical disclosure control purposes.  $n = 616$ . The sample size reduces by one case in the weighted analyses as one sample member has a weight of zero (unweighted  $n = 617$ ).

# Latent Class Analysis

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Latent class analysis is a method used to extract meaningful (qualitatively different) groups (i.e. latent classes) from data.

		Latent Variables	
		Continuous	Categorical
Manifest (i.e. observed) Variables	Continuous	Factor Analysis	Latent Profile Analysis
	Categorical	Latent Trait Analysis (aka Item Response Theory)	Latent Class Analysis

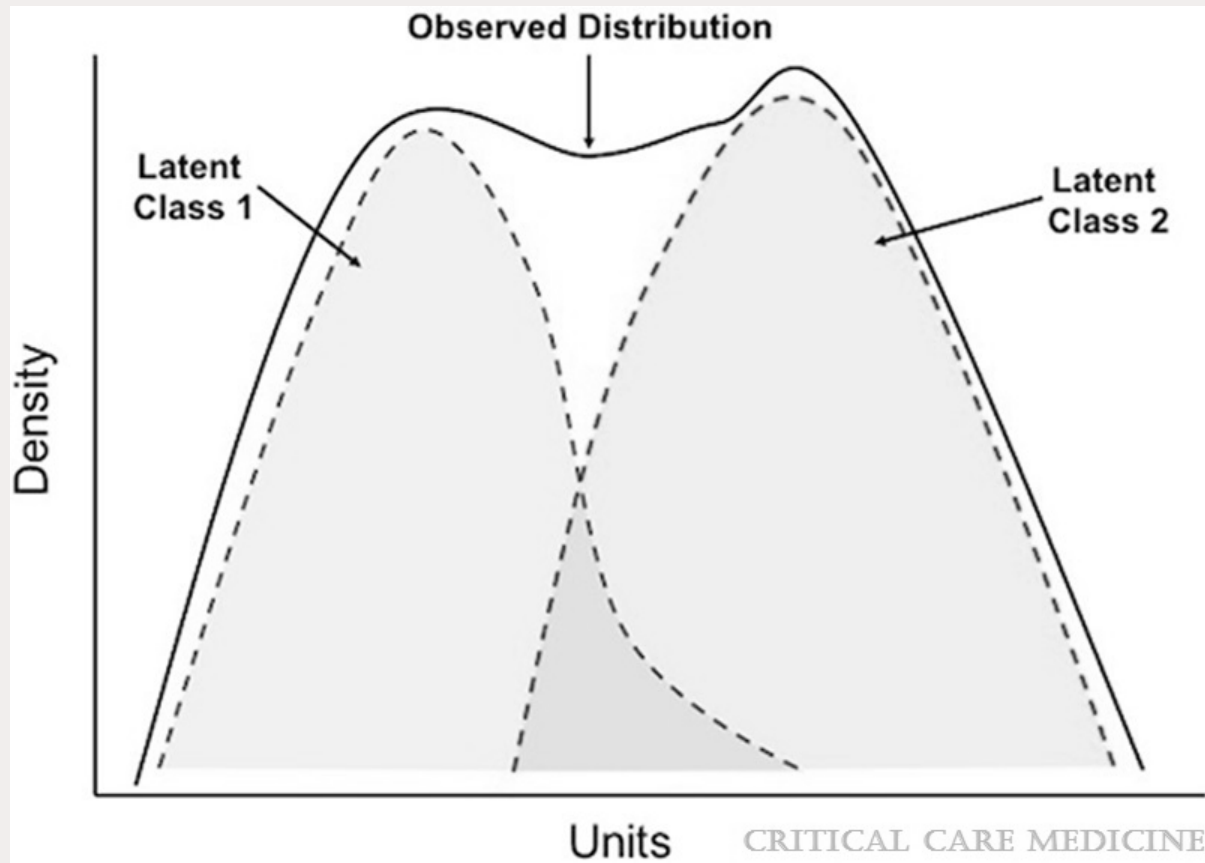
# Latent Class Analysis

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- Theorise your latent concept and identify manifest variables.
- Fit a series of latent class models.
- Select the most appropriate latent class model.
- Describe the patterns in your latent classes.
- Use your latent classes in further analysis (i.e. as an explanatory variable or an outcome variable).



# Under the Hood



Sinha, P., Calfee, C. S., & Delucchi, K. L. (2020). Practitioner's guide to latent class analysis: methodological considerations and common pitfalls. *Critical care medicine*, 49(1), e63-e79.

# Latent Class Analysis

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$$P(y_1, y_2, y_3, y_4) = \sum_{k=1}^K P(X = k) P(y_1, y_2, y_3, y_4 | X = k)$$

Each latent class corresponds to one of  $k$  categories that comprise the underlying categorical latent variable ( $X$ ).

LCA will extract that latent class variable ( $X$ ) with the fewest number of classes to explain the associations between the observed variables ( $y_1, y_2, y_3 \dots y_k$ ).

Magidson, J., Vermunt, J. K., & Madura, J. P., (2020). Latent Class Analysis, In P. Atkinson, S. Delamont, A. Cernat, J.W. Sakshaug, & R.A. Williams (Eds.), Sage Research Methods Foundations. Sage.

# Latent Class Analysis

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$$P(y_1, y_2, y_3, y_4 \mid X = k) = P(y_1 \mid X = k) P(y_2 \mid X = k) P(y_3 \mid X = k) P(y_4 \mid X = k)$$

A key assumption of LCA is that the latent variable explains all the associations between the manifest variables (i.e. the assumption of local independence).

Magidson, J., Vermunt, J. K., & Madura, J. P., (2020). Latent Class Analysis, In P. Atkinson, S. Delamont, A. Cernat, J.W. Sakshaug, & R.A. Williams (Eds.), Sage Research Methods Foundations. Sage.

# Latent Class Analysis

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$$P(y_1, y_2, y_3, y_4) = \sum_{k=1}^K P(X = k) P(y_1 | X = k) P(y_2 | X = k) P(y_3 | X = k) P(y_4 | X = k)$$

More technical introductions:

- McCutcheon, A. L. (1987). Latent Class Analysis. Sage.
- Hagenaars, J. A., & McCutcheon, A. L. (Eds.). (2002). Applied latent class analysis. Cambridge University Press.
- Collins, L. M., & Lanza, S. T. (2009). Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences. John Wiley & Sons.

# Maximum Likelihood Estimation

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- Maximum likelihood estimation is a method used to obtain parameter estimates for statistical models.
- Maximum likelihood estimation consists of procedures for finding estimates of unknown parameters that maximise the likelihood of the observed data, the resulting parameter estimates are called maximum likelihood estimates.
- Maximum likelihood follows an iterative process known as convergence.
- Sometimes models 'fail to converge' (more on that later...)

# Running Latent Class Analysis in Stata

# Software

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## General Purpose Statistical Software:

- Stata (gsem)
- R (poLCA)
- Mplus

## Specialist Software:

- LatentGold
- LEM





# Running Latent Class Analysis in Stata

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- From Stata 16 onwards LCA can be undertaken using the gsem suite of commands.

**STATA  
STRUCTURAL EQUATION MODELING  
REFERENCE MANUAL  
RELEASE 17**

<https://www.stata.com/manuals/sem.pdf>

# Example: Drinking Behaviour

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I like to drink

I drink hard liquor

I have drank in the morning

I have drank at work

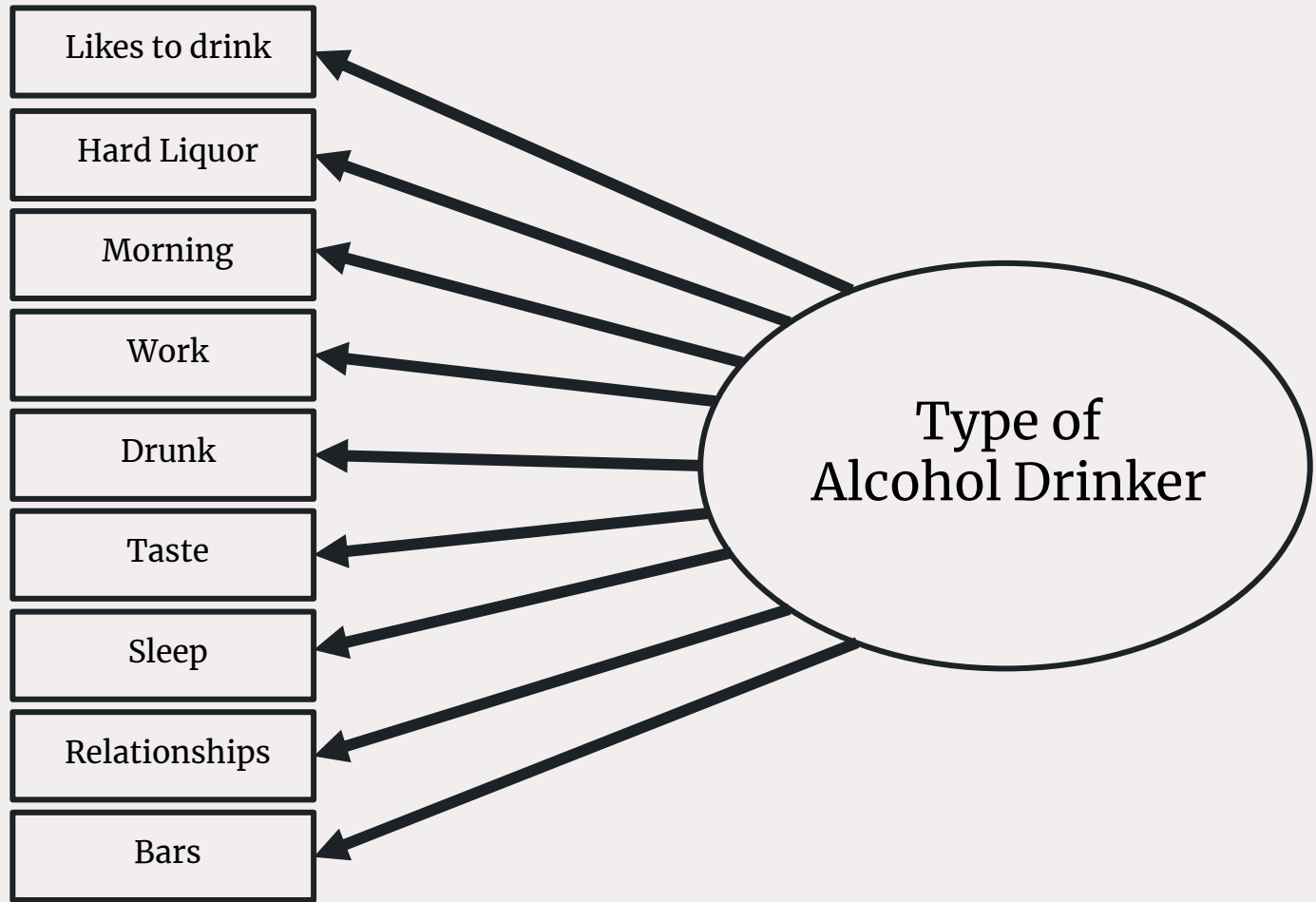
I drink to get drunk

I like the taste of alcohol

I drink to help me sleep

Drinking interferes with my relationships

I frequently visit bars



# Fitting a Latent Class Analysis Model

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We use the **gsem** command to fit a latent class model

```
gsem (var1 var2 var3 var4 var5 var6 <- ), logit lclass(C 3)
```

Our observed variables are all binary so we use the **logit** option

The **lclass (C 3)** option specifies that we want to allow for three categories in a latent class variable named 'C'

```
gsem (like hard morning work drunk taste sleep rel bar <- ), logit lclass(C 3)
```

		Coefficient	Std. err.	z	P> z	[95% conf. interval]	
1.C		(base outcome)					
2.C	_cons	.4287798	.8185974	0.52	0.600	-1.175642	2.033201
3.C	_cons	-1.521675	.6923291	-2.20	0.028	-2.878615	-.1647353

```
gsem (like hard morning work drunk taste sleep rel bar <- ), logit lclass(C 3)
```

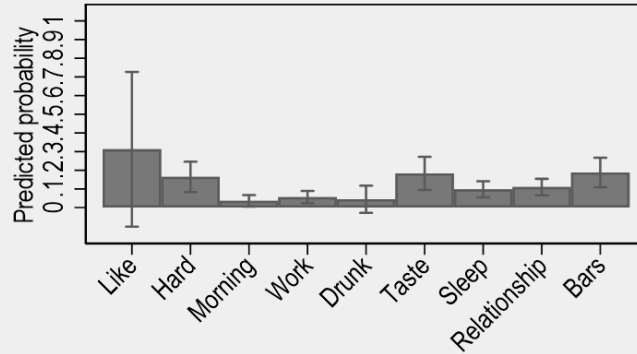
		Coefficient	Std. err.	z	P> z	[95% conf. interval]	
like	_cons	-.7899339	.9859737	-0.80	0.423	-2.722407	1.142539
hard	_cons	-1.628514	.3027822	-5.38	0.000	-2.221956	-1.035071
morning	_cons	-3.295288	.4608422	-7.15	0.000	-4.198523	-2.392054
work	_cons	-2.823975	.3176524	-8.89	0.000	-3.446562	-2.201388
drunk	_cons	-3.069835	.8750441	-3.51	0.000	-4.78489	-1.35478
taste	_cons	-1.496508	.3030282	-4.94	0.000	-2.090432	-.9025834
sleep	_cons	-2.223255	.2496319	-8.91	0.000	-2.712524	-1.733985
rel	_cons	-2.091981	.2295699	-9.11	0.000	-2.541929	-1.642032
bar	_cons	-1.464306	.2636135	-5.55	0.000	-1.980979	-.9476332

```
estat lcmean, nose
```

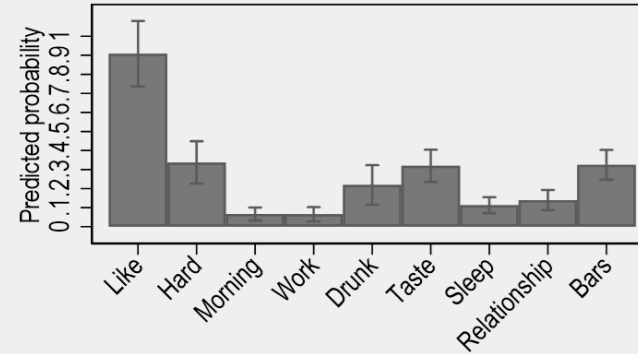
	Margin
1	
like	.3121829
hard	.1640341
morning	.0357332
work	.0560423
drunk	.0443688
taste	.182947
sleep	.0976816
rel	.1098787
bar	.1878096
2	
like	.9082864
hard	.3374061
morning	.0667436
work	.0654803
drunk	.2191517
taste	.3196319
sleep	.1128118
rel	.1398925
bar	.3248739
3	
like	.9232913
hard	.5461479
morning	.4263958
work	.4179356
drunk	.7654785
taste	.471019
sleep	.5123812
rel	.6192121
bar	.3488301

# Latent Class Analysis of Drinking Behaviour

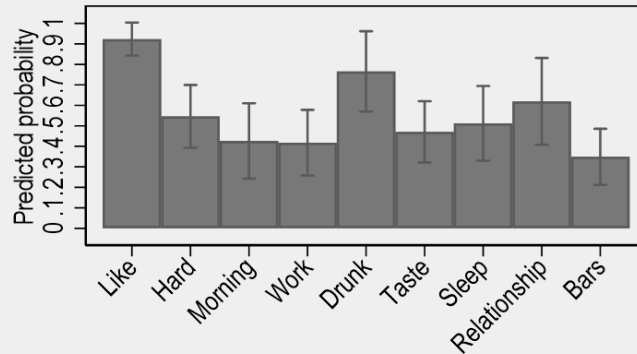
## Latent Class 1 (Abstainers)



## Latent Class 2 (Social Drinkers)



## Latent Class 3 (Problem Drinkers)





3 Class model - modal LC	Freq.	Percent	Cum.
Class 1 Abstainer	288	28.80	28.80
Class 2 Social Drinker	646	64.60	93.40
Class 3 Problem Drinker	66	6.60	100.00
Total	1,000	100.00	

	id	class3~1	class3~2	class3~3	expclass3
4.	4	.1773417	.7967343	.025924	Class 2 Social Drinker
5.	5	.0407349	.9341407	.0251244	Class 2 Social Drinker
6.	6	.6856872	.3119247	.0023881	Class 1 Abstainer
7.	7	.0917532	.9033101	.0049367	Class 2 Social Drinker
8.	8	.2176675	.7657966	.0165359	Class 2 Social Drinker
9.	9	.2897012	.6958461	.0144527	Class 2 Social Drinker
10.	10	.850441	.149076	.000483	Class 1 Abstainer
11.	11	.922773	.0770952	.0001318	Class 1 Abstainer
12.	12	.1111802	.8849409	.003879	Class 2 Social Drinker
13.	13	.1737878	.822176	.0040362	Class 2 Social Drinker
14.	14	.850441	.149076	.000483	Class 1 Abstainer
15.	15	.1737878	.822176	.0040362	Class 2 Social Drinker
16.	16	.2082288	.7899443	.0018269	Class 2 Social Drinker
17.	17	.0193921	.933044	.0475639	Class 2 Social Drinker
18.	18	.0198259	.6659695	.3142046	Class 2 Social Drinker
19.	19	.6856872	.3119247	.0023881	Class 1 Abstainer
20.	20	.922773	.0770952	.0001318	Class 1 Abstainer
21.	21	.1239127	.6570181	.2190692	Class 2 Social Drinker
22.	22	.8212255	.1780553	.0007192	Class 1 Abstainer
23.	23	.0917532	.9033101	.0049367	Class 2 Social Drinker
24.	24	.4565689	.5076751	.035756	Class 2 Social Drinker
25.	25	.922773	.0770952	.0001318	Class 1 Abstainer
26.	26	.0000985	.010796	.9891055	Class 3 Problem Drinker
27.	27	.922773	.0770952	.0001318	Class 1 Abstainer
28.	28	.3537591	.6449012	.0013397	Class 2 Social Drinker
29.	29	.3537591	.6449012	.0013397	Class 2 Social Drinker

# Class Enumeration

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- The model won't tell you how many latent groups there are.
- The process of deciding how many classes to include is called 'class enumeration'.
- To decide how many latent classes to include in your model you should consider statistical fit and substantive interpretability.

## Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
class1	1,000	.	-4348.878	9	8715.755	8759.925
class2	1,000	.	-4251.208	19	8540.416	8633.664
class3	1,000	.	-4231.696	29	8521.392	8663.716
class4	1,000	.	-4225.508	39	8529.016	8720.419

Note: BIC uses N = number of observations. See [R] BIC note.

The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are indexes of how well a model fits, which seek to balance the complexity of the model against the sample size.

AIC and BIC are calculated from maximum likelihood estimates.

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class4	1,000	.	-4225.508	39	8529.016	8720.419

Note: BIC uses N = number of observations. See [R] BIC note.

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# Entropy

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Entropy is a diagnostic statistic which measures the certainty of a posterior classification.

Entropy can help you consider how 'crisp' or 'fuzzy' your model solution is.

Values approaching 1 indicate that there is a clear delineation classes, values approaching 0 indicate that there is not a clear separation between the classes.

```
.  
.          lcaentropy  
Entropy =  .547709
```

Wang, M.-C., Deng, Q., Bi, X., Ye, H., & Yang, W. (2017). Performance of the entropy as an index of classification accuracy in latent profile analysis: A Monte Carlo simulation study. *Acta Psychologica Sinica*, 49(11), 1473-1482.

# Convergence

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```
Iteration 281: log likelihood = -4225.364 (not concave)
Iteration 282: log likelihood = -4225.364 (not concave)
Iteration 283: log likelihood = -4225.364 (not concave)
Iteration 284: log likelihood = -4225.364 (not concave)
Iteration 285: log likelihood = -4225.364 (not concave)
Iteration 286: log likelihood = -4225.364 (not concave)
Iteration 287: log likelihood = -4225.364 (not concave)
Iteration 288: log likelihood = -4225.364 (not concave)
Iteration 289: log likelihood = -4225.364 (not concave)
Iteration 290: log likelihood = -4225.364 (not concave)
Iteration 291: log likelihood = -4225.364 (not concave)
Iteration 292: log likelihood = -4225.364 (not concave)
Iteration 293: log likelihood = -4225.364 (not concave)
Iteration 294: log likelihood = -4225.364 (not concave)
Iteration 295: log likelihood = -4225.364 (not concave)
Iteration 296: log likelihood = -4225.364 (not concave)
Iteration 297: log likelihood = -4225.364 (not concave)
Iteration 298: log likelihood = -4225.364 (not concave)
Iteration 299: log likelihood = -4225.364 (not concave)
Iteration 300: log likelihood = -4225.364 (not concave)
```

convergence not achieved



# Convergence

<code>startvalues()</code> option	Description
<code>factor</code>	runs a factor analysis on all observed variables to obtain preliminary class predictions
<code>randomid, draws(#)</code>	randomly assigns observations to initial classes
<code>randompr, draws(#)</code>	randomly assigns initial class probabilities
<code>jitter, draws(#)</code>	randomly perturbs starting values from a Gaussian approximation to each outcome
<code>classid varname</code>	specifies a variable that identifies the initial class membership for each case
<code>classpr varlist</code>	specifies a list of variables that give the probability of membership in each class

```
gsem (like hard morning work drunk taste sleep rel bar <- ), logit lclass(C 4) ///  
startvalues(randomid, draws(15) seed(1583))
```

# Convergence

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- In practice, researchers often find that their hypothesised LCA models do not converge.
- If this happens you should try different sets of starting values and make use of additional optional commands to help the model converge.
- Sometimes, you need to simply accept that the model will not converge (and report this transparently).

# Latent Class Analysis

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June 2024

Dr Roxanne Connelly

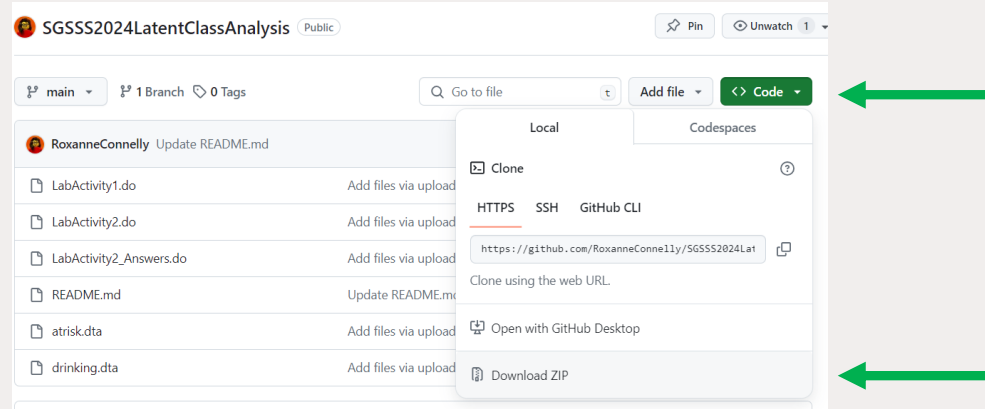
# Computer Lab Activity 1

# Computer Lab Activity 1

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Materials are available here:

<https://github.com/RoxanneConnelly/SGSSS2024LatentClassAnalysis>



**File: LabActivity1.do**

# Timetable

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1000 – 1100	Talk 1
1100 – 1130	Lab Activities
1130 – 1200	Talk 2
1200 – 1230	Lab Activities
1230 – 1300	Final Advice and Questions

# Latent Class Analysis

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June 2024

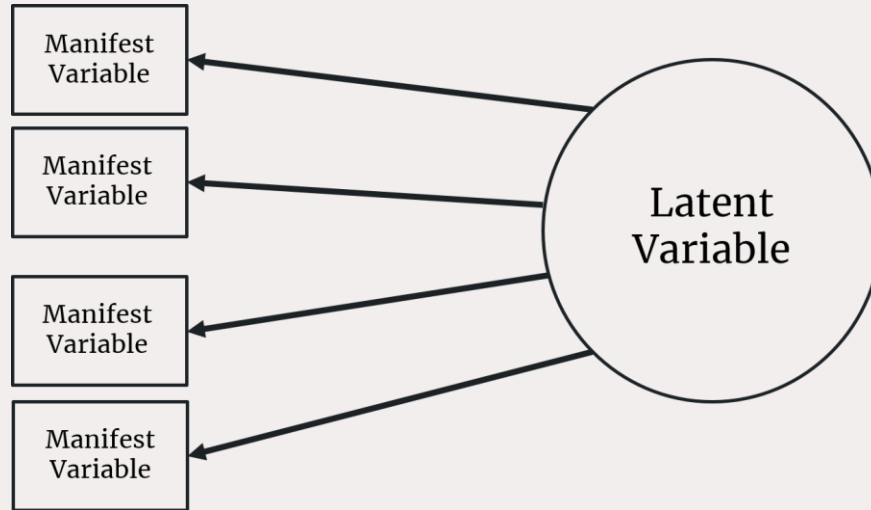
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## Talk 2

# Latent Class Analysis

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Latent class analysis (LCA) is a statistical procedure used to identify **qualitatively different** subgroups.



# Sample Size

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‘more is better, but it depends’

Weller, B. E., Bowen, N. K., & Faubert, S. J. (2020). Latent class analysis: a guide to best practice. *Journal of Black Psychology*, 46(4), 287–311.

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science*, 4(4), 440–461.



# Selecting Indicator Variables

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More indicators and indicators which effectively differentiate between groups will lead to better results

Wurpts, I. C., & Geiser, C. (2014). Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte Carlo study. *Frontiers in Psychology*, 5, 1-15. <https://doi.org/10.3389/fpsyg.2014.00920>

# Selecting the Number of Classes

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## Statistical Model Evaluation + Theoretical Interpretability

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, 14(4), 535-569.

Vermunt, J. K. (2002). Latent class analysis of complex sample survey data: Application to dietary data: Comment. *Journal of the American Statistical Association*, 97(459), 736-737.

Muthén, B. O., & Muthén, L. K. (2000). Integrating person-centered and variable centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical & Experimental Research*, 24(6), 882-891.

# Class Enumeration

Individuals are not placed in a latent class group with 100% certainty:

- You might consider an alternative to modal class allocation (e.g. analyse the probability of class membership)
- You might undertake some sensitivity analysis

list id class3post1 class3post2 class3post3 expclass3 in 4/29

	id	class3~1	class3~2	class3~3	expclass3
4.	4	.1773417	.7967343	.025924	Class 2 Social Drinker
5.	5	.0407349	.9341407	.0251244	Class 2 Social Drinker
6.	6	.6856872	.3119247	.0023881	Class 1 Abstainer
7.	7	.0917532	.9033101	.0049367	Class 2 Social Drinker
8.	8	.2176675	.7657966	.0165359	Class 2 Social Drinker
9.	9	.2897012	.6958461	.0144527	Class 2 Social Drinker
10.	10	.850441	.149076	.000483	Class 1 Abstainer
11.	11	.922773	.0770952	.0001318	Class 1 Abstainer
12.	12	.1111802	.8849409	.003879	Class 2 Social Drinker
13.	13	.1737878	.822176	.0040362	Class 2 Social Drinker
14.	14	.850441	.149076	.000483	Class 1 Abstainer
15.	15	.1737878	.822176	.0040362	Class 2 Social Drinker
16.	16	.2082288	.7899443	.0018269	Class 2 Social Drinker
17.	17	.0193921	.933044	.0475639	Class 2 Social Drinker
18.	18	.0198259	.6659695	.3142046	Class 2 Social Drinker
19.	19	.6856872	.3119247	.0023881	Class 1 Abstainer
20.	20	.922773	.0770952	.0001318	Class 1 Abstainer
21.	21	.1239127	.6570181	.2190692	Class 2 Social Drinker
22.	22	.8212255	.1780553	.0007192	Class 1 Abstainer
23.	23	.0917532	.9033101	.0049367	Class 2 Social Drinker
24.	24	.4565689	.5076751	.035756	Class 2 Social Drinker
25.	25	.922773	.0770952	.0001318	Class 1 Abstainer
26.	26	.0000985	.010796	.9891055	Class 3 Problem Drinker
27.	27	.922773	.0770952	.0001318	Class 1 Abstainer
28.	28	.3537591	.6449012	.0013397	Class 2 Social Drinker
29.	29	.3537591	.6449012	.0013397	Class 2 Social Drinker

# The Naming Fallacy

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Researchers usually assign names to the identified classes, and because of the complexity of the classes, may advertently engage in ‘**naming fallacy**’, wherein the name of the class does not accurately reflect the class membership.

These limitations should be appreciated when reporting latent class analyses.

# Including Covariates in Latent Class Analysis

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Does the composition of the latent class groups vary by socio-demographic characteristics?

Is membership of a latent class group associated with an outcome of interest?

# Including Covariates in Latent Class Analysis

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Should you include the covariates in the same model used to identify the latent class solution?

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved threestep approaches. *Political Analysis*, 18(4), 450-469.

Nylund-Gibson, K., & Masyn, K. E. (2016). Covariates and mixture modeling: Results of a simulation study exploring the impact of misspecified effects on class enumeration. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(6), 782-797.

# Three-Step Approach

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The three step approach:

- Develop your latent class model solution
- Add covariates to this model
- Fix the measurement parameters of the latent class model to those without the covariates included

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: A 3-step approach using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, 21(3), 329-341.

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, 12(1), 3-27.

# Latent Class Analysis

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## Computer Lab Activity 2

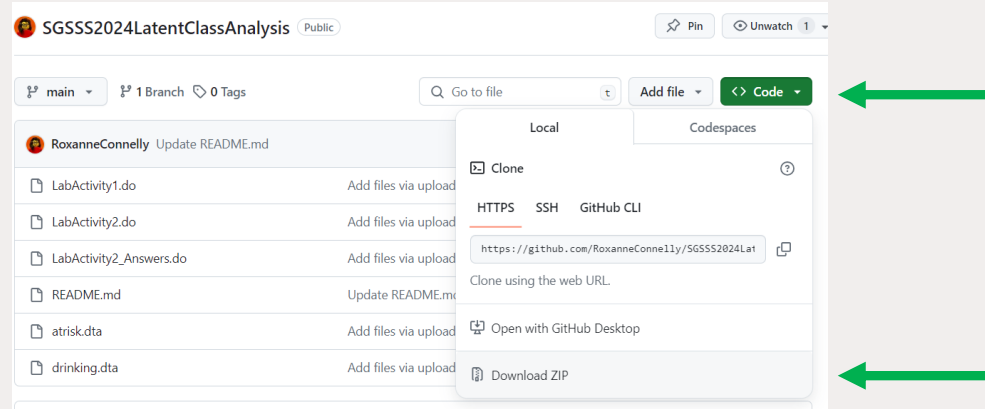


# Computer Lab Activity 2

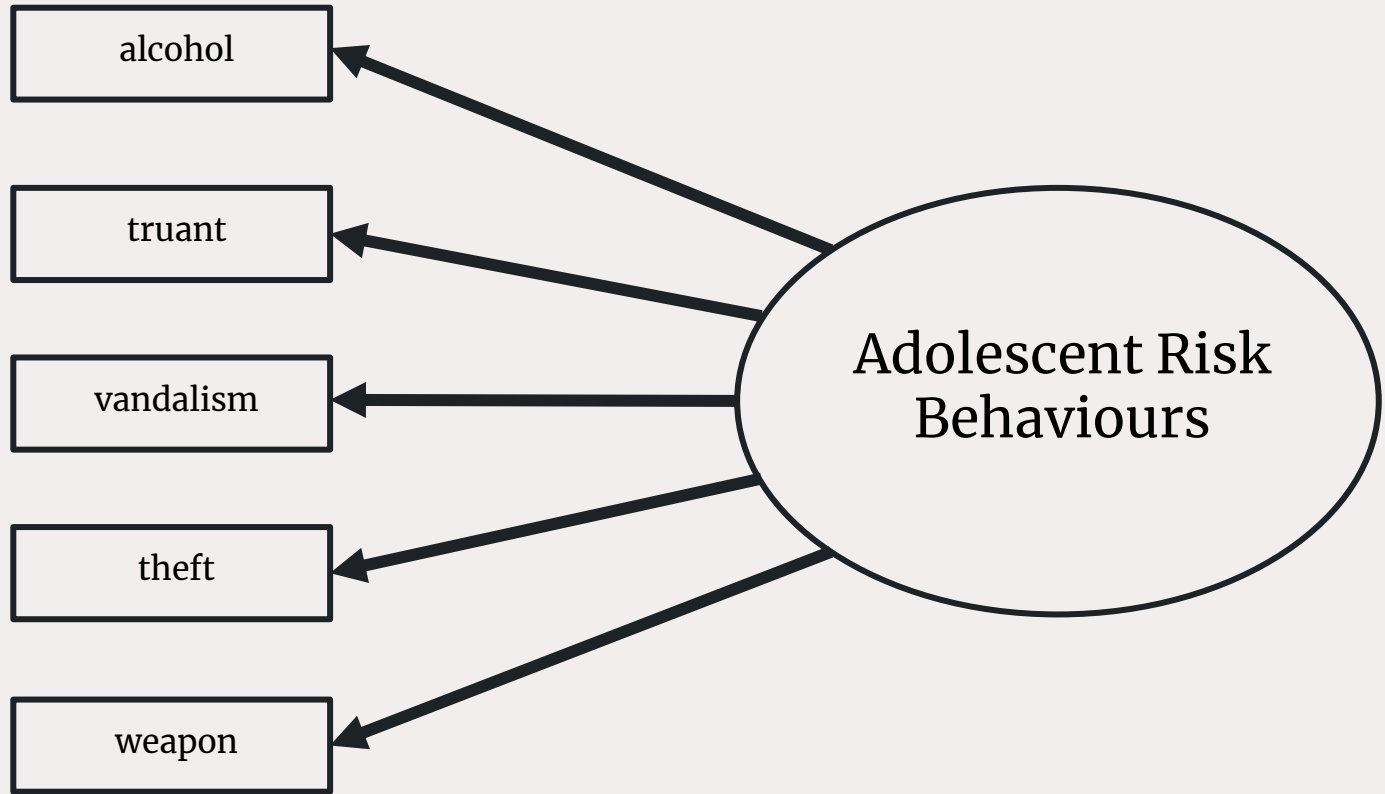
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Materials are available here:

<https://github.com/RoxanneConnelly/SGSSS2024LatentClassAnalysis>



**File: LabActivity2.do or LabActivity2\_Answers.do**



# Timetable

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1000 – 1100	Talk 1
1100 – 1130	Lab Activities
1130 – 1200	Talk 2
1200 – 1230	Lab Activities
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# Latent Class Analysis

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## Final Advice

# Final Advice: Share your Code


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WORLD VIEW • 24 MAY 2018

## Before reproducibility must come preproducibility



Instead of arguing about whether results hold up, let's push to provide enough information for others to repeat the experiments, says Philip Stark.

Philip B. Stark 



Stark, P. B. (2018). Before reproducibility must come preproducibility. *Nature*, 557(7706), 613–614.

“A published paper  
should be considered  
as an advertisement of  
the research.”

(Claerbout 1994)



Claerbout, J. (1994). Seventeen years of super computing and other problems in seismology [Paper presentation]. National Research Council Meeting on High Performance Computing in Seismology. <http://sepwww.stanford.edu/sep/jon/nrc.html>



# **Final Advice: Best Practice In Reporting LCA**

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Make your code available for others to view the full details of your analysis.



# **Final Advice: Best Practice In Reporting LCA**

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Provide a rationale for the manifest variables selected.

# Final Advice: Best Practice In Reporting LCA

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Provide a table of model fit statistics and report how the preferred model was selected.

**Table 2.** Model of fit statistics of the latent class models.

Model	n	ll(model)	df	AIC	BIC	Entropy
Two Class	616	−12000.03	37	24074.06	24237.72	0.81
Three Class	616	−11927.50	54	23962.99	24201.85	0.83
Four Class	616	−11834.21	68	23804.42	24105.20	0.86
Five Class	616	−11739.05	85	23648.10	24024.08	0.94
Six Class	616	−11693.06	103	23592.12	24047.71	0.96
Seven Class	616	−11670.82	120	23581.65	24112.43	0.95
Eight Class	616	−11659.57	135	23589.13	24186.27	0.94
Nine Class	616	−11605.72	142	23495.43	24123.54	0.93

Note: The sample size reduces by one case in the weighted analyses as one sample member has a weight of zero (unweighted  $n = 617$ ).

# Final Advice: Best Practice In Reporting LCA

Provide a table summarising the characteristics of each latent class group.

**Table 3.** Prior probabilities for the six latent class solution.

Ascribed label	'Elite'	'The established middle class'	'The socially engaged middle class'	'The culturally engaged middle class'	'The traditional working class'	'The precariat'
% Allocated to Latent Class	–	31	–	11	35	19
Prior Probabilities						
<i>Economic Capital</i>						
Equivalised Net Monthly Household Income (mean)	7298.64	1559.42	1568.76	1494.50	1232.39	1348.61
Own Home	1.00	0.91	0.86	0.95	0.75	0.52
<i>Social Capital</i>						
Number of Friends (mean)	6.14	5.16	25.03	7.45	4.91	3.96
Active in Trade Union	0.15	0.09	0.05	0.09	0.02	0.06
Active in Professional Organisation	0.68	0.16	0.37	0.37	0.04	0.00
<i>Highbrow Cultural Capital</i>						
Classical Music Concerts	0.57	0.23	0.23	0.34	0.03	0.00
Historic Buildings	0.42	0.86	0.61	0.95	0.12	0.13
Museums / Galleries	0.85	0.84	0.78	0.98	0.21	0.29
Plays/Theatre/ Pantomime	1.00	0.88	0.80	0.77	0.33	0.20
Ballet Performance	0.14	0.13	0.23	0.14	0.00	0.00
<i>Emerging Cultural Capital</i>						
Social Media	0.58	0.64	0.42	0.88	0.83	0.28
Regularly use the Internet	1.00	0.92	1.00	1.00	1.00	0.24
Gym/Fitness Classes	0.60	0.45	0.55	0.93	0.44	0.22
Rock/Pop/Jazz Concert	0.82	0.59	0.58	0.69	0.22	0.10
Cycle	0.42	0.46	0.43	0.99	0.28	0.12
Racquet Sports	0.13	0.24	0.66	0.66	0.09	0.06
Golf	0.27	0.19	0.19	0.28	0.07	0.03

Note: – indicates that the values in the cell have been suppressed for statistical disclosure control purposes.  $n = 616$ . The sample size reduces by one case in the weighted analyses as one sample member has a weight of zero (unweighted  $n = 617$ ).

# **Final Advice: Best Practice In Reporting LCA**

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Don't forget about the characteristics of your data  
(e.g. complex samples and missing data).

# Final Advice: Extensions to LCA

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This is only the beginning, Latent Class Analysis can do much more...

- You can extend Latent Class Analysis to include different types of variables.
- You can undertake LCA separately by group (e.g. men and women).
- There might be more than one latent variable.

# Workshop Summary

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You should now know:

- What latent class analysis is.
- How latent class analysis is used in the social sciences.
- How to undertake a latent class analysis.
- How to select the number of latent classes.
- How to allocate sample members to latent classes using the modal allocation method.
- How to overcome (some) model convergence issues.
- How to report a latent class analysis.

# Latent Class Analysis

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## Questions

# Latent Class Analysis

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