

# Logit Equations for Latent Class Model Probabilities

Jeroen K. Vermunt

Department of Methodology and Statistics, Tilburg University

[www.jeroenvermunt.nl](http://www.jeroenvermunt.nl)

# Introduction

- LC model probabilities are typically modelled using a (multinomial) logistic regression parameterization.
- In Latent GOLD these appear in the Parameters output.
- In this video I will explain:
  - why we use this parameterization
  - how the logit parameters are related to the probabilities appearing in Profile
  - how to interpret these parameters depending on the coding used

# Why using this logistic parameterization?

- ML estimation is much easier without range constraints: logit parameters can take on values between minus and plus infinity, while probabilities are restricted to be between 0 and 1.
- Inference (z-tests and Wald tests) for unbounded parameters are more reliable.
- It allows for interesting extensions, such as models with local dependencies, models for ordinal indicators, models with multiple latent variables, and mixture regression and mixture growth models.

# Logit equation for response probabilities

$$P(y_j | X = c) = \frac{\exp(\alpha_{y_j}^j + \beta_{y_j c}^j)}{\sum_{m=1}^{M_j} \exp(\alpha_m^j + \beta_{mc}^j)}$$

- $\alpha_{y_j}^j$  is the intercept parameter for a category of item  $j$
- $\beta_{y_j c}^j$  is the slope parameter of class  $c$  for a category of item  $j$

# Logit equation for class proportions

$$P(X = c) = \frac{\exp(\gamma_{0c})}{\sum_{c'=1}^C \exp(\gamma_{0c'})}$$

- In a simple LC model this equation contains only the intercepts  $\gamma_{0c}$
- However, more extended models may include covariates affecting the classes, or multiple latent variables affecting one another

# Parameters under effect & dummy coding

Models for Indicators	Cluster1	Cluster2	Cluster3	Wald	p-value	R <sup>2</sup>
<b>accuracy</b>						
<b>mostly true</b>	0.7450	0.8501	-1.5951	5.8756	0.053	0.2047
<b>not true</b>	-0.7450	-0.8501	1.5951			
<b>cooperat</b>						
<b>interested</b>	1.9487	-0.9131	-1.0356	12.0583	0.017	0.1346
<b>cooperative</b>	0.4051	-0.0532	-0.3520			
<b>Impatient,Hostile</b>	-2.3538	0.9663	1.3875			
<b>understa</b>						
<b>Good</b>	1.4306	-1.0983	-0.3323	10.2440	0.0060	0.4013
<b>Fair/Poor</b>	-1.4306	1.0983	0.3323			
<b>purpose</b>						
<b>GOOD PURPOSE</b>	0.7676	0.9045	-1.6721	35.6370	3.4e-7	0.3373
<b>DEPENDS</b>	-0.3144	-0.0620	0.3764			
<b>WASTE OF TIME AND \$</b>	-0.4532	-0.8425	1.2957			
<b>Intercepts</b>	<b>Overall</b>	<b>Wald</b>	<b>p-value</b>			
<b>accuracy</b>						
<b>mostly true</b>	-0.5508	2.2925	0.13			
<b>not true</b>	0.5508					
<b>cooperat</b>						
<b>interested</b>	1.9533	53.9749	1.9e-12			
<b>cooperative</b>	0.3263					
<b>Impatient,Hostile</b>	-2.2796					
<b>understa</b>						
<b>Good</b>	0.8509	1.9512	0.16			
<b>Fair/Poor</b>	-0.8509					
<b>purpose</b>						
<b>GOOD PURPOSE</b>	1.0637	39.2610	3.0e-9			
<b>DEPENDS</b>	-0.6106					
<b>WASTE OF TIME AND \$</b>	-0.4531					
<b>Model for Clusters</b>						
<b>Intercept</b>	<b>Cluster1</b>	<b>Cluster2</b>	<b>Cluster3</b>	<b>Wald</b>	<b>p-value</b>	
	0.6585	-0.1180	-0.5405	35.6042	1.9e-8	

Models for Indicators	Cluster1	Cluster2	Cluster3	Wald	p-value	R <sup>2</sup>
<b>accuracy</b>						
<b>mostly true</b>	0.0000	-0.0000	-0.0000	5.8756	0.053	0.2047
<b>not true</b>	-0.0000	-0.2102	4.6801			
<b>cooperat</b>						
<b>interested</b>	0.0000	-0.0000	-0.0000	12.0583	0.017	0.1346
<b>cooperative</b>	-0.0000	2.4034	2.2272			
<b>Impatient,Hostile</b>	-0.0000	6.1818	6.7256			
<b>understa</b>						
<b>Good</b>	0.0000	-0.0000	-0.0000	10.2440	0.0060	0.4013
<b>Fair/Poor</b>	-0.0000	5.0578	3.5257			
<b>purpose</b>						
<b>GOOD PURPOSE</b>	0.0000	-0.0000	-0.0000	35.6370	3.4e-7	0.3373
<b>DEPENDS</b>	-0.0000	0.1156	3.1306			
<b>WASTE OF TIME AND \$</b>	-0.0000	-0.5262	4.1886			
<b>Intercepts</b>	<b>Overall</b>	<b>Wald</b>	<b>p-value</b>			
<b>accuracy</b>						
<b>mostly true</b>	-0.0000	16.9581	3.8e-5			
<b>not true</b>	-0.3884					
<b>cooperat</b>						
<b>interested</b>	-0.0000	23.9399	6.3e-6			
<b>cooperative</b>	-3.1704					
<b>Impatient,Hostile</b>	-8.5353					
<b>understa</b>						
<b>Good</b>	-0.0000	1.5866	0.21			
<b>Fair/Poor</b>	-4.5630					
<b>purpose</b>						
<b>GOOD PURPOSE</b>	-0.0000	271.2944	1.2e-59			
<b>DEPENDS</b>	-2.7564					
<b>WASTE OF TIME AND \$</b>	-2.7375					
<b>Model for Clusters</b>						
<b>Intercept</b>	<b>Cluster1</b>	<b>Cluster2</b>	<b>Cluster3</b>	<b>Wald</b>	<b>p-value</b>	
	-0.0000	-0.7764	-1.1990	35.6042	1.9e-8	

# Computation of Profile using Parameters

- Effect coding

$$P(\textit{Accuracy} = 1 \mid X = 2) = \frac{\exp(-0.5508 + 0.8501)}{\exp(-0.5508 + 0.8501) + \exp(0.5508 - 0.8501)} = 0.6453$$

- Dummy first coding

$$P(\textit{Accuracy} = 1 \mid X = 2) = \frac{\exp(0 + 0)}{\exp(0 + 0) + \exp(-0.3884 - 0.2102)} = 0.6453$$

# Final remarks

- In simple applications on LC analysis, you don't need to worry about the logit parameters. Looking at Profile suffices.
- However, for extensions of the basic model, we need the logistic parameterization.
- Profile output is directly linked to the logit parameters.
- Under effect coding, the parameters indicate whether particular indicator-cluster combinations are more (or less) likely than average.
- Under dummy coding, the parameters are log-odds ratios. These can be exponentiated to obtain odds-ratios.