





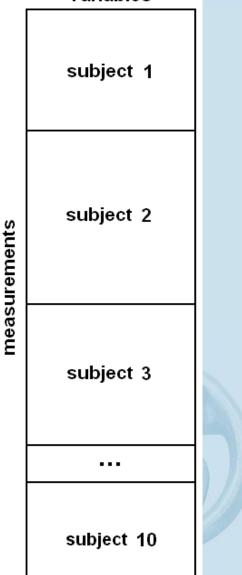
Clusterwise SCA-P

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Introduction

variables



 data from different subjects with multiple measurements of a number of variables

➔ differences and similarities between subjects in underlying structure of the data?



Illustrative application

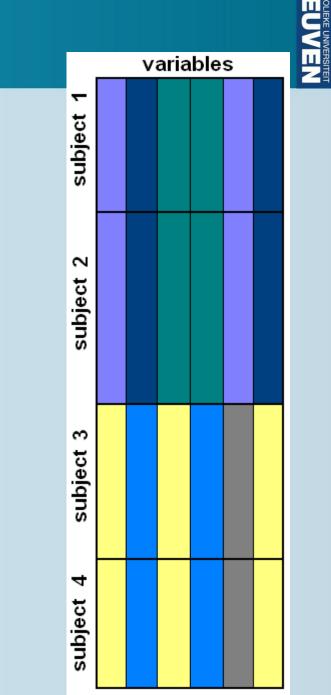


	variables						
ments	subject 1	 Data (Vansteelandt et al., 2006): 10 subjects with eating disorder (anorexia and bulimia nervosa) 					
	subject 2	 22 variables measuring: drive for thinness, positive and negative emotional states, urge to be physically active, physical activity 					
measurements	subject 3	 9 random measurement moments per day, during a week <u>Research questions:</u> 					
	 subject 10	 (1) underlying structure of the variables? (2) interindividual differences in underlying structure? 					

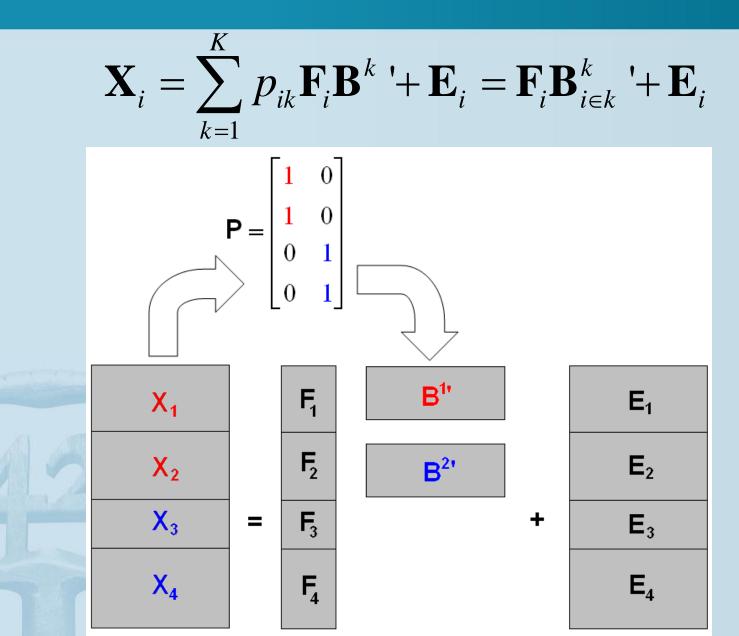
Clusterwise SCA: Idea

- general idea:
- partition subjects into clusters
- perform separate SCA per cluster





Clusterwise SCA: Model



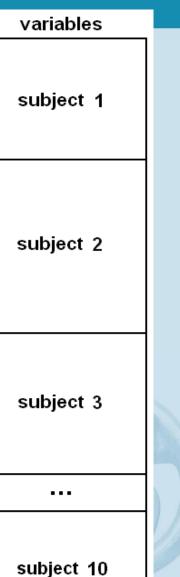
Clusterwise SCA-P: Model

$$\mathbf{X}_{i} = \sum_{k=1}^{K} p_{ik} \mathbf{F}_{i} \mathbf{B}^{k} + \mathbf{E}_{i} = \mathbf{F}_{i} \mathbf{B}_{i \in k}^{k} + \mathbf{E}_{i}$$

- for now, number of components per cluster equal for all clusters
- more general than Clusterwise SCA-ECP (De Roover et al., 2010):

 variances of components and correlations between components are allowed to vary between subjects within a cluster
 → insight in differences between subjects in (co)variation of the components

Illustrative application



measurements

Preprocessing of eating disorder data:

- centre per subject
 differences in mean scores between subjects removed
- standardize over the 10 subjects (instead of per subject)
 differences in variability of the scores retained

Illustrative application: Loadings

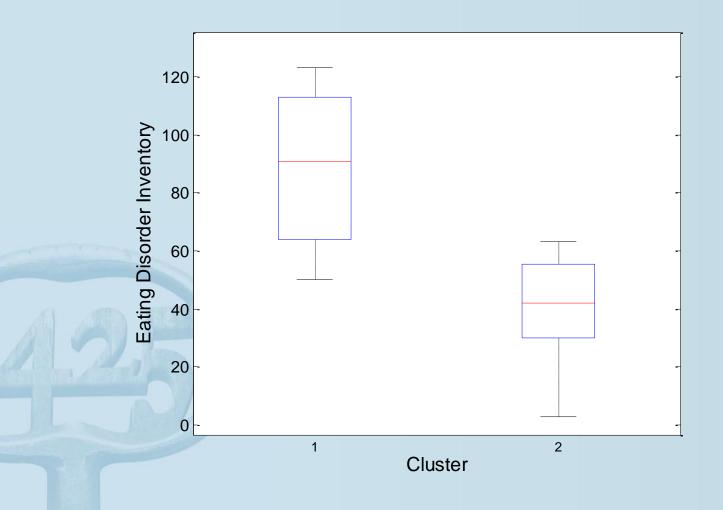


rotation criterion: F 1964)	rotation criterion: HKIC (Harris & Kaiser, 1964)		u ster 1 ubjects)	Cluster 2 (5 subjects)	
		PA/NA	(urge) ph. act. & DFT	PA/NA F	PA & ph.act.
positive and	pleased	.80	.19	.42	.47
negative affect	happy	.80	.20	.32	.62
(PA/NA)	appreciated	.61	.14	12	.76
	love	.56	.23	.01	.69
	sad	79	17	77	.08
	angry	79	01	60	.13
	lonely	71	01	62	02
	ashamed	68	.05	21	.08
	anxious	75	.03	41	.03
	tense	68	.10	49	24
	guilty	81	.05	44	.00
and the second sec	irritated	58	.07	55	07
urge to be	want to move	08	.89	.30	23
physically active	want to sport	13	.94	.11	21
(urge ph. act.)	want to be active	07	.92	.28	27
physical activity	am active	.20	.87	10	.55
(ph. act.)	am moving	.23	.87	12	.59
	am sporting	.29	.88	.00	.19
drive for	want to burn calories	16	.89	.10	13
thinness (DFT)	want to loose weight	48	.32	.02	43
	feel fat	66	.33	02	13
	feel ugly	60	.55	02	20

Illustrative application: Validation of clustering



significant difference between clusters in mean EDI (p = .04)



Illustrative application: Variances/correlations per cluster



		variances	variances		
	subject	PA/NA	(urge) ph. act. & DFT	correlations	
cluster 1	1	.91	.82	.17	
	2	1.01	.71	28	
	3	.89	1.31	18	
	4	1.20	1.11	05	
	10	1.03	.81	.05	
		overall correlation cluster 1			
		variances	variances		
	subject	PA/NA	PA & physical activity	correlations	
cluster 2	5	.51	1.45	52	
	6	1.56	1.31	.45	
	7	.46	.36	.49	
	8	1.08	1.34	.45	
	9	1.59	.66	.12	
			overall correlation cluste	er 2 .21	

Illustrative application: Variances/correlations per cluster

	.39 correlation with EDI		'	11 correlation with EDI		.99 corre with E	
	subject		ariances variances PA/NA (urge) ph. act. & DFT		ncos		
						correlations	
cluster		.91		(urgo) prir dotr d	.82	.17	
	2	1.01			.71	28	
	3	.89			1.31	18	
	4	1.20			1.11	05	
	10	1.03			.81	.05	
				verall correlation cl	05		
	va		variances				
	subject	PA/NA		PA & physical ac	tivity	correlations	
cluster	2 5	.51			1.45	52	
	6	1.56			1.31	.45	
	7	.46			.36	.49	
	8	1.08			1.34	.45	
	9	1.59			.66	.12	
			overall correlation cluster 2			.21	
			.89 correlation		1	\	
.21 correlation						60 corre	lation
with EDI			with EDI			with E	DI
					1		

Discussion



Clusterwise SCA-P:

- captures structural differences and similarities in a parsimonious manner
- makes it possible to examine differences in component variances and correlations between the subjects within a cluster
- is applicable to all kinds of multivariate nested data, e.g., subjects nested within groups
- number of components will be allowed to vary over clusters in the future