



RadoNorm
Managing risks from radon and NORM

*On-line, interactive training course
The art of public opinion survey analysis:
Surveying the public on Radon & NORM*

April 2021



Day 4: Analysis of survey data: Exploratory Techniques

29 April 2021

<https://zoom.us/j/92190920610?pwd=bGNlcmxUcSs3aTBVeFpOT2l4eWFFQT09>

Time (CET)	Activity	Lead
09:30-10:30	Exploratory measurement techniques; reliability	Peter
10:30-10:45	<i>Break (15 minutes)</i>	
10:45-12:00	Factor analysis, cluster analysis	Peter
12:00-13:30	<i>Break (1 hour 30 minutes)</i>	
13:30-13:35	Instructions for individual and group work	Plenary
13:35-15:45	Group 1: Testing latent constructs of own nomological network (SPSS)	Peter, Melisa
	Group 2: Evaluating national reports	Tanja, Peter
15:45-16:00	Summary/Quiz	



RadoNorm
Managing risks from radon and NORM

*Exploratory measurement techniques:
Factor analysis, reliability analysis, and cluster
analysis*

Peter Thijssen
Thursday 29 April 2021



Factor analysis

In order to test the validity of indicators
as measures of latent constructs

Q- versus R-factor analysis

DATA MATRIX

Q cases

R Variables

VIP's	X ₁	X ₂	X ₃	Totaal
1	Woman	20	15	35
2	Man	40	7	47
3	Man	45	8	53
4	Woman	30	10	40
5	Woman	25	5	30
6	Man	35	9	41
7	Woman	40	8	48
Total		235	62	297

Dimensionality of a set of indicators Factor analysis (FA)

Looking for underlying (latent) common meaning contents that are available in a number of observed variables

For example “efficacy scale” -> to reduce the risk of natural radiation

- Internal locus of control
- External locus of control

2 families of FA

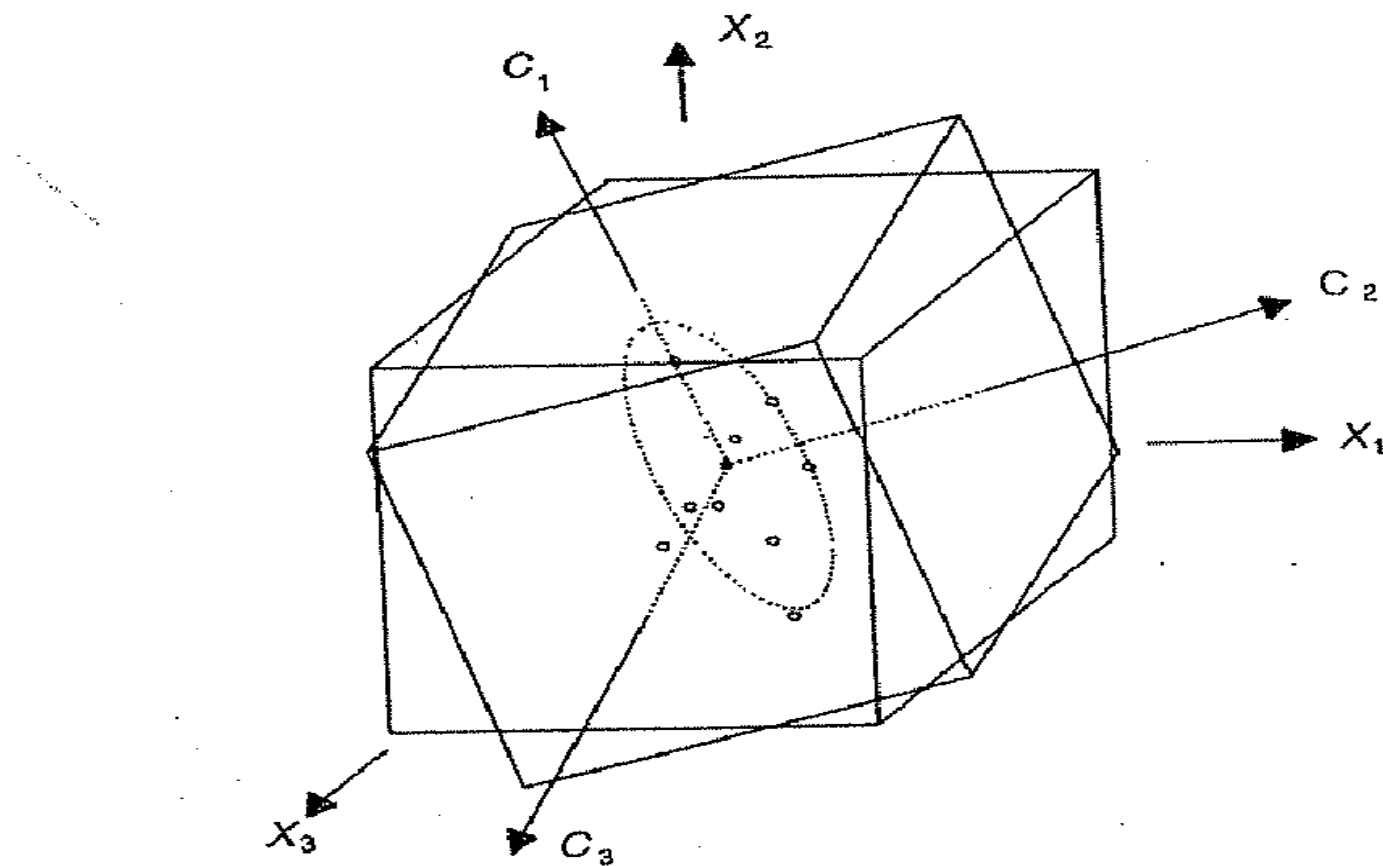
1. Principal components analysis
2. Factor analysis

Principal Component Analysis (PCA)

WHAT?

- 1) Focus on total variance
- 2) Looking for the same number of components ('latent constructs') than there are observed variables, given that:
 - Components are *orthogonal* (uncorrelated)
 - The components sequentially extract the *maximal amount of variance* from the variables (=principal axis method)
- (3 => Selecting the necessary components, in search of a '*simple structure*')
if step 3 is included PCA ~ PFA

Geometric interpretation of PCA



Principal Factor Analysis (PFA)

Crucial elements

- 1) Partitioning the initial item variance in a common component, specific component and an error component.
- 2) Looking for a limited number of factors ('latent constructs') that explain the *common variance* as good as possible. These factors can be *orthogonal* (uncorrelated) or *oblique* (correlated).
- 3) => Selecting the necessary factors, in search of a '*simple structure*'

FA - Terminology

Factor loading a_{ij} (matrix A: Factor pattern)

$$z_1 = a_{11}f_1 + a_{12}f_2 + a_{13}f_3 (+ e_1)$$

Regression coefficients in a model with a standardized observed variable as dependent and the factors as independents.

Factor (regression)scores u_{ij}

$$f_1 = u_{11}z_1 + u_{12}z_2 + u_{13}z_3$$

Regression coefficients in a model with a standardized factor as dependent and the standardized observed variables as independents.

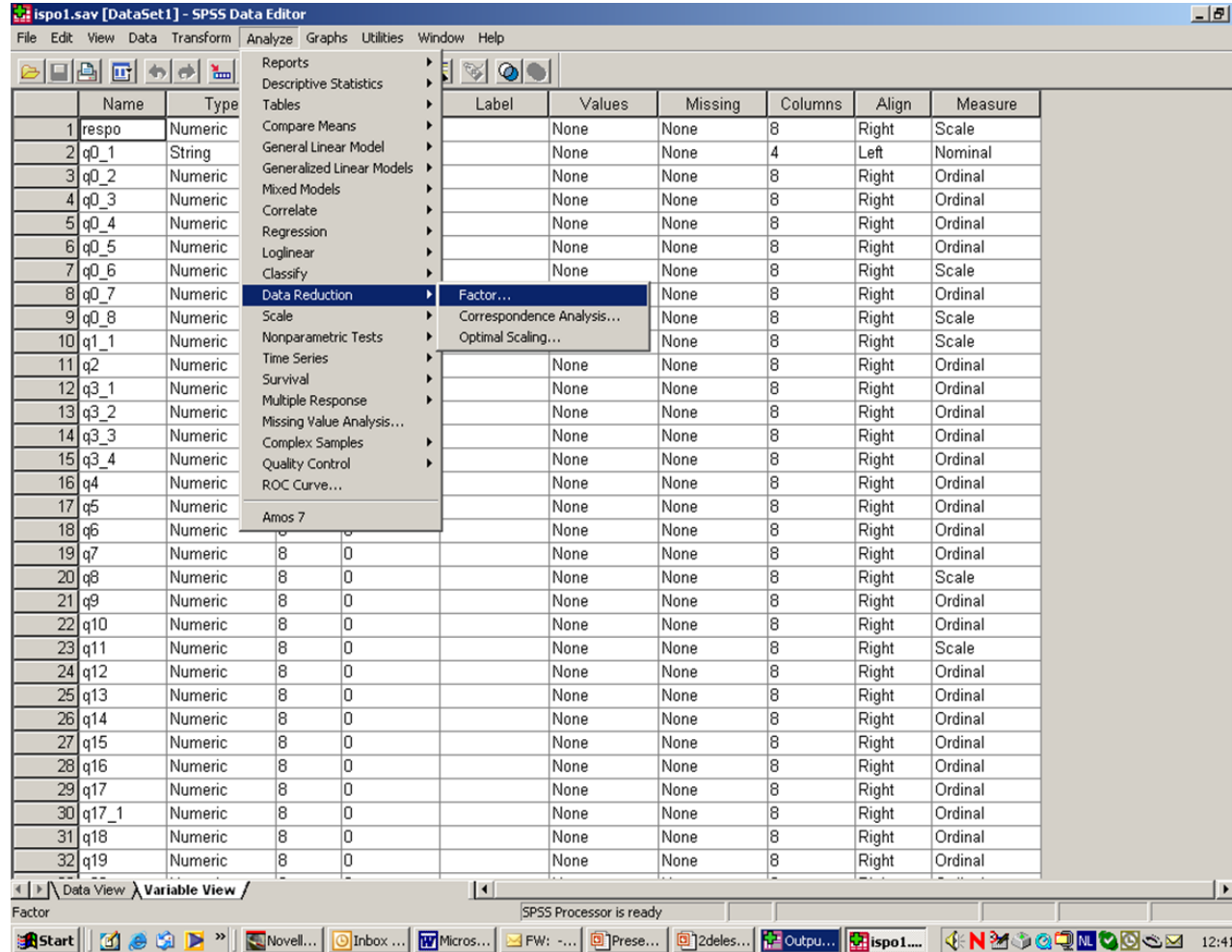
Eigenvalue: variance of the projections of each observations on a certain factor;
sum of the squared factor loadings

FA – How many factors in the simple structure?

Communality: (common variance) How many percent of the variance of a variable is explained by a (number of) factor(s)

SPSS

Data Reduction: Factor



The screenshot shows the SPSS Data Editor window for 'ispo1.sav [DataSet1]'. The 'Analyze' menu is open, and 'Data Reduction' is selected. The 'Factor...' option is highlighted. The data table shows 32 variables (respo, q0_1 to q19) with their types and missing values.

	Name	Type	Label	Values	Missing	Columns	Align	Measure
1	respo	Numeric		None	None	8	Right	Scale
2	q0_1	String		None	None	4	Left	Nominal
3	q0_2	Numeric		None	None	8	Right	Ordinal
4	q0_3	Numeric		None	None	8	Right	Ordinal
5	q0_4	Numeric		None	None	8	Right	Ordinal
6	q0_5	Numeric		None	None	8	Right	Ordinal
7	q0_6	Numeric		None	None	8	Right	Scale
8	q0_7	Numeric		None	None	8	Right	Ordinal
9	q0_8	Numeric		None	None	8	Right	Scale
10	q1_1	Numeric		None	None	8	Right	Scale
11	q2	Numeric		None	None	8	Right	Ordinal
12	q3_1	Numeric		None	None	8	Right	Ordinal
13	q3_2	Numeric		None	None	8	Right	Ordinal
14	q3_3	Numeric		None	None	8	Right	Ordinal
15	q3_4	Numeric		None	None	8	Right	Ordinal
16	q4	Numeric		None	None	8	Right	Ordinal
17	q5	Numeric		None	None	8	Right	Ordinal
18	q6	Numeric		None	None	8	Right	Ordinal
19	q7	Numeric		None	None	8	Right	Ordinal
20	q8	Numeric		None	None	8	Right	Scale
21	q9	Numeric		None	None	8	Right	Ordinal
22	q10	Numeric		None	None	8	Right	Ordinal
23	q11	Numeric		None	None	8	Right	Scale
24	q12	Numeric		None	None	8	Right	Ordinal
25	q13	Numeric		None	None	8	Right	Ordinal
26	q14	Numeric		None	None	8	Right	Ordinal
27	q15	Numeric		None	None	8	Right	Ordinal
28	q16	Numeric		None	None	8	Right	Ordinal
29	q17	Numeric		None	None	8	Right	Ordinal
30	q17_1	Numeric		None	None	8	Right	Ordinal
31	q18	Numeric		None	None	8	Right	Ordinal
32	q19	Numeric		None	None	8	Right	Ordinal

SPSS

Factor analysis

Descriptives

*ispo1.sav [DataSet1] - SPSS Data Editor

File Edit View Data Transform Analyze Graphs Utilities Window Help

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure
1	respo	Numeric	8	0		None	None	8	Right	Scale
2	q0_1	Ordinal	8	0		None	None	4	Left	Nominal
3	q0_2	Ordinal	8	0		None	None	8	Right	Ordinal
4	q0_3	Ordinal	8	0		None	None	8	Right	Ordinal
5	q0_4	Ordinal	8	0		None	None	8	Right	Ordinal
6	q0_5	Ordinal	8	0		None	None	8	Right	Ordinal
7	q0_6	Ordinal	8	0		None	None	8	Right	Scale
8	q0_7	Ordinal	8	0		None	None	8	Right	Ordinal
9	q0_8	Ordinal	8	0		None	None	8	Right	Scale
10	q1_1	Ordinal	8	0		None	None	8	Right	Scale
11	q2	Ordinal	8	0		None	None	8	Right	Ordinal
12	q3	Ordinal	8	0		None	None	8	Right	Ordinal
13	q3	Ordinal	8	0		None	None	8	Right	Ordinal
14	q3	Ordinal	8	0		None	None	8	Right	Ordinal
15	q3	Ordinal	8	0		None	None	8	Right	Ordinal
16	q4	Ordinal	8	0		None	None	8	Right	Ordinal
17	q5	Numeric	8	0		None	None	8	Right	Ordinal
18	q6	Numeric	8	0		None	None	8	Right	Ordinal
19	q7	Numeric	8	0		None	None	8	Right	Ordinal
20	q8	Numeric	8	0		None	None	8	Right	Scale
21	q9	Numeric	8	0		None	None	8	Right	Ordinal
22	q10	Numeric	8	0		None	None	8	Right	Ordinal
23	q11	Numeric	8	0		None	None	8	Right	Scale
24	q12	Numeric	8	0		None	None	8	Right	Ordinal
25	q13	Numeric	8	0		None	None	8	Right	Ordinal
26	q14	Numeric	8	0		None	None	8	Right	Ordinal
27	q15	Numeric	8	0		None	None	8	Right	Ordinal
28	q16	Numeric	8	0		None	None	8	Right	Ordinal
29	q17	Numeric	8	0		None	None	8	Right	Ordinal
30	q17_1	Numeric	8	0		None	None	8	Right	Ordinal
31	q18	Numeric	8	0		None	None	8	Right	Ordinal
32	q19	Numeric	8	0		None	None	8	Right	Ordinal

Factor Analysis

Variables: q61_a, q61_b, q61_c, q61_d, q61_e, q61_f

Selection Variable: Value...

Descriptives... Extraction... Rotation... Scores... Options...

Factor Analysis: Descriptives

Statistics

- ☐ Univariate descriptives
- ☒ Initial solution

Correlation Matrix

- ☒ Coefficients
- ☐ Inverse
- ☐ Significance levels
- ☐ Reproduced
- ☐ Determinant
- ☐ Anti-image
- ☐ KMO and Bartlett's test of sphericity

Continue Cancel Help

SPSS Processor is ready

Filter On

Start Nov... Inb... Inb... Micr... data Met... poli... Out... Syn... *is... 10:50

Political efficacy Inspired by NES US

Q61.a There's no sense in voting; the *parties* do what they want to do anyway.

No opinion= 5; missing= 1 - **teken**

Q61.b *Parties* are only interested in my vote, not in my opinion.

No opinion= 6; missing= 2 - **teken**

Q61.c If people like me let the *politicians* know what we think, then they will take our opinion into account.

No opinion= 52; missing= 1 + **teken => spiegelen**

Q61.d Most *politicians* promise a lot, but don't do anything.

No opinion= 0; missing= 2 - **teken**

Q61.e As soon as they are elected, *politicians* think they are better than people like me.

No opinion= 15; missing= 2 - **teken**

Q61.f Most of our *politicians* are competent people who know what they are doing.

No opinion= 11; missing= 1 + **teken => spiegelen**

FA – Everything starts with the correlation matrix

Correlation Matrix

	q61_a	q61_b	q61_c	q61_d	q61_e	q61_f
Correlation q61_a	1,000	,649	-,325	,483	,502	-,153
q61_b	,649	1,000	-,398	,520	,550	-,195
q61_c	-,325	-,398	1,000	-,313	-,332	,182
q61_d	,483	,520	-,313	1,000	,628	-,233
q61_e	,502	,550	-,332	,628	1,000	-,238
q61_f	-,153	-,195	,182	-,233	-,238	1,000

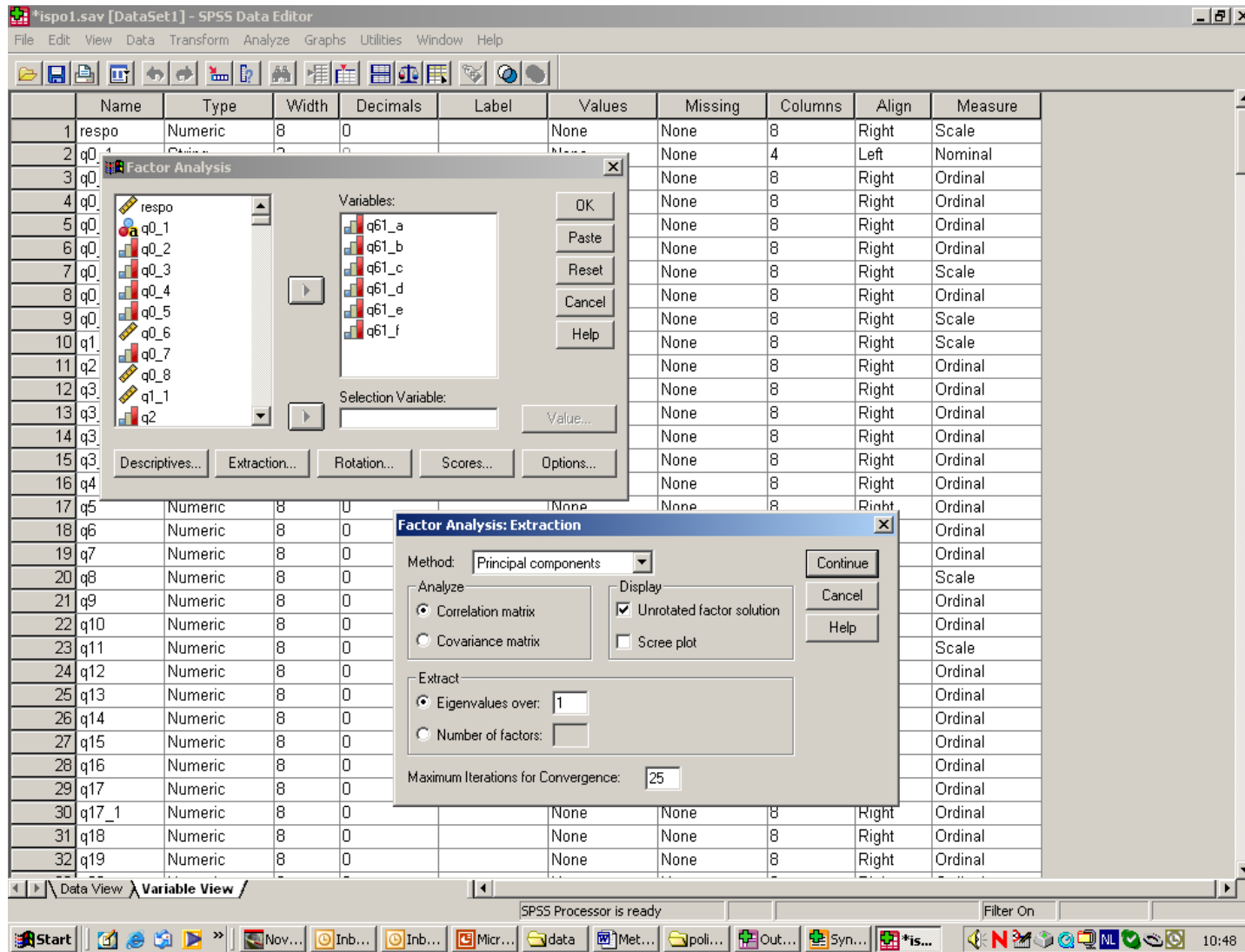
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,817
Bartlett's Test of Sphericity	Approx. Chi-Square	2091,581
	df	15
	Sig.	,000

SPSS

Factor analysis

Descriptives



The screenshot shows the SPSS Data Editor window with a dataset named 'ispol.sav'. The variable list includes 'respo' (Numeric) and 'q0_1' through 'q19' (mostly Numeric, some Ordinal). Two dialog boxes are open:

- Factor Analysis:** Variables: q61_a, q61_b, q61_c, q61_d, q61_e, q61_f. Selection Variable: (empty). Buttons: Descriptives..., Extraction..., Rotation..., Scores..., Options...
- Factor Analysis: Extraction:** Method: Principal components. Analyze: ☒ Correlation matrix, ☐ Covariance matrix. Display: ☒ Unrotated factor solution, ☐ Scree plot. Extract: ☒ Eigenvalues over: 1, ☐ Number of factors: (empty). Maximum Iterations for Convergence: 25. Buttons: Continue, Cancel, Help.

FA – How many factors?

Kaiser's Criterion: factors with an eigenvalue higher than 1
or an explained variance of at least 60%...

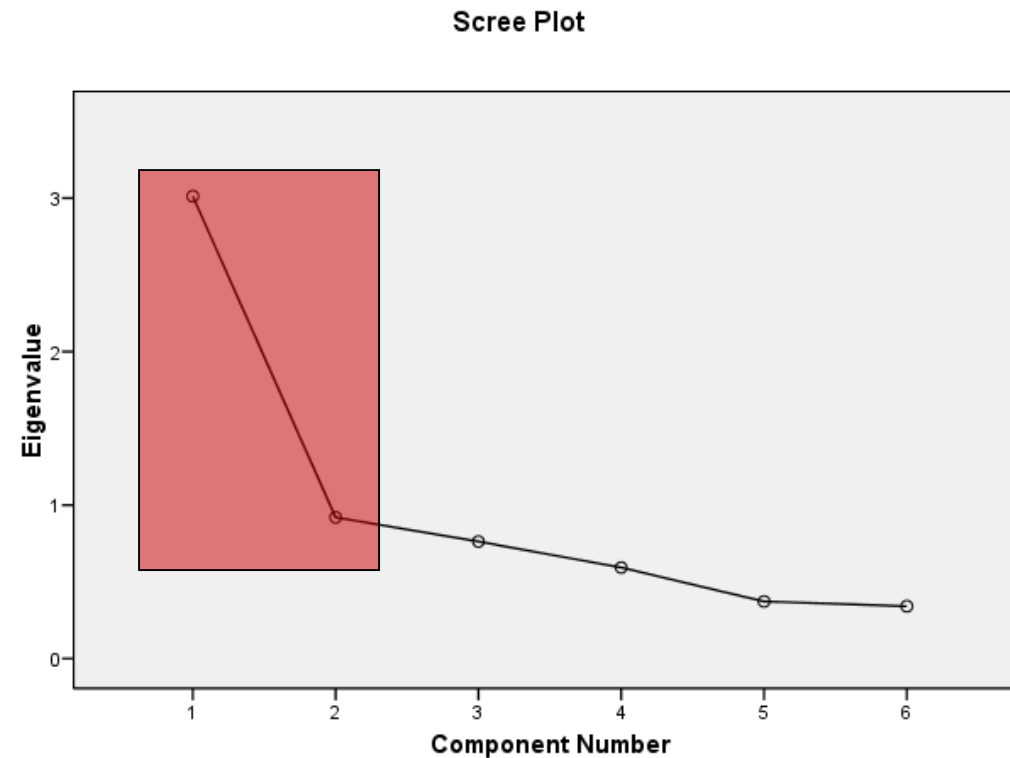
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,011	50,191	50,191	3,011	50,191	50,191
2	,920	15,331	65,523			
3	,763	12,711	78,234			
4	,593	9,882	88,115			
5	,372	6,203	94,318			
6	,341	5,682	100,000			

Extraction Method: Principal Component Analysis.

FA – How many factors?

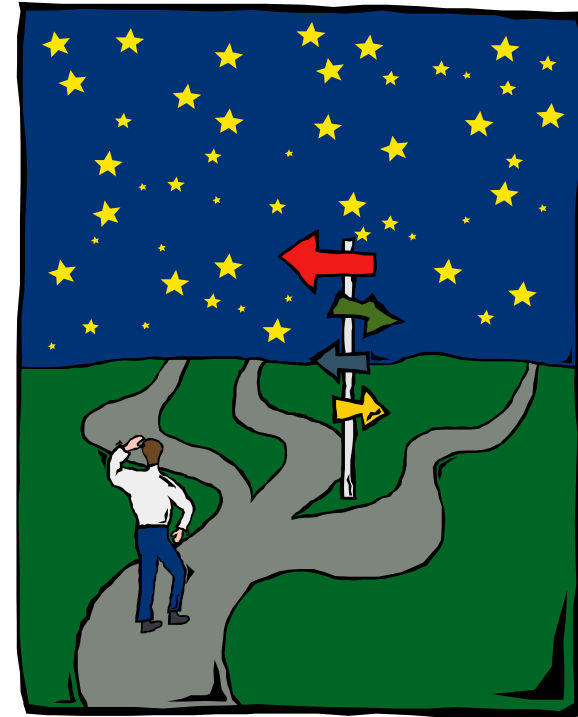
Cattell's Criterion: looking for the elbow in a scree plot of the eigenvalues



FA – How many factors ?

Criterion of Theo Ry:

Do you see a valid theoretical explanation for a certain dimensionalization?



FA – How many factors?

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,011	50,191	50,191	3,011	50,191	50,191	2,859	47,650	47,650
2	,920	15,331	65,523	,920	15,331	65,523	1,072	17,872	65,523
3	,763	12,711	78,234						
4	,593	9,882	88,115						
5	,372	6,203	94,318						
6	,341	5,682	100,000						

Extraction Method: Principal Component Analysis.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,011	50,191	50,191	2,601	43,358	43,358	1,510	25,175	25,175
2	,920	15,331	65,523	,286	4,765	48,122	1,377	22,947	48,122
3	,763	12,711	78,234						
4	,593	9,882	88,115						
5	,372	6,203	94,318						
6	,341	5,682	100,000						

Extraction Method: Principal Axis Factoring.

SPSS

Factor analysis

Rotation

*ispo1.sav [DataSet1] - SPSS Data Editor

File Edit View Data Transform Analyze Graphs Utilities Window Help

	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure
1	respo	Numeric	8	0		None	None	8	Right	Scale
2	q0_1	Scale	4	0		None	None	4	Left	Nominal
3	q0_2	Scale	4	0		None	None	4	Left	Nominal
4	q0_3	Scale	4	0		None	None	4	Left	Nominal
5	q0_4	Scale	4	0		None	None	4	Left	Nominal
6	q0_5	Scale	4	0		None	None	4	Left	Nominal
7	q0_6	Scale	4	0		None	None	4	Left	Nominal
8	q0_7	Scale	4	0		None	None	4	Left	Nominal
9	q0_8	Scale	4	0		None	None	4	Left	Nominal
10	q1_1	Scale	4	0		None	None	4	Left	Nominal
11	q2	Scale	4	0		None	None	4	Left	Nominal
12	q3	Scale	4	0		None	None	4	Left	Nominal
13	q3	Scale	4	0		None	None	4	Left	Nominal
14	q3	Scale	4	0		None	None	4	Left	Nominal
15	q3	Scale	4	0		None	None	4	Left	Nominal
16	q4	Scale	4	0		None	None	4	Left	Nominal
17	q5	Numeric	8	0		None	None	8	Right	Ordinal
18	q6	Numeric	8	0		None	None	8	Right	Ordinal
19	q7	Numeric	8	0		None	None	8	Right	Ordinal
20	q8	Numeric	8	0		None	None	8	Right	Scale
21	q9	Numeric	8	0		None	None	8	Right	Ordinal
22	q10	Numeric	8	0		None	None	8	Right	Ordinal
23	q11	Numeric	8	0		None	None	8	Right	Scale
24	q12	Numeric	8	0		None	None	8	Right	Ordinal
25	q13	Numeric	8	0		None	None	8	Right	Ordinal
26	q14	Numeric	8	0		None	None	8	Right	Ordinal
27	q15	Numeric	8	0		None	None	8	Right	Ordinal
28	q16	Numeric	8	0		None	None	8	Right	Ordinal
29	q17	Numeric	8	0		None	None	8	Right	Ordinal
30	q17_1	Numeric	8	0		None	None	8	Right	Ordinal
31	q18	Numeric	8	0		None	None	8	Right	Ordinal
32	q19	Numeric	8	0		None	None	8	Right	Ordinal

Factor Analysis

Variables: q61_a, q61_b, q61_c, q61_d, q61_e, q61_f

Selection Variable:

Descriptives... Extraction... Rotation... Scores... Options...

Factor Analysis: Rotation

Method: ☒ None ☐ Quartimax ☐ Varimax ☐ Equamax ☐ Direct Oblimin ☐ Promax

Delta: 0 Kappa: 4

Display: ☒ Rotated solution ☐ Loading plot(s)

Maximum Iterations for Convergence: 25

Continue Cancel Help

SPSS Processor is ready

Filter On

Start Nov... Inb... Inb... Mic... data Met... poli... Out... Syn... *is... 11:05

Looking for a
'simple structure'

Via rotation:

Orthogonal
Varimax

Meaningful factor loadings: rule of thumb $> 0,50$

Political efficacy Inspired by NES US

Q61.a There's no sense in voting; the *parties* do what they want to do anyway.

No opinion= 5; missing= 1 - **teken**

Q61.b *Parties* are only interested in my vote, not in my opinion.

No opinion= 6; missing= 2 - **teken**

Q61.c If people like me let the *politicians* know what we think, then they will take our opinion into account.

No opinion= 52; missing= 1 + **teken => spiegelen**

Q61.d Most *politicians* promise a lot, but don't do anything.

No opinion= 0; missing= 2 - **teken**

Q61.e As soon as they are elected, *politicians* think they are better than people like me.

No opinion= 15; missing= 2 - **teken**

Q61.f Most of our *politicians* are competent people who know what they are doing.

No opinion= 11; missing= 1 + **teken => spiegelen**

PCA versus PFA

Communalities

	Initial	Extraction
q61_a	1,000	,664
q61_b	1,000	,708
q61_c	1,000	,339
q61_d	1,000	,614
q61_e	1,000	,646
q61_f	1,000	,960

Extraction Method: Principal Component Analysis.

Communalities

	Initial	Extraction
q61_a	,463	,537
q61_b	,522	,798
q61_c	,190	,211
q61_d	,455	,606
q61_e	,482	,643
q61_f	,078	,093

Extraction Method: Principal Axis Factoring.

FA - 'Simple structure'

Component Matrix^a

	Component	
	1	2
q61_a	,776	,250
q61_b	,823	,177
q61_c	-,576	,081
q61_d	,783	,027
q61_e	,803	,034
q61_f	-,377	,904

Extraction Method: Principal Component Analysis.
a. 2 components extracted.

Factor Matrix^a

	Factor	
	1	2
q61_a	,711	,177
q61_b	,830	,330
q61_c	-,458	-,034
q61_d	,733	-,262
q61_e	,762	-,249
q61_f	-,282	,118

Extraction Method: Principal Axis Factoring.
a. Attempted to extract 2 factors. More than 25 iterations required. (Convergence=,002).
Extraction was terminated.

Rotated Component Matrix^a

	Component	
	1	2
q61_a	,814	,031
q61_b	,840	-,052
q61_c	-,533	,233
q61_d	,761	-,185
q61_e	,782	-,184
q61_f	-,119	,973

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Rotated Factor Matrix^a

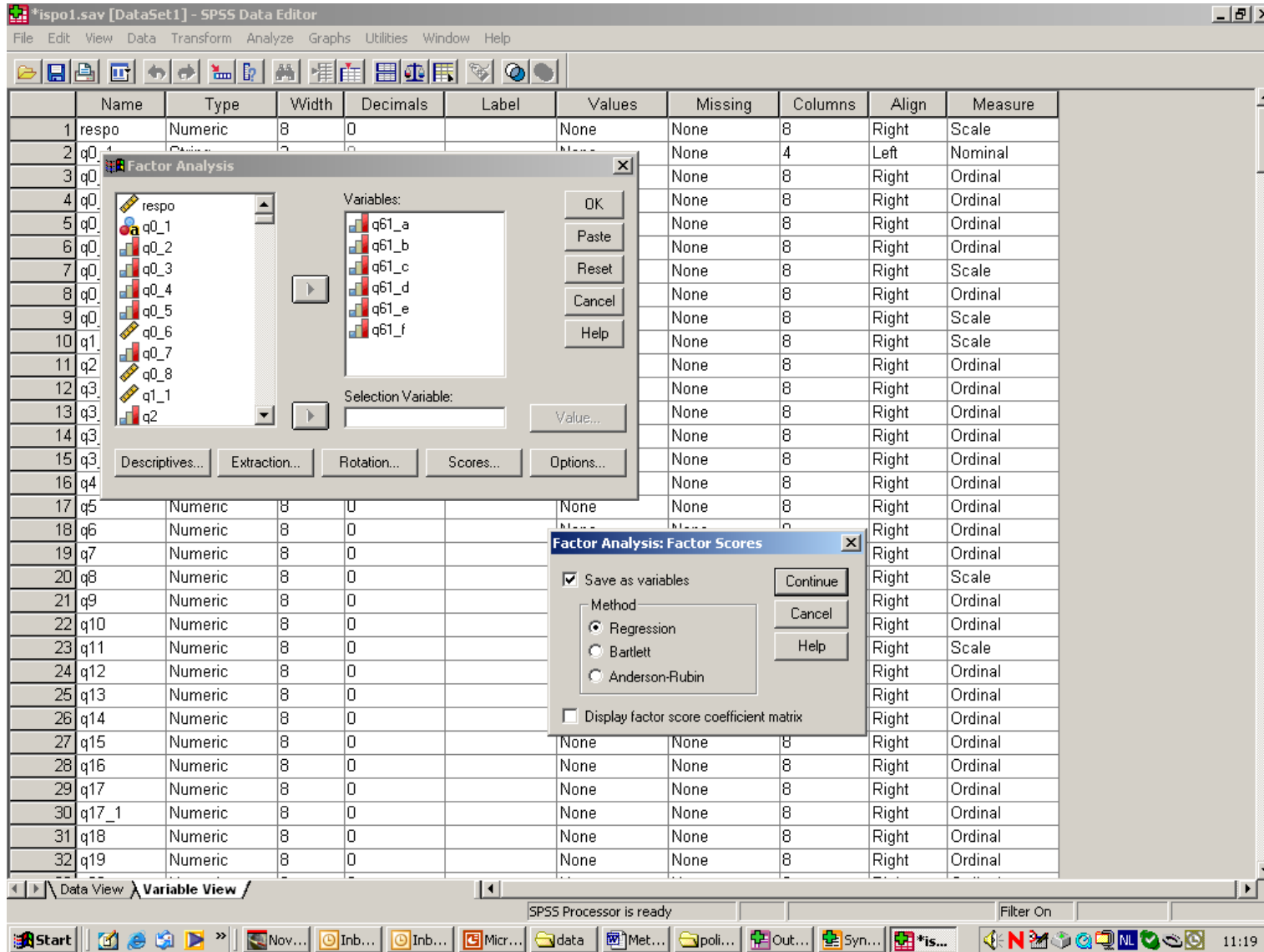
	Factor	
	1	2
q61_a	,638	,360
q61_b	,830	,329
q61_c	-,356	-,290
q61_d	,353	,693
q61_e	,383	,705
q61_f	-,124	-,279

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

SPSS

Factor analysis

Rotation



The screenshot shows the SPSS Data Editor window with a dataset named 'isp01.sav'. The dataset has 32 rows and 11 columns. The columns are: Name, Type, Width, Decimals, Label, Values, Missing, Columns, Align, and Measure. The rows contain data for variables like 'respo', 'q0_1', 'q0_2', 'q0_3', 'q0_4', 'q0_5', 'q0_6', 'q0_7', 'q0_8', 'q1_1', 'q2', 'q3', 'q4', 'q5', 'q6', 'q7', 'q8', 'q9', 'q10', 'q11', 'q12', 'q13', 'q14', 'q15', 'q16', 'q17', 'q17_1', 'q18', and 'q19'.

The 'Factor Analysis' dialog box is open, showing the following variables selected for analysis: q61_a, q61_b, q61_c, q61_d, q61_e, and q61_f. The 'Selection Variable' is set to 'Value...'. The 'Rotation' button is highlighted.

The 'Factor Analysis: Factor Scores' sub-dialog box is also open, showing the following options:

- ☒ Save as variables
- Method:
 - ☒ Regression
 - ☐ Bartlett
 - ☐ Anderson-Rubin
- ☐ Display factor score coefficient matrix

Saving and explaining factorscores

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,360 ^a	,129	,128	,85855727

a. Predictors: (Constant), age_vla, autor

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	1,290	,108		11,908	,000
autor	-,182	,015	-,349	-12,558	,000
age_vla	-,133	,061	-,061	-2,195	,028

a. Dependent Variable: REGR factor score 1 for analysis 1

Reliability analysis

In order to test the internal consistency of indicators
as measures of a unidimensional latent construct

Reliable Indicators

$$x_i = \tau_i + e_i$$

Test-retest reliability

- > correlations over time $r(x_{t1}, x_{t2})$ or $r(x_{t1}, y_{t2})$
- BUT trade-off reminder – real change

Internal consistency

- > split-half $r(\sum x_{\text{helft1}}, \sum x_{\text{helft2}})$
- BUT many possible partitions
- > Cronbach's alpha: mean correlation of all possible partitions

Cronbach's alpha (1)

Alpha= proportion common variance

Covariances = common variance

$$\sigma_{12} = \text{cov ar} (x_1 x_2) = \frac{1}{n-1} \sum_{i=1}^n (x_{i1} - \bar{x}_1)(x_{i2} - \bar{x}_2)$$

Individual **variance** = unique variance

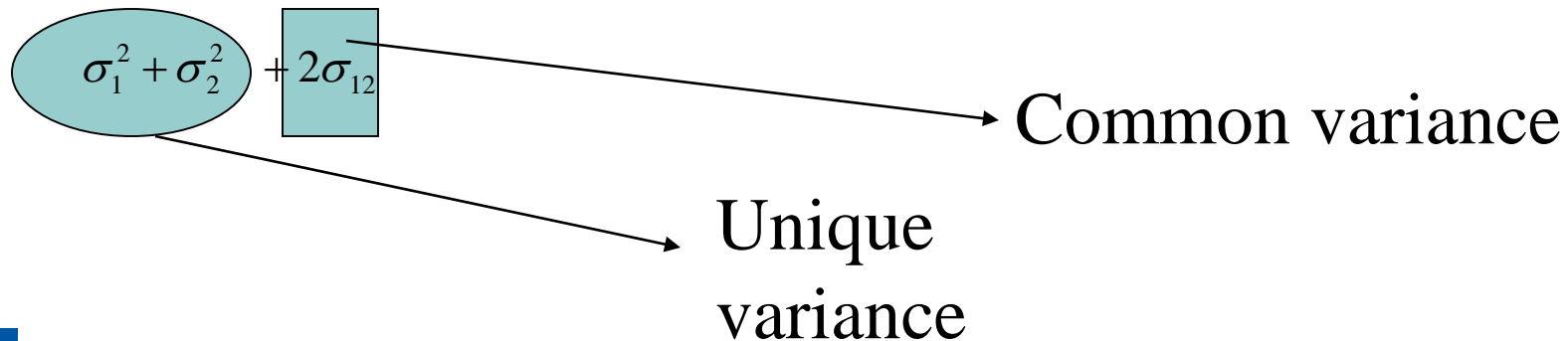
$$\sigma_1^2 = \text{var} (x_1) = \frac{1}{n-1} \sum_{i=1}^n (x_{i1} - \bar{x}_1)^2 = \frac{\sum_{i=1}^n x_{i1}^2}{n-1} - \frac{n\bar{x}^2}{n-1}$$

Cronbach's alpha (2)

Variance of scale scores = sum scores

$$\text{var}(x_1 + x_2) = \frac{1}{n-1} \sum_{i=1}^n (x_{i1} + x_{i2} - \bar{x}_1 - \bar{x}_2)^2 = \frac{1}{n-1} \sum_{i=1}^n [(x_{i1} - \bar{x}_1) + (x_{i2} - \bar{x}_2)]^2 =$$

$$\frac{1}{n-1} \sum_{i=1}^n (x_{i1} - \bar{x}_1)^2 + \frac{1}{n-1} \sum_{i=1}^n (x_{i2} - \bar{x}_2)^2 + \frac{2}{n-1} \sum_{i=1}^n (x_{i1} - \bar{x}_1)(x_{i2} - \bar{x}_2) =$$



Cronbach's alpha (3)

Variance of scale scores = sum scores

-> Logic for 4 items

$$\text{var } S = \text{var } (x_1 + x_2 + x_3 + x_4) =$$

$$\sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \sigma_4^2 + \sigma_{12} + \sigma_{21} + \sigma_{13} + \sigma_{31} + \sigma_{14} + \sigma_{41} + \sigma_{23} + \sigma_{32} + \sigma_{24} + \sigma_{42} + \sigma_{34} + \sigma_{43}$$

$$\text{Var } S_i = \sum_{i=1}^n \sigma_i^2 + \sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij}$$

= unique variance + common variance

Cronbach's alpha (4)

$$\alpha = \frac{\sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij}}{\sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij} + \sum_{i=1}^n \sigma_i^2} = \frac{ESS}{TSS}$$

Alpha is comparable with R^2

Problem: more items \Rightarrow alpha higher

Cronbach's alpha (5)

$$\alpha_{adj} = \frac{\sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij}}{\left(\sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij} + \sum_{i=1}^n \sigma_i^2 \right)} = \frac{n}{(n-1)} \cdot \alpha \quad \text{because } n^2 - n = n \cdot (n-1)$$

$n \cdot n = n^2$ elements in covariance matrix

with n diagonal elements

Adjusted alpha comparable with adjusted R^2

Political efficacy Inspired by NES US

Q61.a There's no sense in voting; the *parties* do what they want to do anyway.

No opinion= 5; missing= 1 - **teken**

Q61.b *Parties* are only interested in my vote, not in my opinion.

No opinion= 6; missing= 2 - **teken**

Q61.c If people like me let the *politicians* know what we think, then they will take our opinion into account.

No opinion= 52; missing= 1 + **teken => spiegelen**

Q61.d Most *politicians* promise a lot, but don't do anything.

No opinion= 0; missing= 2 - **teken**

Q61.e As soon as they are elected, *politicians* think they are better than people like me.

No opinion= 15; missing= 2 - **teken**

Q61.f Most of our *politicians* are competent people who know what they are doing.

No opinion= 11; missing= 1 + **teken => spiegelen**

Political efficacy – Flanders

Covariance matrix

Inter-Item Covariance Matrix

	q61_a	q61_b	q61_cS	q61_d	q61_e	q61_fS
q61_a	1,625	,853	,385	,621	,684	,174
q61_b	,853	1,063	,382	,540	,606	,180
q61_cS	,385	,382	,866	,293	,330	,151
q61_d	,621	,540	,293	1,014	,675	,209
q61_e	,684	,606	,330	,675	1,141	,227
q61_fS	,174	,180	,151	,209	,227	,796

$$\sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij} = (2.0,853) + (2.0,385) + \dots + (2.0,227) = 12,620$$

$$\sum_{i=1}^n \sigma_i^2 = 1,652 + 1,063 + 0,866 + 1,014 + 1,141 + 0,796 = 6,505$$

Political efficacy – Flanders (Belgium)

Cronbach's alpha (6 items)

$$\alpha_{adj} = \frac{n}{(n-1)} \cdot \frac{\sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij}}{\sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n \sigma_{ij} + \sum_{i=1}^n \sigma_i^2} = \frac{6}{(6-1)} \cdot \frac{12,620}{(12,620 + 6,505)} = 0,792$$

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
q61_a	13,4926	12,066	,614	,463	,744
q61_b	13,9606	12,943	,690	,522	,724
q61_cS	13,7572	15,177	,425	,190	,786
q61_d	13,9579	13,433	,634	,455	,739
q61_e	13,6152	12,940	,656	,482	,732
q61_fS	13,0175	16,447	,260	,078	,816

Political efficacy – Flanders (Belgium)

Cronbach's alpha (6 items)

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
q61_a	10,1499	9,736	,639	,463	,774
q61_b	10,6179	10,624	,708	,521	,750
q61_cS	10,4145	12,801	,418	,184	,829
q61_d	10,6152	11,174	,633	,451	,773
q61_e	10,2726	10,716	,656	,477	,765

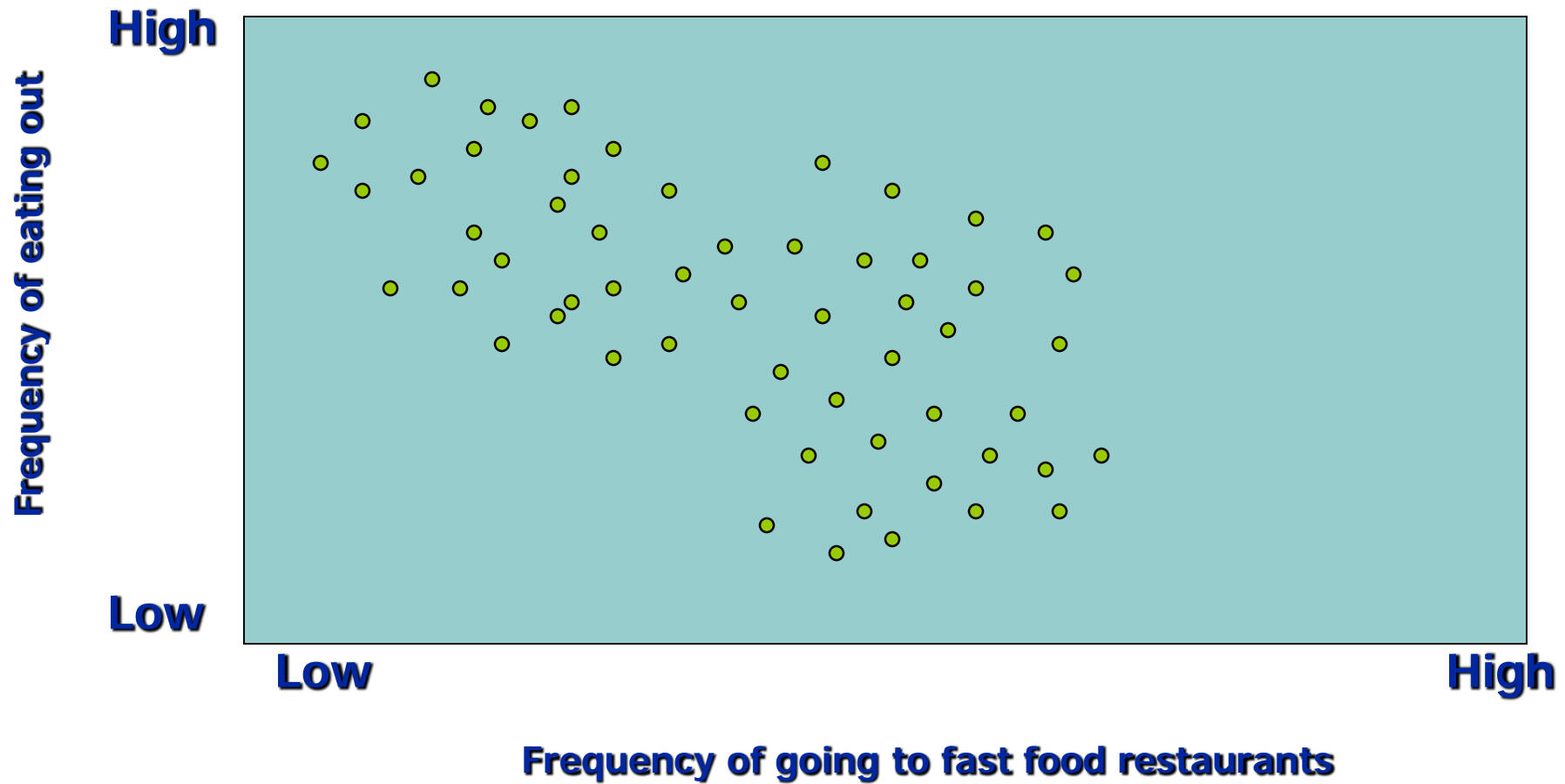
Cluster analysis

In order to construct groups of respondents that are internally homogeneous and externally heterogeneous based on a set of quantitative indicators

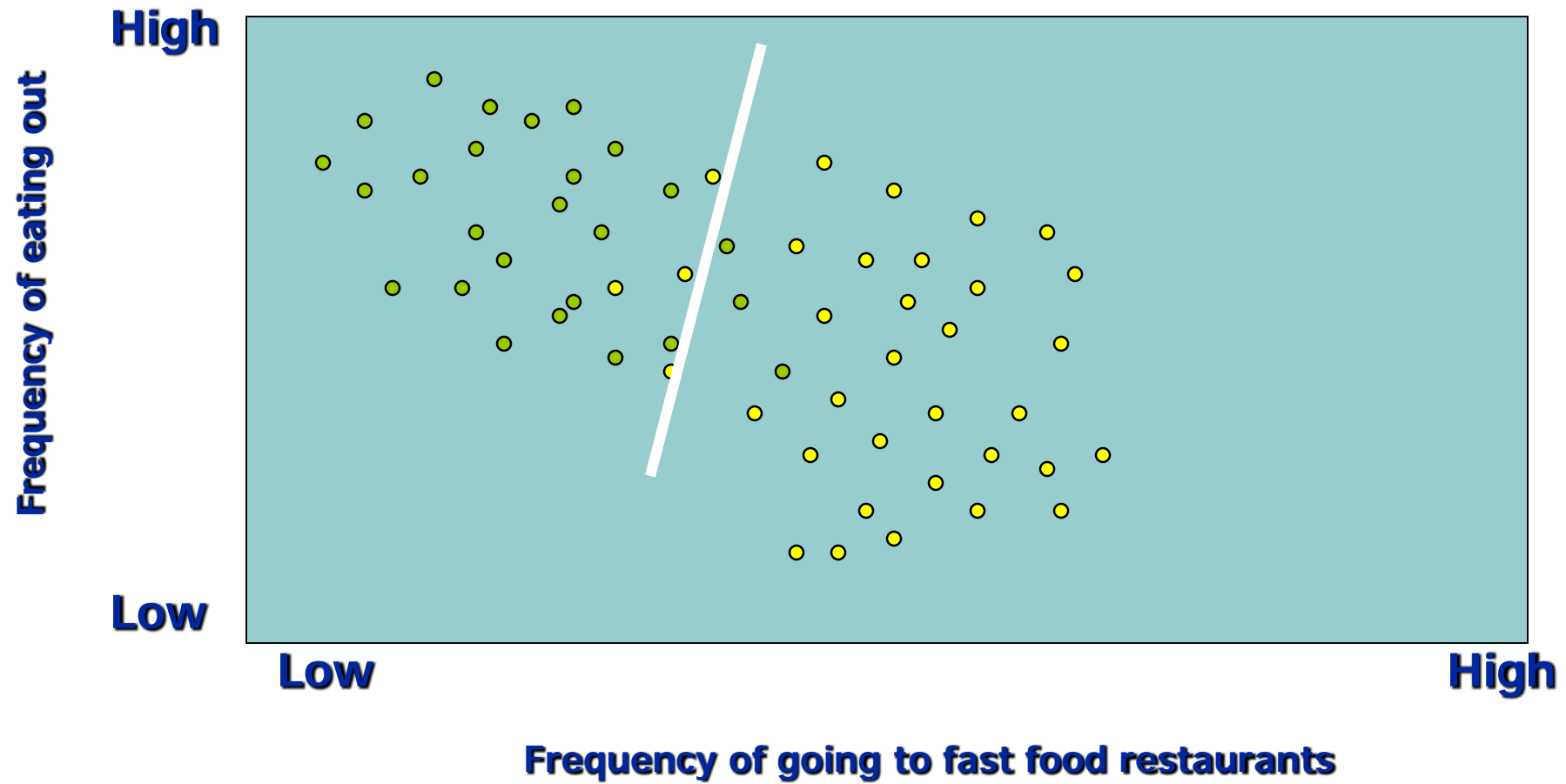
Cluster analysis characteristics

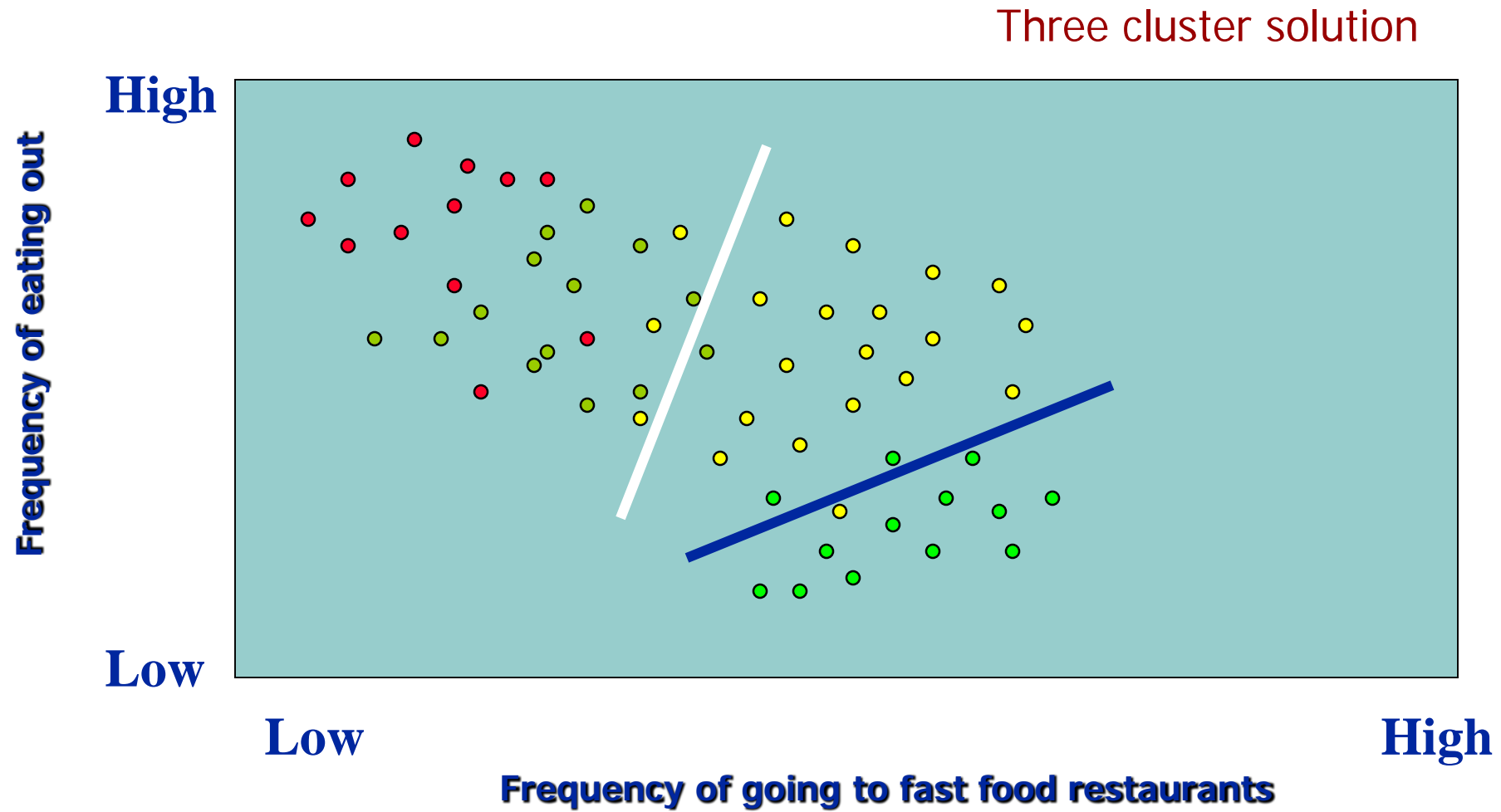
- Data reductive technique
- Symmetric technique
- Explorative, inductive, descriptive
 - Garbage in, Garbage out
- Q-technique (cases) versus R-technique (variables)
 - Clusters: focus on the rows of a data-matrix
- Clusters versus factoren

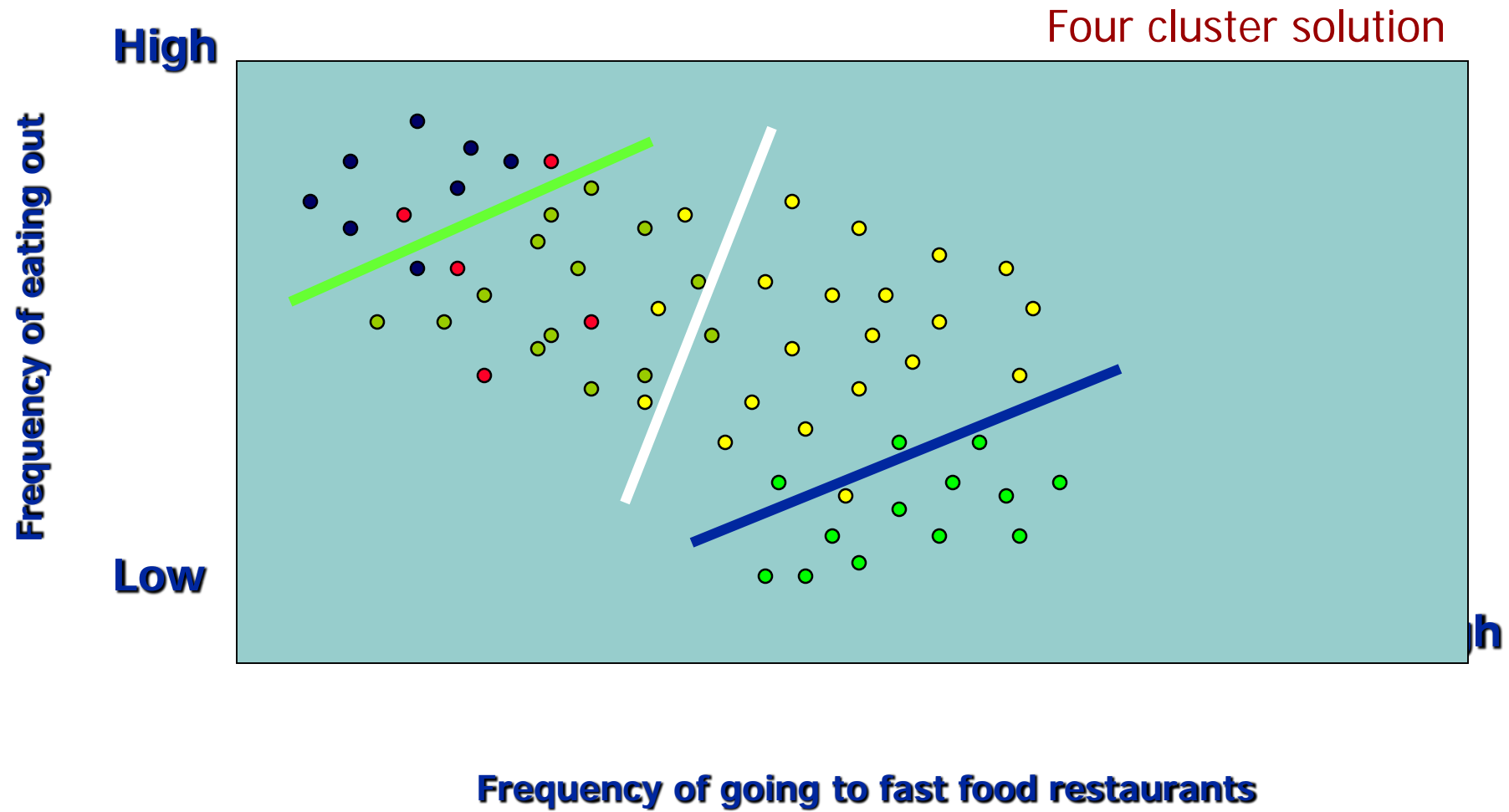
No unique solution:
!!! cluster analysis always generates clusters



Two cluster solution







Clusteranalyse: Objectieven

- Opstellen van een classificatie van cases
 - cf. taxonomie/typologie (*analogie met planten, dieren, psychiatrische taxonomy*)
- Reduceren van de complexiteit tussen de cases
- (vaak) Tussenstap in de globale analyse

van fundamenteel belang...

- Relevante variabelen
 - variabele impliceert variatie
 - analyseniveau (relatief versus absoluut)
- Geschikte onderzoekselementen
 - hiaten of uitschieters
 - boxdiagram of multivariate maatstaf

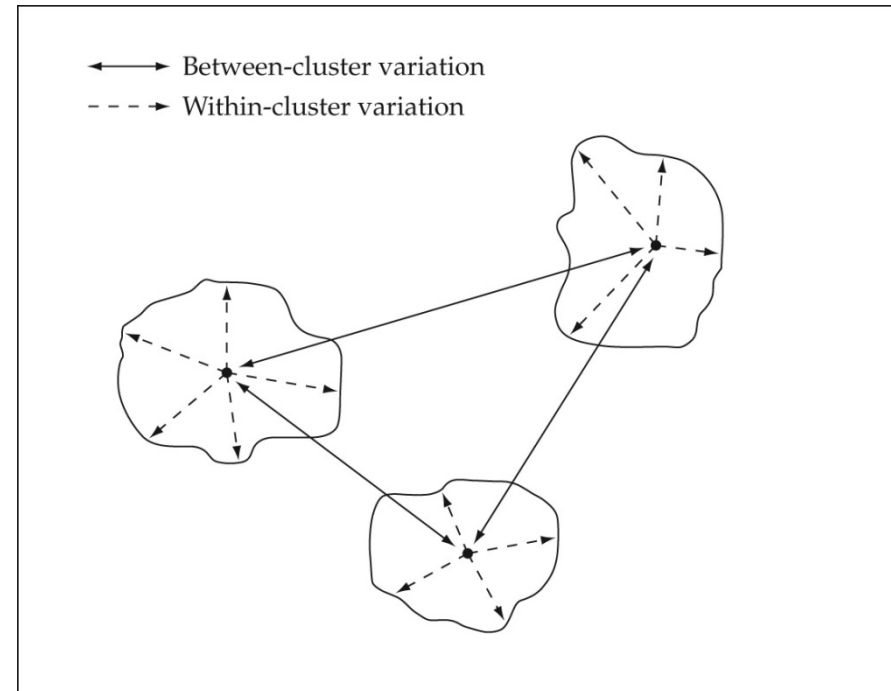
	V1	V2	V3
case1			
case2			
case3			

3 important questions....

1. What kind of measure do we use to assess the likeness or similarity of cases ? Do we need a standardized measure?
2. What kind of strategy do we follow in the amalgamation procedure (formation of clusters)?
3. How many clusters do we use

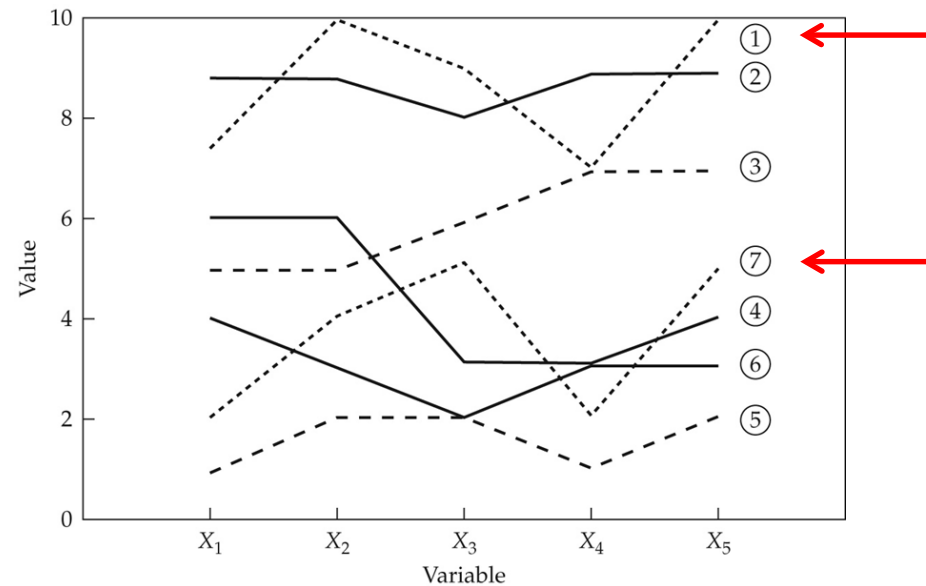
Yet,...1 universal aim

- Obtaining a limited number of mutually exclusive clusters
- Maximizing internal homogeneity (within cluster variation) and maximal external heterogeneity (between cluster variation)



Question 1a: Which similarity measure?

- **Possibility A:** measures of association or correlation
 - Focus on similarity of pattern of the scores, NOT on the level of the scores
 - Suitable for nominal/ordinal measurement level

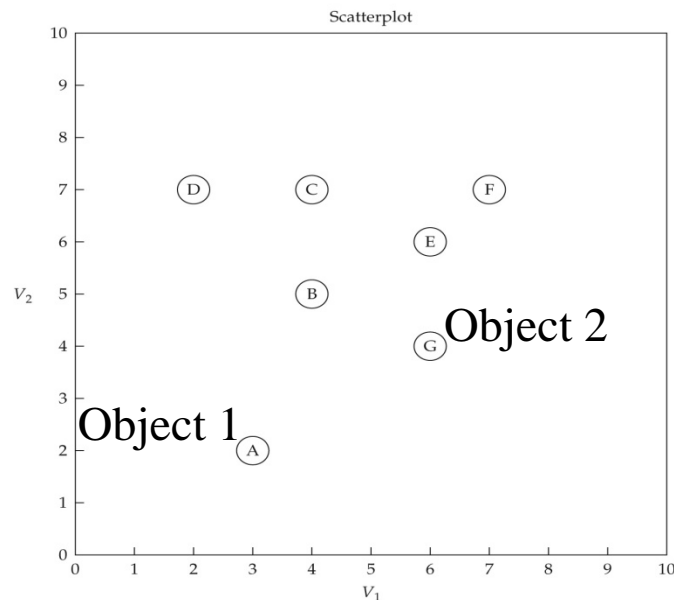


Question 1b: Which similarity measure?

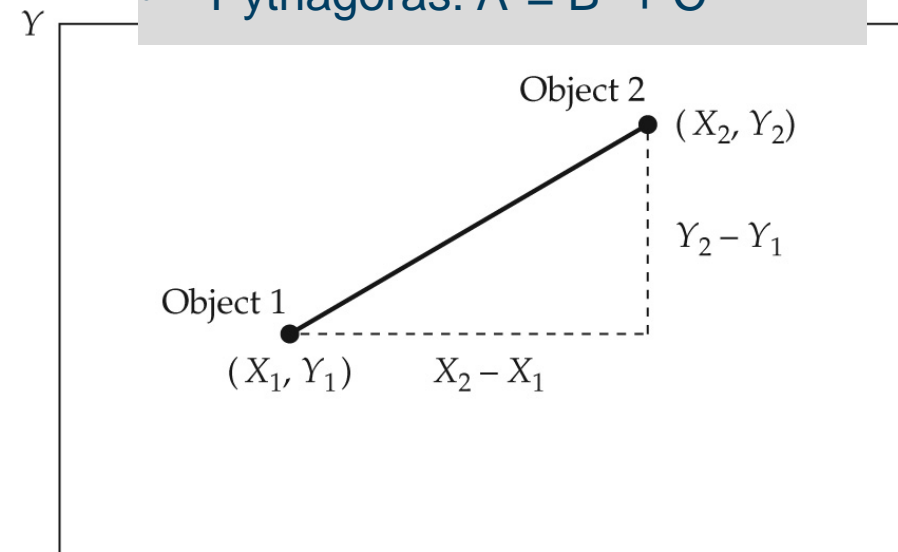
- **Possibility A:** distance measures (proximities, often based on Euclidian distance)
 - Focus on level of the scores, NOT on the pattern of the scores
 - Suitable for quantitative measurement level

- Squared Euclidean distance
- City-block (Manhattan) distance
- Chebychev distance
- Mahalanobis distance (D2)
(for Multicollinear variables)

Clustering Variable	Data Values						
	Respondents						
	A	B	C	D	E	F	G
V ₁	3	4	4	2	6	7	6
V ₂	2	5	7	7	6	7	4



- **Pythagoras: $A^2 = B^2 + C^2$**



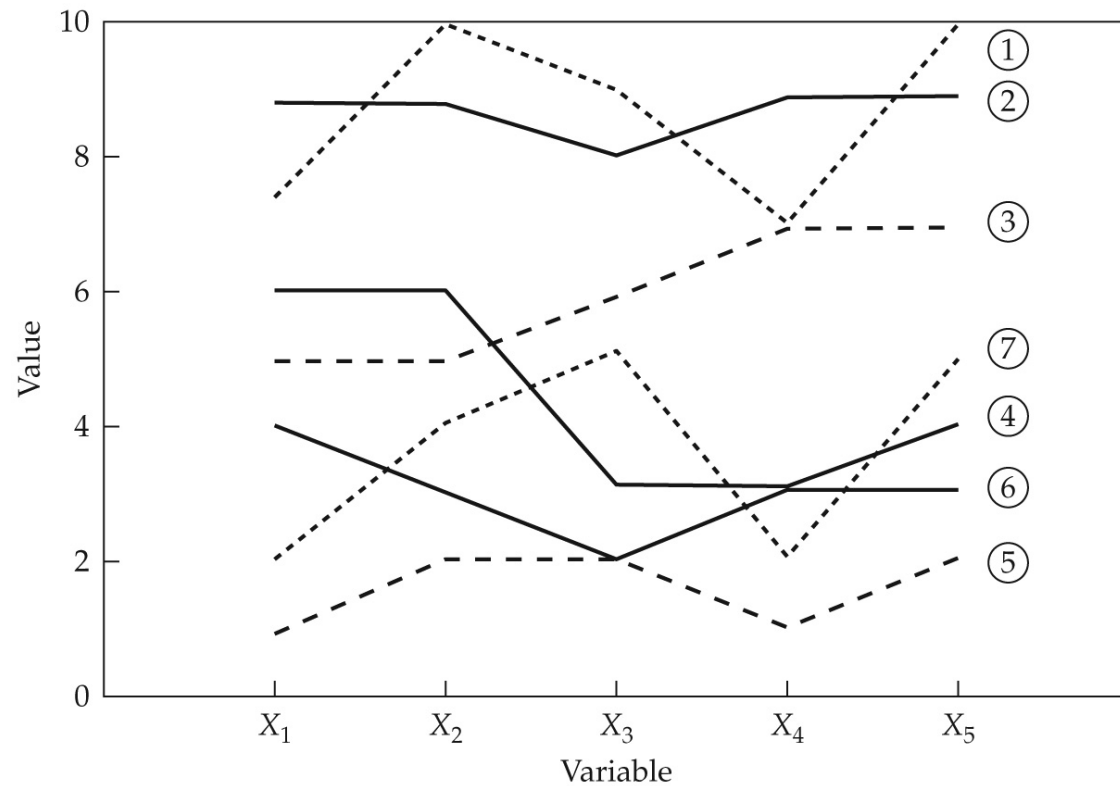
$$\text{Distance} = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2}$$

Dissimilarity matrix in SPSS

Squared Euclidean Distance					
Case	1	2	3	4	5
1		325,000	425,000	500,000	50,000
2	325,000		200,000	125,000	125,000
3	425,000	200,000		25,000	225,000
4	500,000	125,000	25,000		250,000
5	50,000	125,000	225,000	250,000	

Question 1c: Which similarity measure?

● Correlation versus distance



Smallest **distance**:

- between 1 and 2

Highest distance:

- between 1 and 5

- between 2 and 5

Highest **correlation**:

- between 1 and 5

- between 1 and 7

Never forget: use standardised variables to compute distance

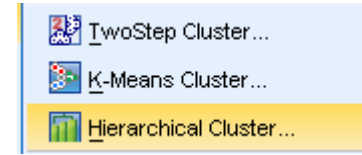
$$z_i = \frac{(x_i - \bar{x})}{s}$$

Differences in measurement unit have a strong impact on the formation of cluster

Question 2: Which agglomeration schedule

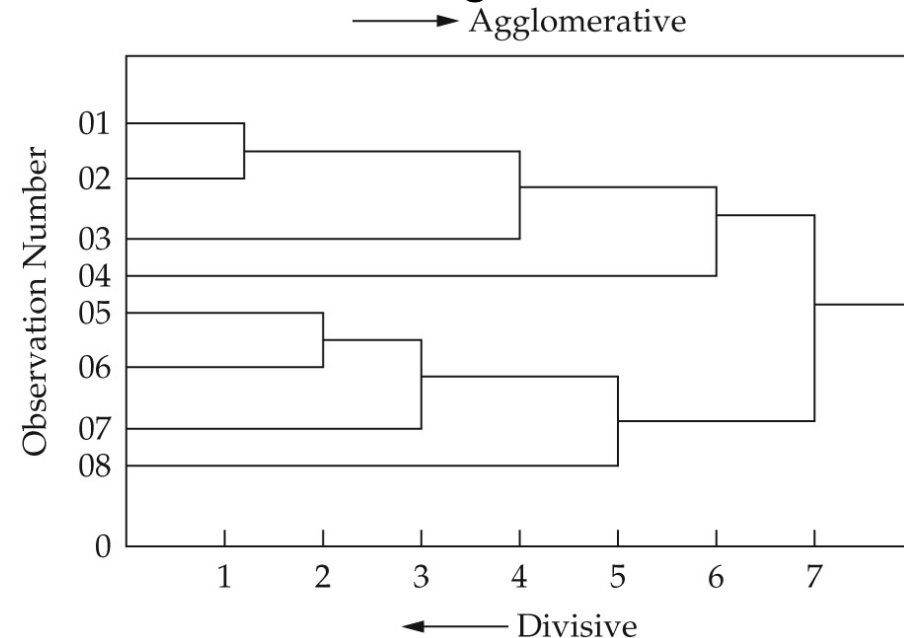
- **Hierarchical cluster methods**

- Clusters are nested
- agglomerative (bottom-up) versus divisive (top-down)
- Time – and labour intensive



- **Non-hierarchical cluster methods**

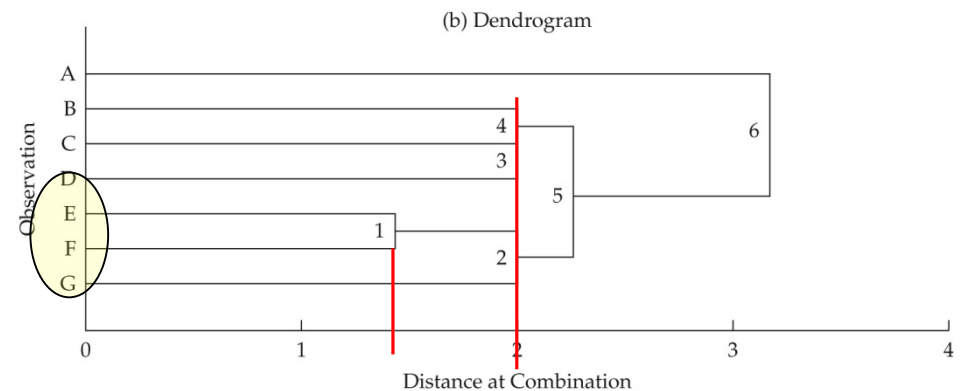
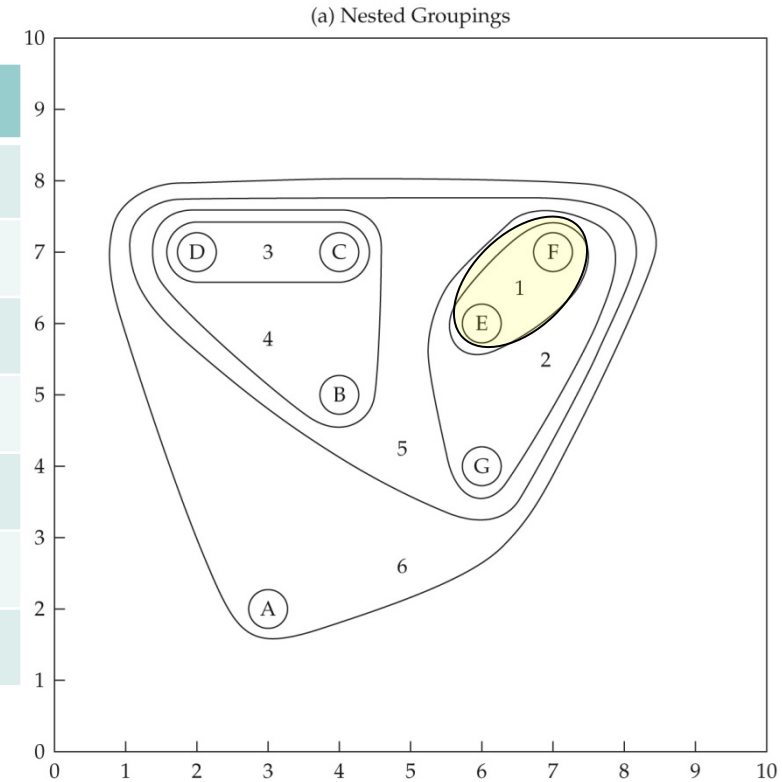
- Clusters are non-nested e.g. SPSS '*K-means clustering*'
- Less costly
- Iterative process based on. 'seeds'



Nested structure of hierarchical clustering

	A	B	C	D	E	F	G
A							
B	3,162						
C	5,099	2,000					
D	5,099	2,828	2,000				
E	5,000	2,236	2,236	4,123			
F	6,403	3,606	3,000	5,000	1,414		
G	3,606	2,236	3,606	5,000	2,000	3,162	

Internal homogeneity of the clusters decreases in each consecutive step (mean distance in clusters)



Question 2: Hierarchical agglomeration methods

- Nearest (single linkage) versus Farthest neighbour (complete linkage) procedure
- Between-groups linkage (average linkage)
- Within-groups linkage

- **Ward's method**
(min. Sum of Squares (SS) of each cluster pair that can be formed in each step)

- Centroid method

Best buy

Use Squared-Euclidean distance

Question 3: optimal number of clusters

- Grafical: dendrogram or icicle-plot
- Numerical: 'agglomeration schedule'
(based on a strong increase in within-cluster distance)
- Theoretical: external and predictive validation

Vraag 3: het optimale # clusters

- Grafical: dendrogram or icicle-plot

Standard classification:

Cluster A:

Paranoid, schizoid,
schizotypal

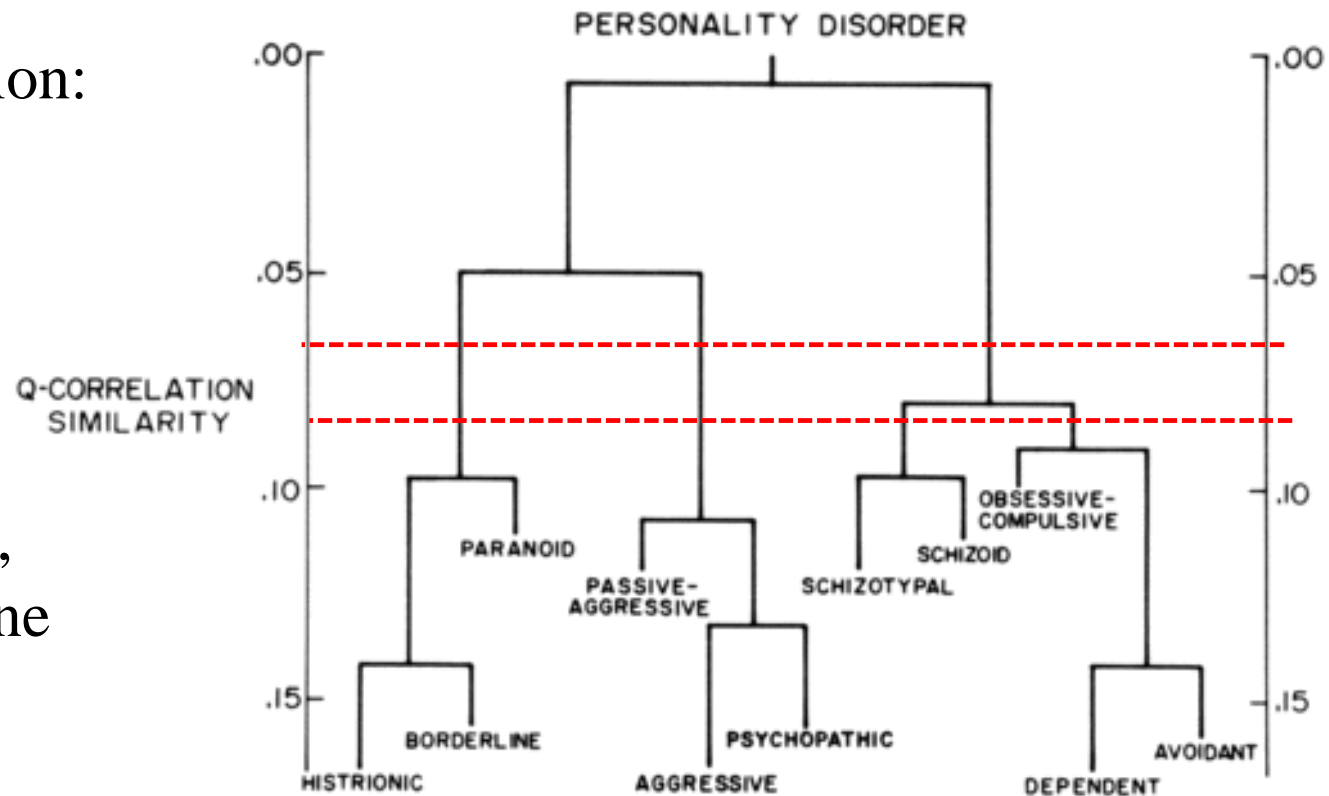
Cluster B:

Theatral, narcissical,
anti-social, borderline

Cluster C:

Avoidant, dependent,

 obsessive-compulsive



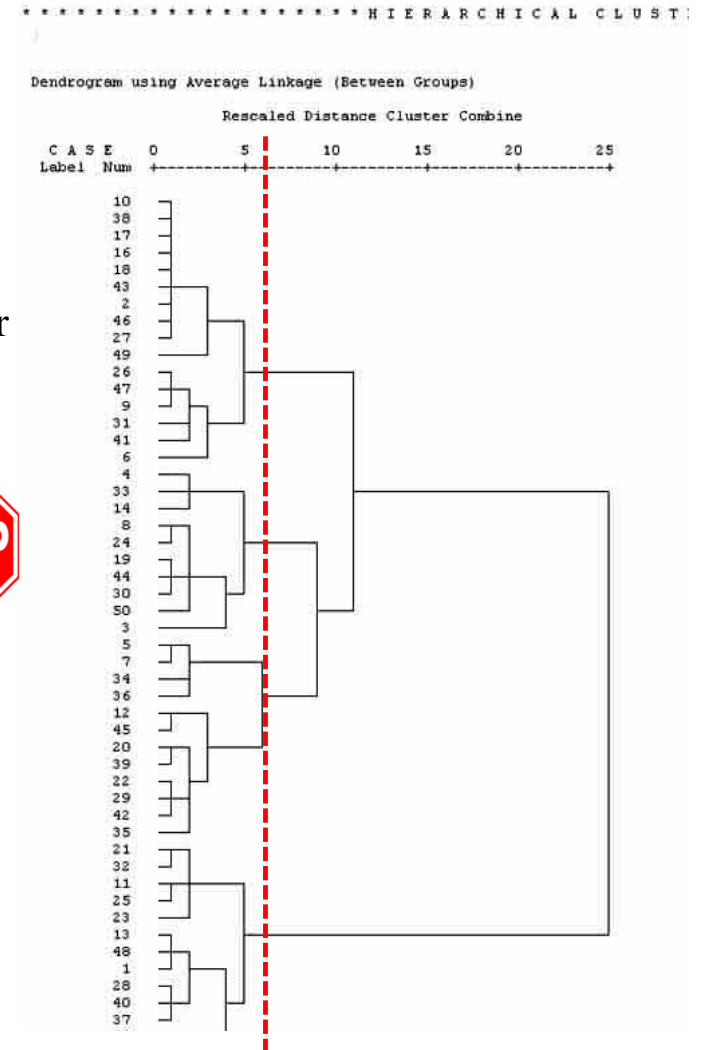
Question 3: optimal number of clusters

- Numerical: 'agglomeration schedule'
(strong increase qua within-cluster distance)

Agglomeration Schedule

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	3	5	28.090	0	0	4
2	2	4	32.020	0	0	3
3	2	6	51.110	2	0	6
4	3	7	54.685	1	0	5
5	1	3	87.913	0	4	6
6	1	2	217.950	5	3	7
7	1	8	242.579	6	0	0

big jump=
strongly dissimilar
clusters are
agglomerated



Question 3: optimal number of clusters

Comparison: dendrogram - agglomeration

Agglomeration Schedule

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	3	5	28.090	0	0	4
2	2	4	32.020	0	0	3
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5	1	3	87.913	0	4	
6	1	2	217.950	5	3	
7	1	8	242.579	6	0	

