

Principal Components & Multiple Correspondence Analyses

with resampling approaches for stability assessments

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RRI RTC

May 01, 2019

Overview

- ▶ Something here

Overview

- ▶ Something here
- ▶ Where to find everything

Introduction

Slide A

Slide A

Slide B

Slide B

Taxonomy

The actual data

PCA

Stuff

PCA

How & When to use it

CA

Stuff

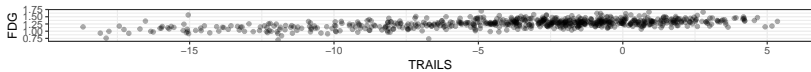
CA

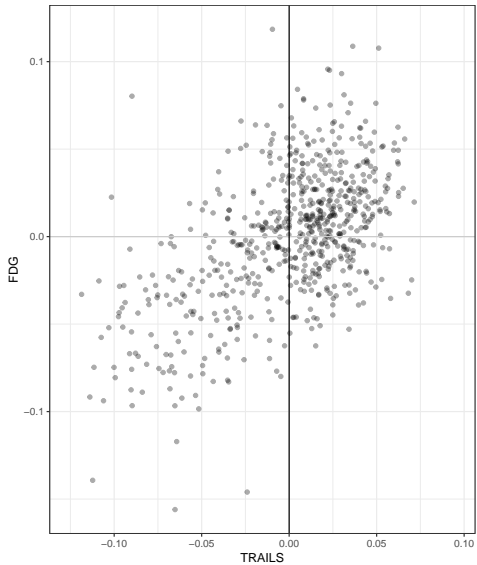
How & When to use it

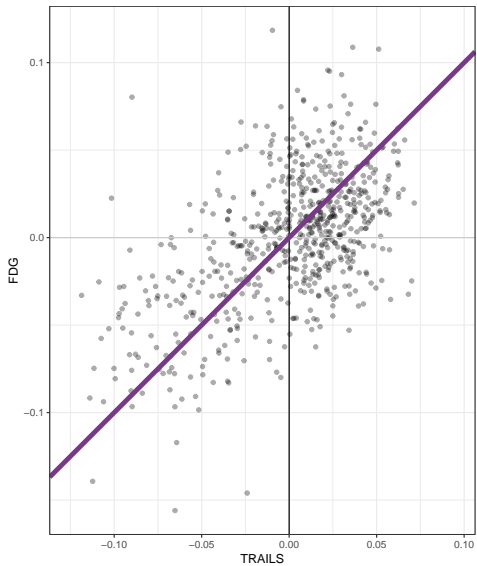
Today

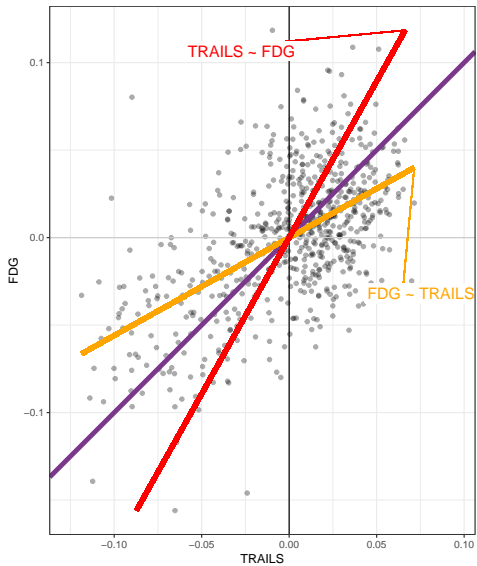
Some alternatives

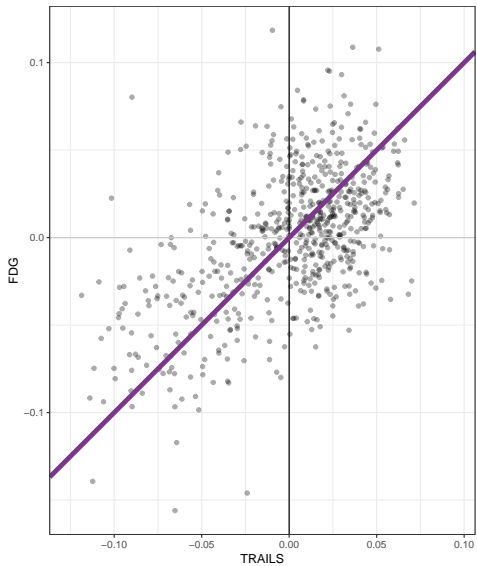
Principal Components Analysis

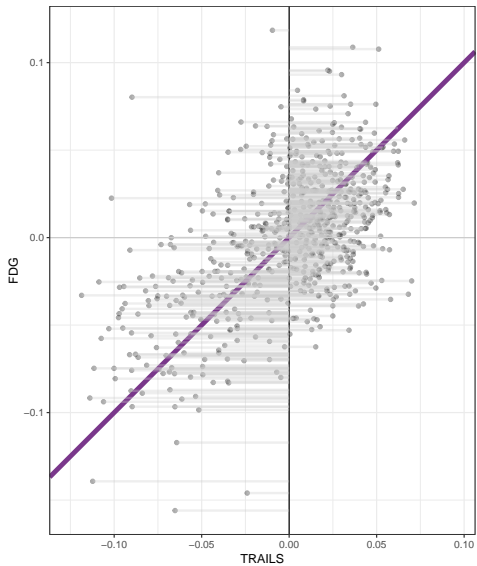


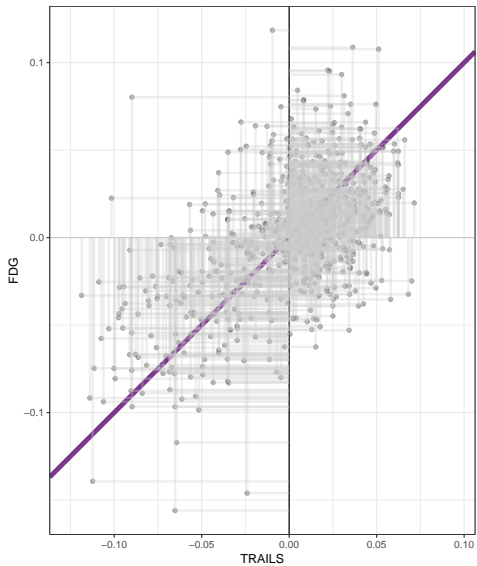


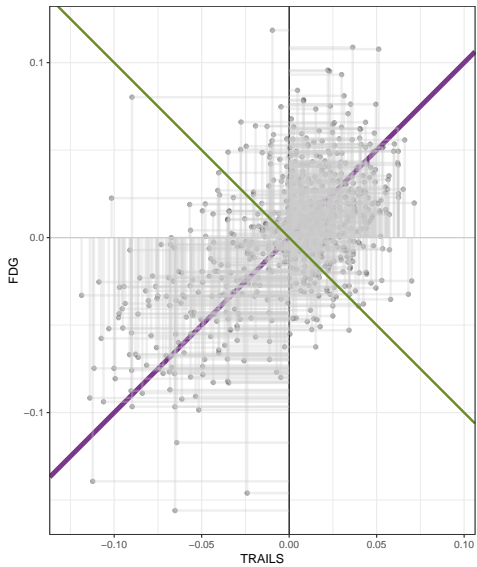






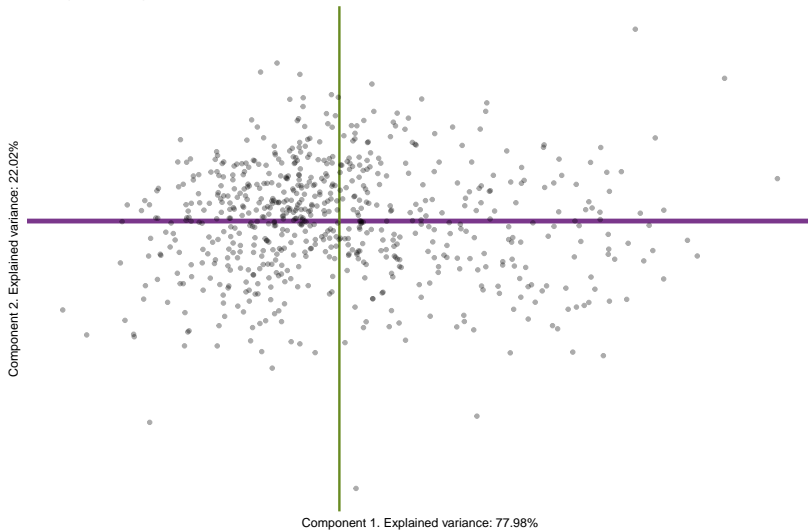




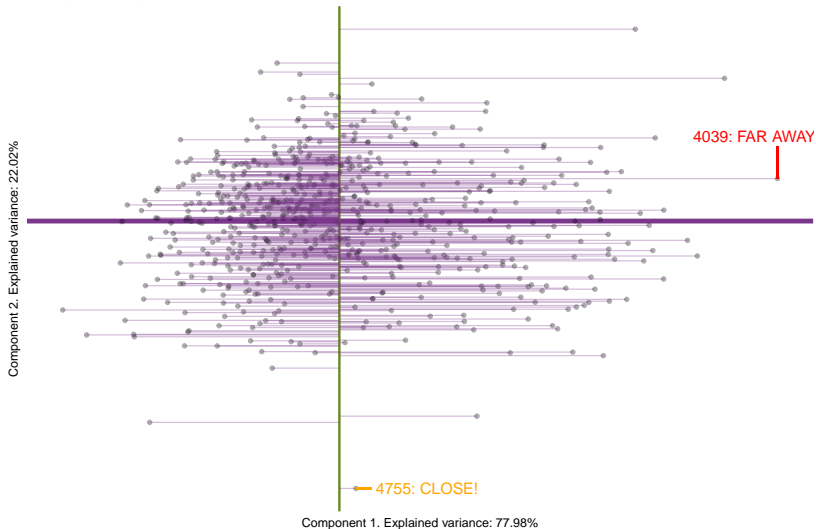


The SVD

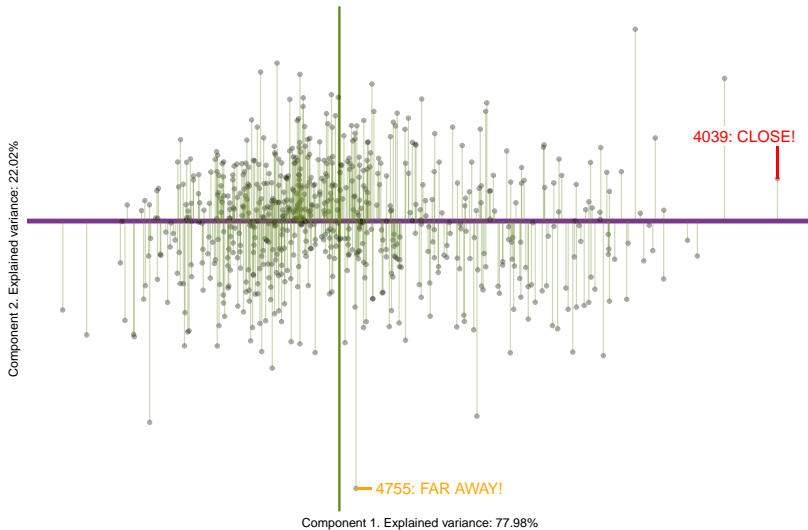
PCA of Trails & FDG:
Participants' Component Scores



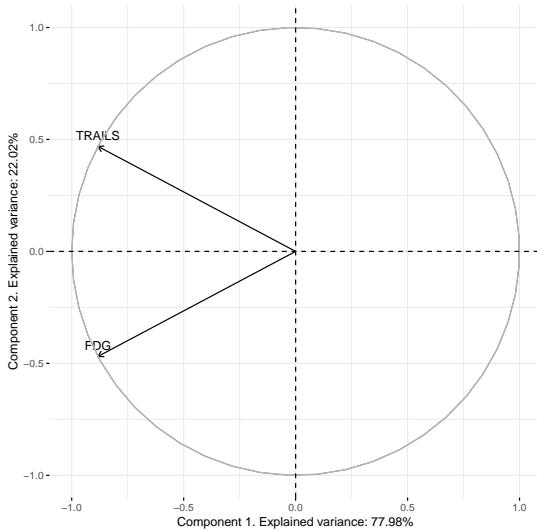
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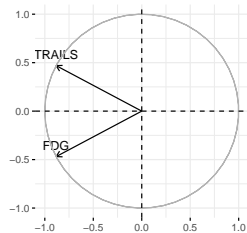
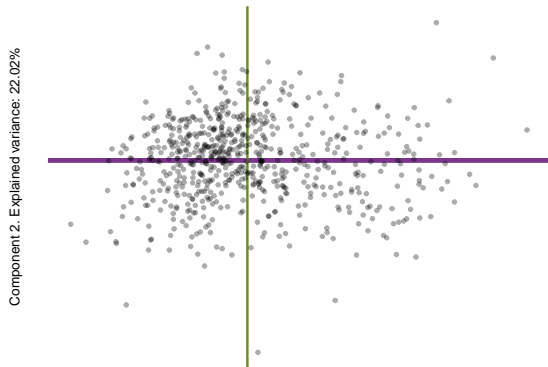
PCA of Trails & FDG:
Participants' Component Scores



PCA:
Variable-Component Correlations

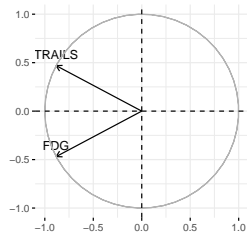
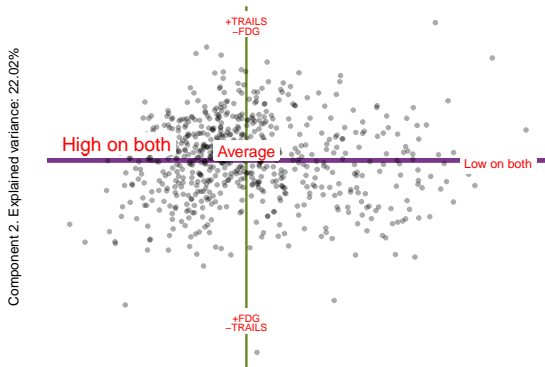


PCA:
Trails & FDG



Component 1. Explained variance: 77.98%

PCA:
Trails & FDG

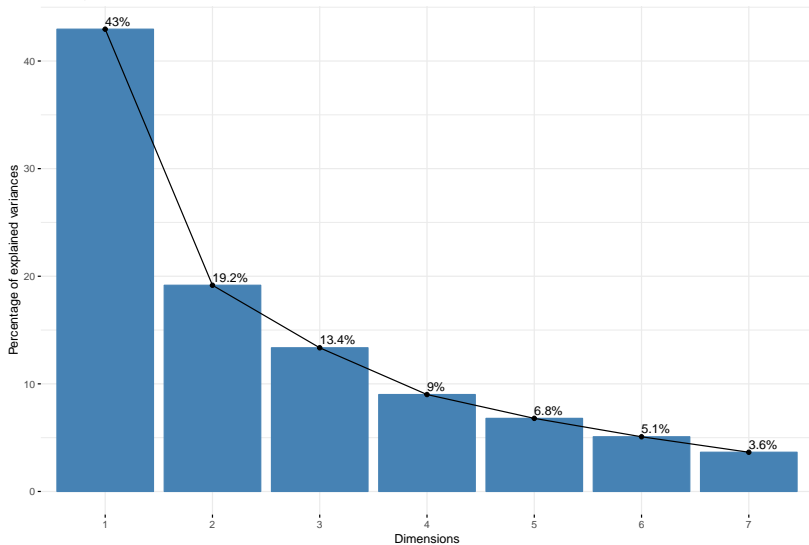


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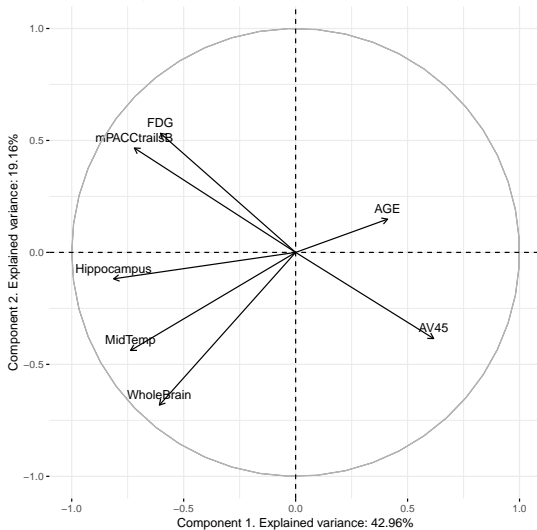
Scaling up

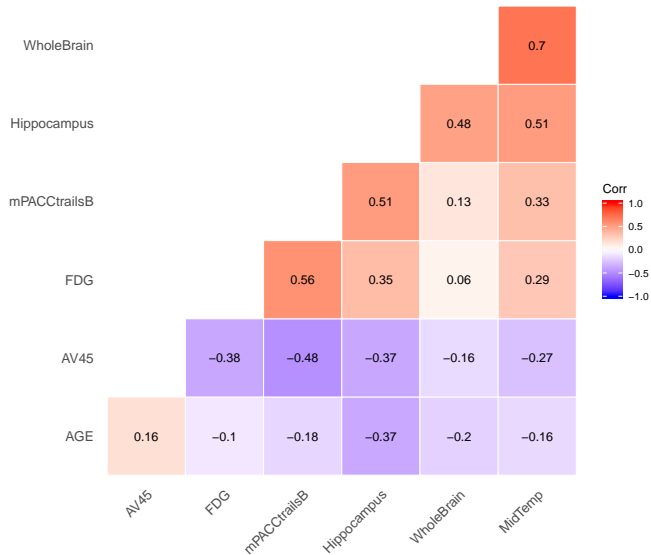
here: show the table and perhaps the code? maybe the code per slide for easy slides?

Scree plot

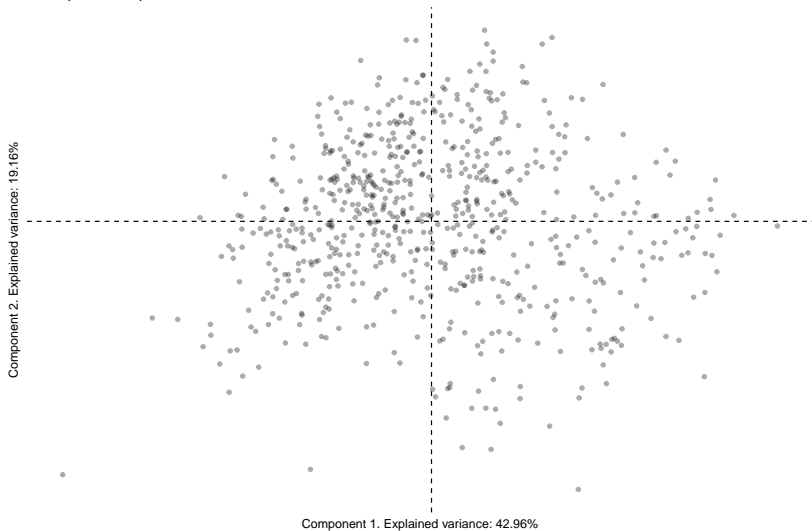


PCA:
Variable-Component Correlations



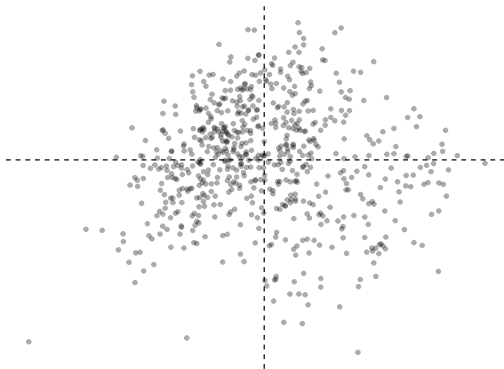


PCA:
Participants Component Scores

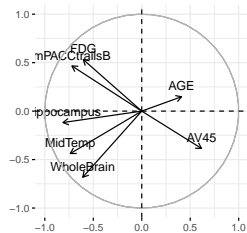


PCA:
Trails & FDG

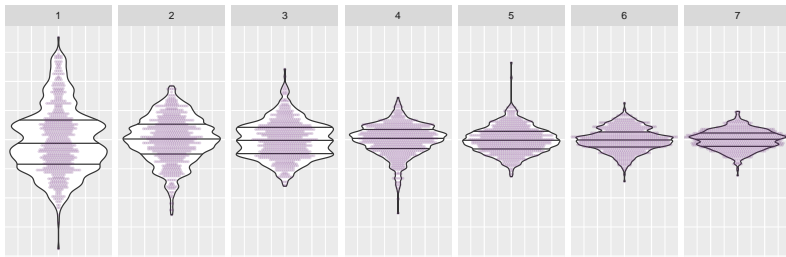
Component 2. Explained variance: 19.16%



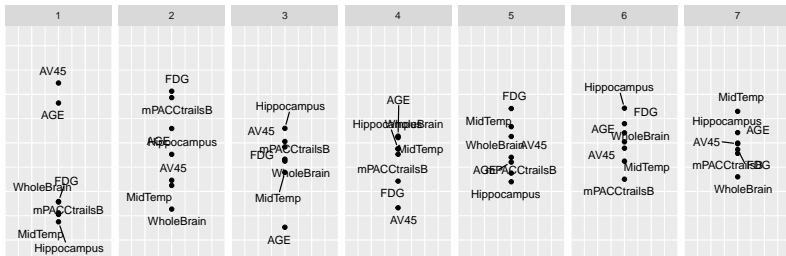
Component 1. Explained variance: 42.96%



COMPONENT_SCORES



CORRELATIONS



Correspondence analyses

I don't know something.

Illustrative data

	DX	PTRACCAT
5023	CN	Asian
5026	MCI	White
5027	Dementia	White
5028	Dementia	White
5031	MCI	White
5037	Dementia	Black
5040	CN	Black
5047	MCI	Black
5054	Dementia	White
5058	Dementia	Asian
5063	Dementia	White

Disjunctive data

	DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
5023	0	1	0	0	0	0	1
5026	1	0	0	1	0	0	0
5027	0	0	1	1	0	0	0
5028	0	0	1	1	0	0	0
5031	1	0	0	1	0	0	0
5037	0	0	1	0	0	1	0
5040	0	1	0	0	0	1	0
5047	1	0	0	0	0	1	0
5054	0	0	1	1	0	0	0
5058	0	0	1	0	0	0	1
5063	0	0	1	1	0	0	0

Disjunctive data

	DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
5023	0	1	0	0	0	0	1
5026	1	0	0	1	0	0	0
5027	0	0	1	1	0	0	0
5028	0	0	1	1	0	0	0
5031	1	0	0	1	0	0	0
5037	0	0	1	0	0	1	0
5040	0	1	0	0	0	1	0
5047	1	0	0	0	0	1	0
5054	0	0	1	1	0	0	0
5058	0	0	1	0	0	0	1
5063	0	0	1	1	0	0	0

- ▶ Row sums are total number of *original* variables

Disjunctive data

	DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
5023	0	1	0	0	0	0	1
5026	1	0	0	1	0	0	0
5027	0	0	1	1	0	0	0
5028	0	0	1	1	0	0	0
5031	1	0	0	1	0	0	0
5037	0	0	1	0	0	1	0
5040	0	1	0	0	0	1	0
5047	1	0	0	0	0	1	0
5054	0	0	1	1	0	0	0
5058	0	0	1	0	0	0	1
5063	0	0	1	1	0	0	0

- ▶ Row sums are total number of *original* variables
- ▶ Sum within a variable (e.g. DX) is total number of rows

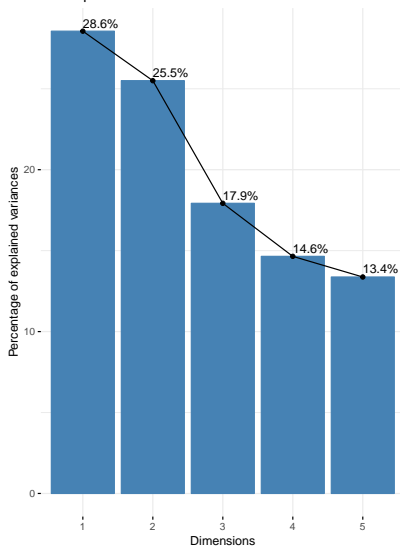
Disjunctive data

	DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
5023	0	1	0	0	0	0	1
5026	1	0	0	1	0	0	0
5027	0	0	1	1	0	0	0
5028	0	0	1	1	0	0	0
5031	1	0	0	1	0	0	0
5037	0	0	1	0	0	1	0
5040	0	1	0	0	0	1	0
5047	1	0	0	0	0	1	0
5054	0	0	1	1	0	0	0
5058	0	0	1	0	0	0	1
5063	0	0	1	1	0	0	0

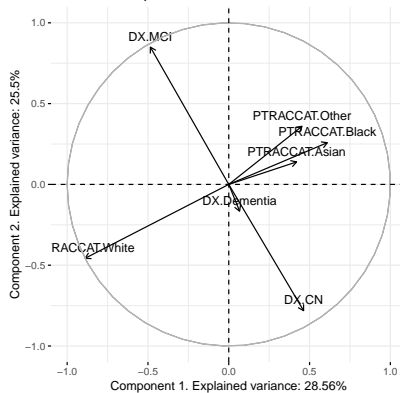
- ▶ Row sums are total number of *original* variables
- ▶ Sum within a variable (e.g. DX) is total number of rows
- ▶ Sum of the table is rows \times columns

A bad idea: PCA

Scree plot



PCA:
Variable-Component Correlations



Why is that a bad idea?

	DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
<i>DX.MCI</i>	1	-0.815	-0.363	0.045	0.032	-0.043	-0.072
<i>DX.CN</i>	-0.815	1	-0.243	-0.047	0	0.067	0.003
<i>DX.Dementia</i>	-0.363	-0.243	1	0	-0.053	-0.035	0.116
<i>PTRACCAT.White</i>	0.045	-0.047	0	1	-0.562	-0.657	-0.45
<i>PTRACCAT.Other</i>	0.032	0	-0.053	-0.562	1	-0.031	-0.021
<i>PTRACCAT.Black</i>	-0.043	0.067	-0.035	-0.657	-0.031	1	-0.025
<i>PTRACCAT.Asian</i>	-0.072	0.003	0.116	-0.45	-0.021	-0.025	1

	DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
<i>DX.MCI</i>	365	0	0	341	11	10	3
<i>DX.CN</i>	0	235	0	213	6	12	4
<i>DX.Dementia</i>	0	0	65	60	0	1	4
<i>PTRACCAT.White</i>	341	213	60	614	0	0	0
<i>PTRACCAT.Other</i>	11	6	0	0	17	0	0
<i>PTRACCAT.Black</i>	10	12	1	0	0	23	0
<i>PTRACCAT.Asian</i>	3	4	4	0	0	0	11

A better idea

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- ▶ Deals with categories, counts (amongst others)

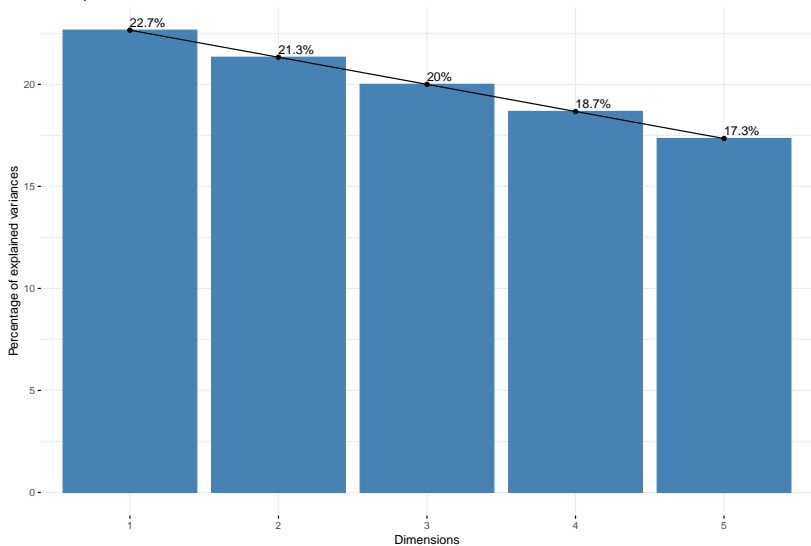
A better idea

- ▶ Correspondence analysis (CA)
 - ▶ Think of it as a χ^2 PCA
- ▶ Deals with categories, counts (amongst others)
- ▶ Row and column component scores exist on same scale

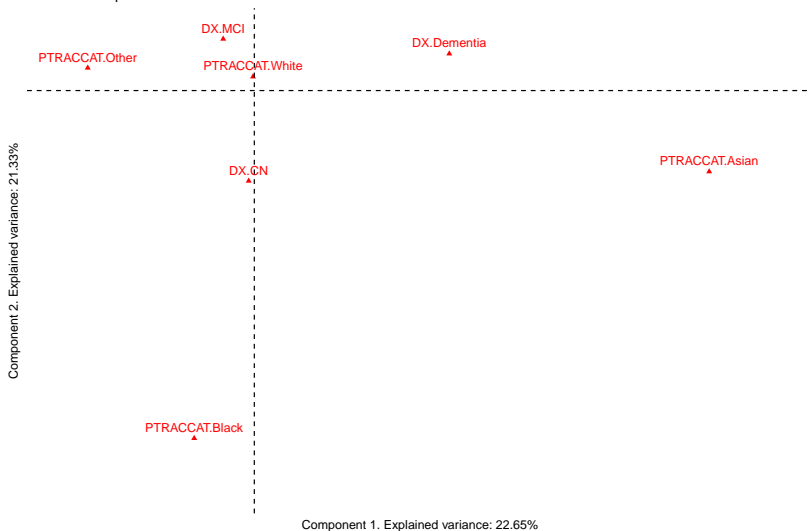
A better idea

- ▶ Correspondence analysis (CA)
 - ▶ Think of it as a χ^2 PCA
- ▶ Deals with categories, counts (amongst others)
- ▶ Row and column component scores exist on same scale
 - ▶ CA is a *bivariate* technique

Scree plot

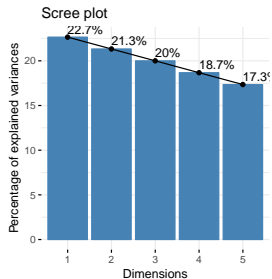


CA:
Variable Component Scores



	DX	PTRACCAT
5023	CN	Asian
5026	MCI	White
5027	Dementia	White
5028	Dementia	White
5031	MCI	White
5037	Dementia	Black
5040	CN	Black
5047	MCI	Black
5054	Dementia	White
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	DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
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5026	1	0	0	1	0	0	0
5027	0	0	1	1	0	0	0
5028	0	0	1	1	0	0	0
5031	1	0	0	1	0	0	0
5037	0	0	1	0	0	1	0
5040	0	1	0	0	0	1	0
5047	1	0	0	0	0	1	0
5054	0	0	1	1	0	0	0
5058	0	0	1	0	0	0	1
5063	0	0	1	1	0	0	0



Multiple correspondence analysis

- ▶ An extension of CA

Multiple correspondence analysis

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- ▶ Accommodates multiple categorical variables (CA only does 2)

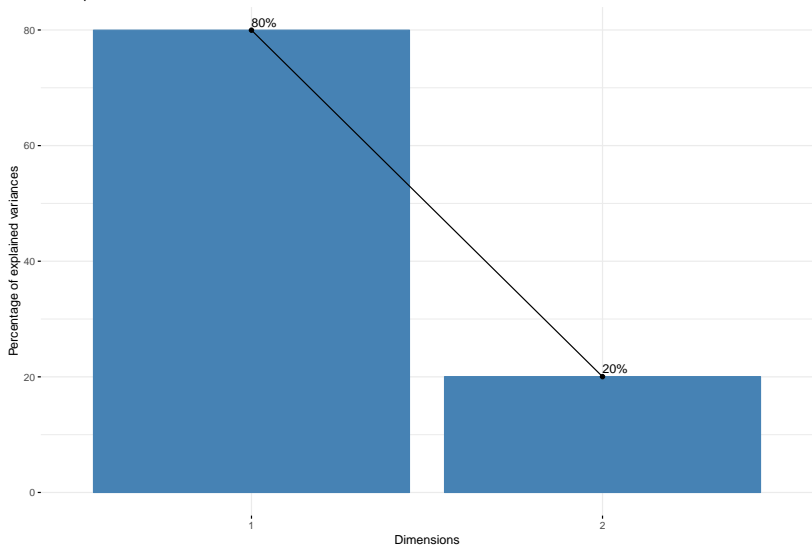
Multiple correspondence analysis

- ▶ An extension of CA
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- ▶ Corrects the dimensionality

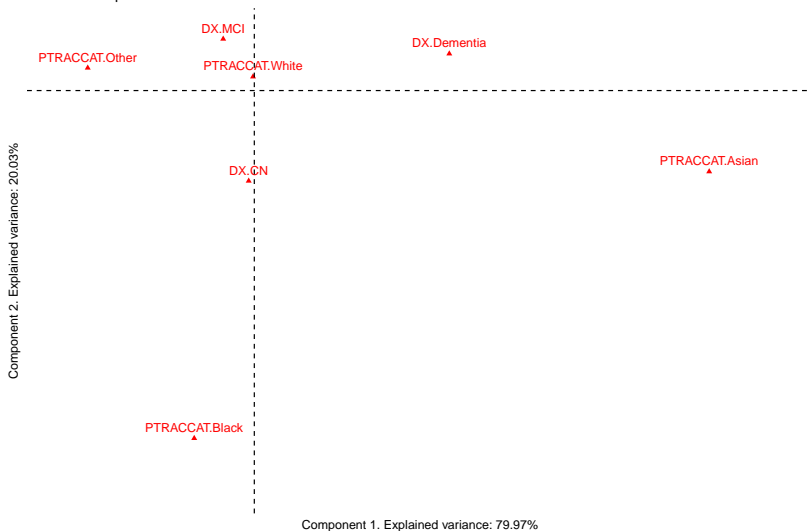
Multiple correspondence analysis

- ▶ An extension of CA
- ▶ Accommodates multiple categorical variables (CA only does 2)
- ▶ Corrects the dimensionality
- ▶ Has nearly magical properties (we'll see later)

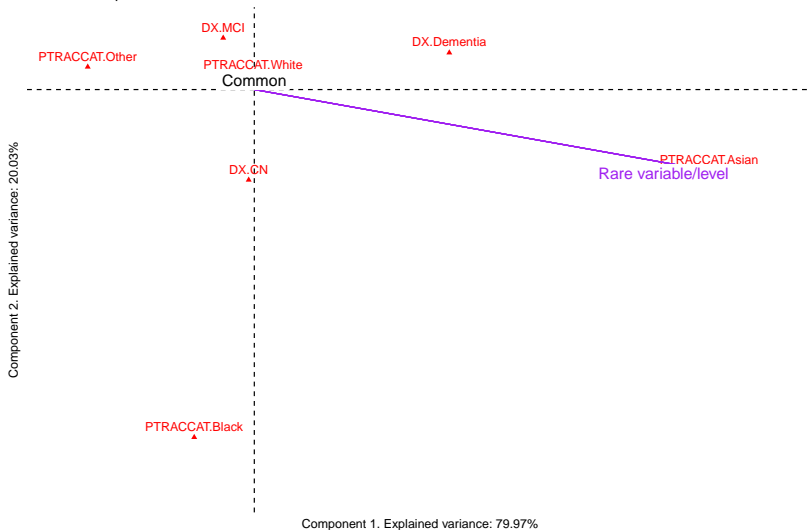
Scree plot



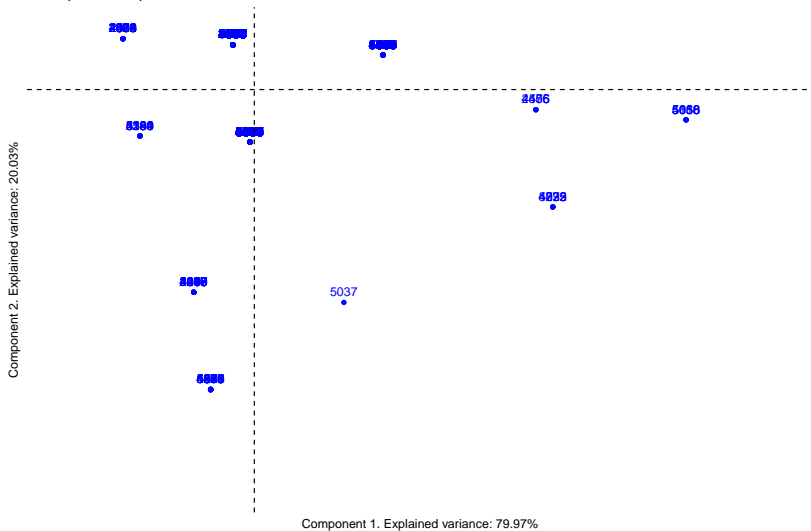
MCA:
Variable Component Scores



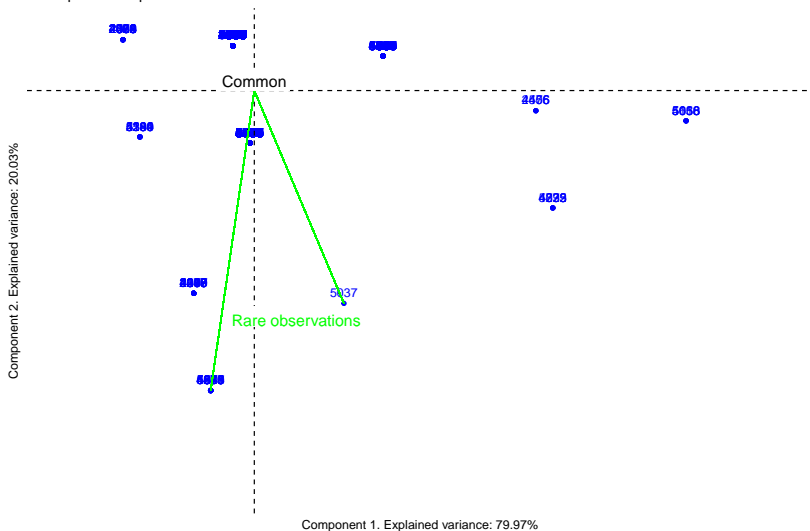
MCA:
Variable Component Scores



MCA:
Participants Component Scores



MCA:
Participants Component Scores



Why does it look like that?

DX.MCI	DX.CN	DX.Dementia	PTRACCAT.White	PTRACCAT.Other	PTRACCAT.Black	PTRACCAT.Asian
1	0	0	1	0	0	0
1	0	0	0	1	0	0
1	0	0	0	0	1	0
0	1	0	0	1	0	0
1	0	0	0	0	0	1
0	1	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	0	0	0
0	1	0	0	0	0	1
0	0	1	0	0	0	1
0	0	1	0	0	1	0

Compare the results

	PCA Comp. 1	PCA Comp. 2	PCA Comp. 3	PCA Comp. 4	PCA Comp. 5
MCA Comp. 1	0.17	-0.25	0.92	0.06	-0.26
MCA Comp. 2	-0.78	0.36	0.28	-0.42	0.03

- ▶ CA & MCA produce identical results, except MCA:

Compare the results

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- ▶ CA & MCA produce identical results, except MCA:
 - ▶ Drops components

Compare the results

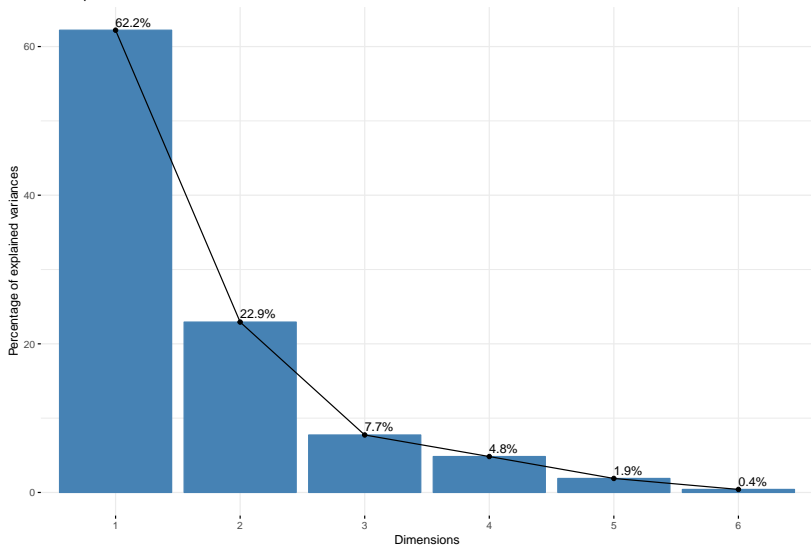
	PCA Comp. 1	PCA Comp. 2	PCA Comp. 3	PCA Comp. 4	PCA Comp. 5
MCA Comp. 1	0.17	-0.25	0.92	0.06	-0.26
MCA Comp. 2	-0.78	0.36	0.28	-0.42	0.03

- ▶ CA & MCA produce identical results, except MCA:
 - ▶ Drops components
 - ▶ Corrects explained variance

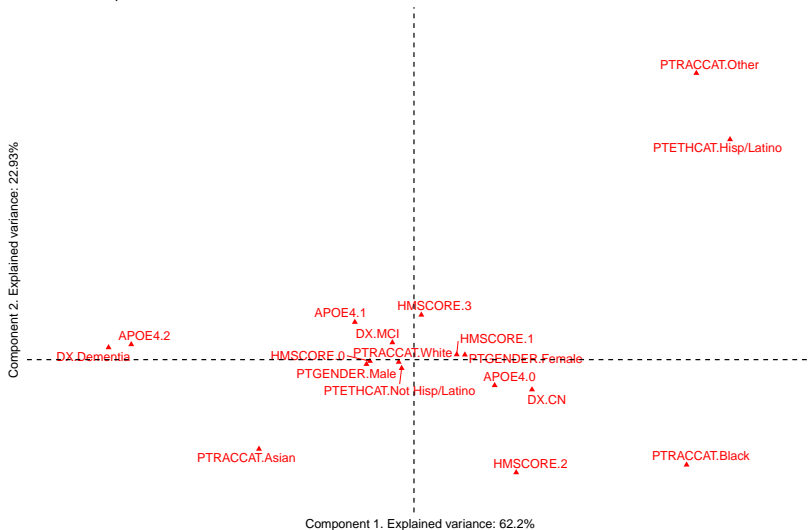
Scaling up

How the data here a bit

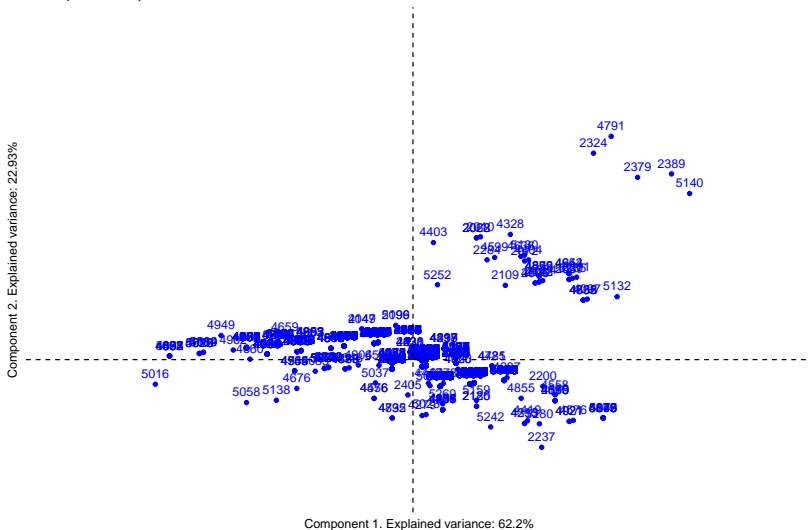
Scree plot



MCA:
Variable Component Scores

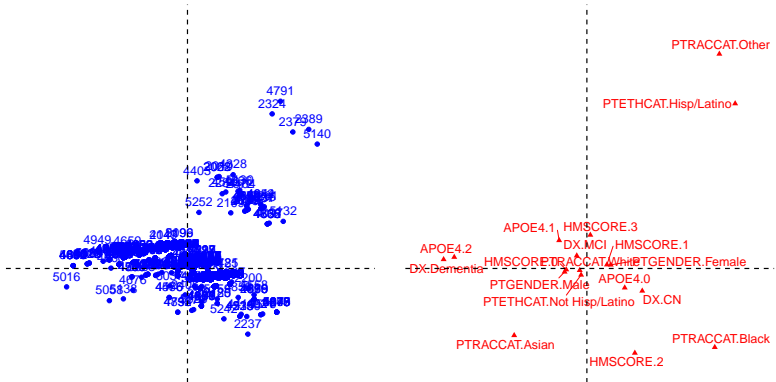


MCA:
Participants Component Scores



MCA

Component 2. Explained variance: 22.93%



Component 1. Explained variance: 62.2%

A very important detour

	PTGENDER	PTETHCAT
5023	Female	Not Hisp/Latino
5026	Female	Not Hisp/Latino
5027	Male	Not Hisp/Latino
5028	Male	Not Hisp/Latino
5031	Female	Hisp/Latino
5037	Male	Not Hisp/Latino
5040	Female	Not Hisp/Latino
5047	Female	Not Hisp/Latino
5054	Female	Not Hisp/Latino
5058	Male	Not Hisp/Latino
5063	Female	Not Hisp/Latino

Two variables with strictly two levels (i.e., binary data)

A very important detour

	PTGENDER.Male	PTGENDER.Female	PTETHCAT.Not Hisp/Latino	PTETHCAT.Hisp/Latino
5023	0	1	1	0
5026	0	1	1	0
5027	1	0	1	0
5028	1	0	1	0
5031	0	1	0	1
5037	1	0	1	0
5040	0	1	1	0
5047	0	1	1	0
5054	0	1	1	0
5058	1	0	1	0
5063	0	1	1	0

Disjunctive coding of two variables with strictly two levels (i.e., binary data) into four columns

A very important detour

	PTGENDER	PTETHCAT
5023	Female	Not Hisp/Latino
5026	Female	Not Hisp/Latino
5027	Male	Not Hisp/Latino
5028	Male	Not Hisp/Latino
5031	Female	Hisp/Latino
5037	Male	Not Hisp/Latino
5040	Female	Not Hisp/Latino
5047	Female	Not Hisp/Latino
5054	Female	Not Hisp/Latino
5058	Male	Not Hisp/Latino
5063	Female	Not Hisp/Latino

Two variables with strictly two levels (i.e., binary data)

A very important detour

	PTGENDER	PTETHCAT
5023	1	0
5026	1	0
5027	0	0
5028	0	0
5031	1	1
5037	0	0
5040	1	0
5047	1	0
5054	1	0
5058	0	0
5063	1	0

Binary coding of two variables with strictly two levels (i.e., binary data) in two columns

A very important detour

	PTGENDER	PTETHCAT
5023	0	1
5026	0	1
5027	1	1
5028	1	1
5031	0	0
5037	1	1
5040	0	1
5047	0	1
5054	0	1
5058	1	1
5063	0	1

Alternate but equivalent binary coding of two variables with strictly two levels (i.e., binary data) in two columns

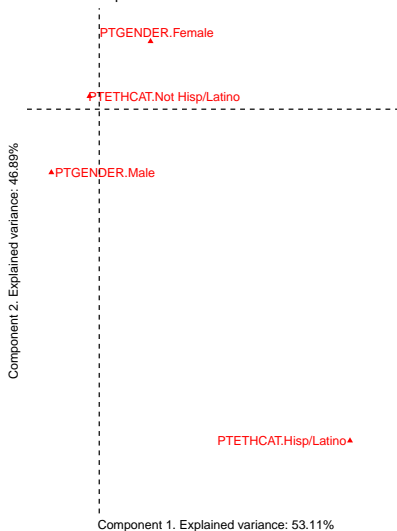
Always a bad idea?

- ▶ MCA on the disjunctive coded data

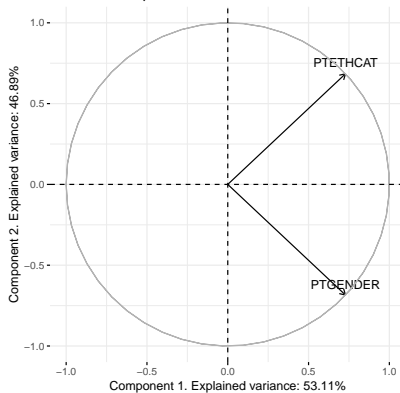
Always a bad idea?

- ▶ MCA on the disjunctive coded data
- ▶ PCA on the binary coded data

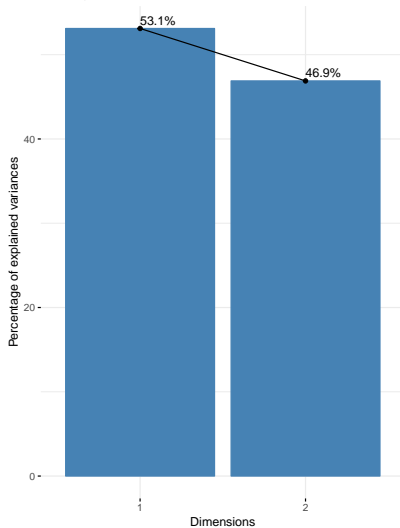
MCA:
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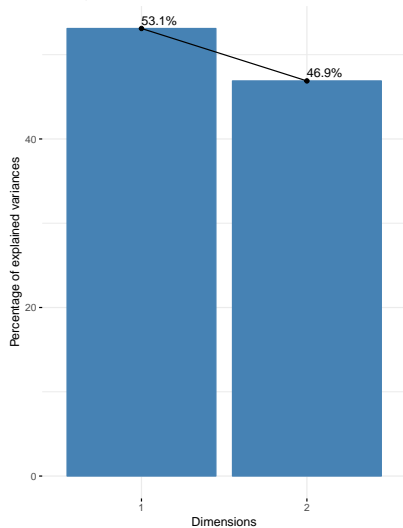
PCA:
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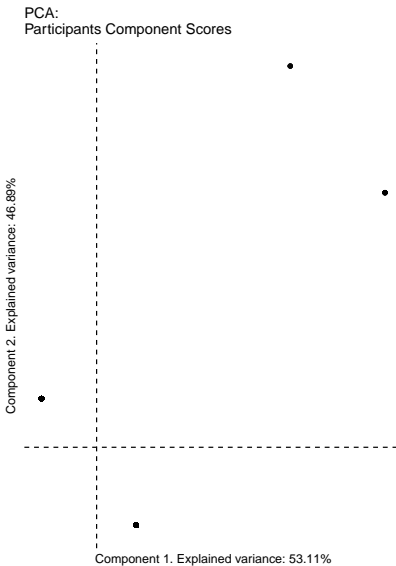
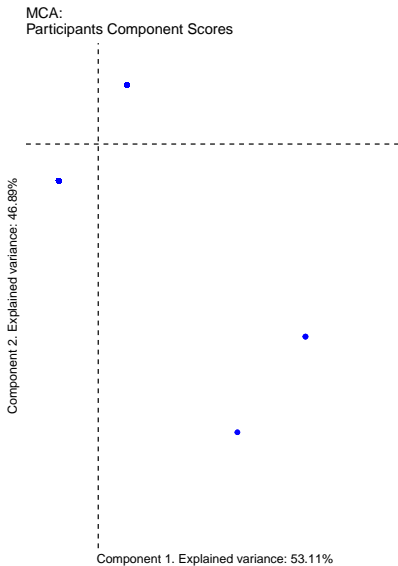
MCA:
Scree plot



PCA:
Scree plot



Oh, weird!



Component 2 is "flipped"
We will revisit this

	PCA Comp. 1	PCA Comp. 2
MCA Comp. 1	1	0
MCA Comp. 2	0	-1

Oh, double weird!

Let's get weird

	PTGENDER	PTETHCAT
PTGENDER	1.00	0.06
PTETHCAT	0.06	1.00

Let's get weird

	PTGENDER	PTETHCAT
PTGENDER	1.00	0.06
PTETHCAT	0.06	1.00

► $\phi = 0.06$

Let's get weird

	PTGENDER	PTETHCAT
PTGENDER	1.00	0.06
PTETHCAT	0.06	1.00

- ▶ $\phi = 0.06$
- ▶ Deep connections between χ^2 , Normal, binomial (and others)

Let's get weird

	PTGENDER	PTETHCAT
PTGENDER	1.00	0.06
PTETHCAT	0.06	1.00

- ▶ $\phi = 0.06$
- ▶ Deep connections between χ^2 , Normal, binomial (and others)
- ▶ We can expand the idea of “binary” or “binomial”

An old friend

	mPACCtrailsB	FDG
5023	1.12	0.13
5026	0.46	-1.31
5027	-2.77	-1.48
5028	-1.59	-0.97
5031	-0.92	-0.87
5037	-1.86	-2.00
5040	0.94	-0.21
5047	-0.25	3.05
5054	-0.80	-1.05
5058	-1.12	-2.13
5063	-2.31	-2.49

We perform PCA on these data

Escofier's Geometric Magic

- ▶ One of the “fuzzy” or “bipolar” coding schemes

Escofier's Geometric Magic

- ▶ One of the “fuzzy” or “bipolar” coding schemes
- ▶ Take each Z-scored continuous variable

Escofier's Geometric Magic

- ▶ One of the “fuzzy” or “bipolar” coding schemes
- ▶ Take each Z-scored continuous variable
- ▶ Duplicate it as $\left[\frac{1-Z}{2} \frac{1+Z}{2} \right]$

Escofier's Geometric Magic

	mPACCtrailsB-	mPACCtrailsB+	FDG-	FDG+
5023	-0.06	1.06	0.43	0.57
5026	0.27	0.73	1.16	-0.16
5027	1.88	-0.88	1.24	-0.24
5028	1.30	-0.30	0.98	0.02
5031	0.96	0.04	0.93	0.07
5037	1.43	-0.43	1.50	-0.50
5040	0.03	0.97	0.60	0.40
5047	0.62	0.38	-1.03	2.03
5054	0.90	0.10	1.03	-0.03
5058	1.06	-0.06	1.57	-0.57
5063	1.66	-0.66	1.74	-0.74

Escofier's Geometric Magic

	mPACCtrailsB-	mPACCtrailsB+	FDG-	FDG+
5023	-0.06	1.06	0.43	0.57
5026	0.27	0.73	1.16	-0.16
5027	1.88	-0.88	1.24	-0.24
5028	1.30	-0.30	0.98	0.02
5031	0.96	0.04	0.93	0.07
5037	1.43	-0.43	1.50	-0.50
5040	0.03	0.97	0.60	0.40
5047	0.62	0.38	-1.03	2.03
5054	0.90	0.10	1.03	-0.03
5058	1.06	-0.06	1.57	-0.57
5063	1.66	-0.66	1.74	-0.74

- Row sums are total number of *original* variables

Escofier's Geometric Magic

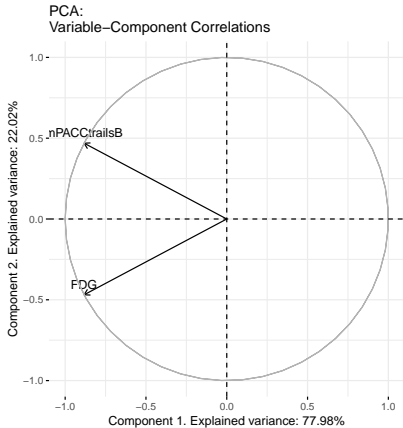
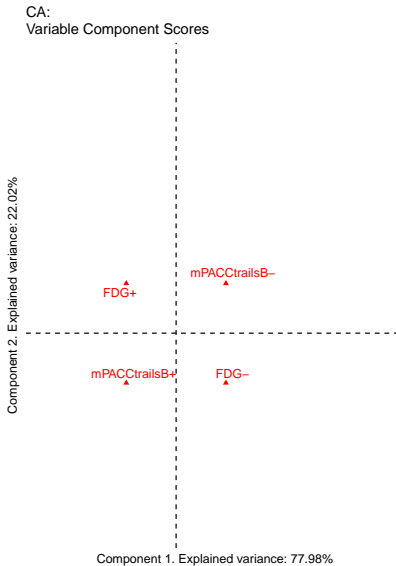
	mPACCtrailsB-	mPACCtrailsB+	FDG-	FDG+
5023	-0.06	1.06	0.43	0.57
5026	0.27	0.73	1.16	-0.16
5027	1.88	-0.88	1.24	-0.24
5028	1.30	-0.30	0.98	0.02
5031	0.96	0.04	0.93	0.07
5037	1.43	-0.43	1.50	-0.50
5040	0.03	0.97	0.60	0.40
5047	0.62	0.38	-1.03	2.03
5054	0.90	0.10	1.03	-0.03
5058	1.06	-0.06	1.57	-0.57
5063	1.66	-0.66	1.74	-0.74

- ▶ Row sums are total number of *original* variables
- ▶ Sum within a variable (e.g., FDG) is total number of rows

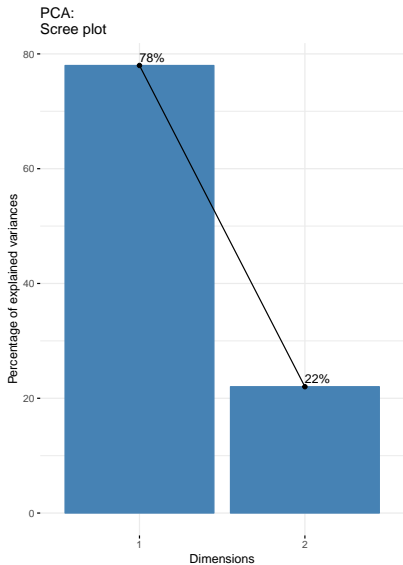
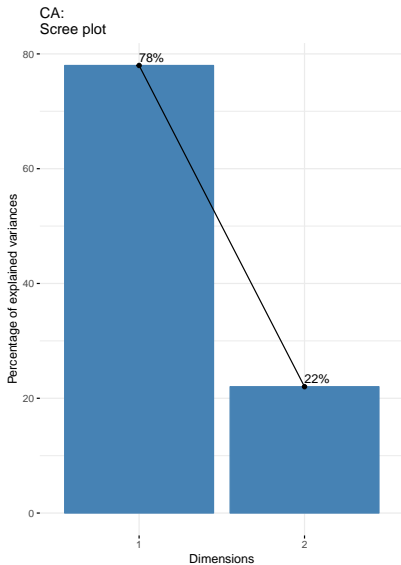
Escofier's Geometric Magic

	mPACCtrailsB-	mPACCtrailsB+	FDG-	FDG+
5023	-0.06	1.06	0.43	0.57
5026	0.27	0.73	1.16	-0.16
5027	1.88	-0.88	1.24	-0.24
5028	1.30	-0.30	0.98	0.02
5031	0.96	0.04	0.93	0.07
5037	1.43	-0.43	1.50	-0.50
5040	0.03	0.97	0.60	0.40
5047	0.62	0.38	-1.03	2.03
5054	0.90	0.10	1.03	-0.03
5058	1.06	-0.06	1.57	-0.57
5063	1.66	-0.66	1.74	-0.74

- ▶ Row sums are total number of *original* variables
- ▶ Sum within a variable (e.g., FDG) is total number of rows
- ▶ Sum of the table is rows \times columns

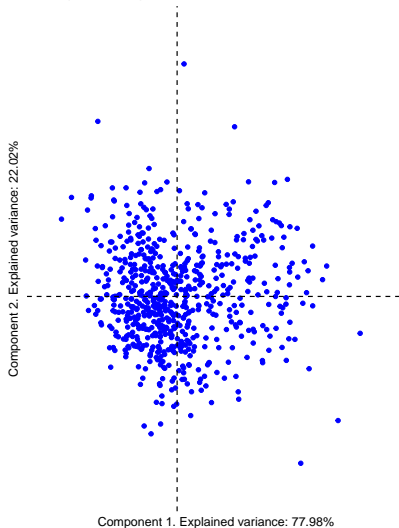


Oh, interesting!
Take note: each variable has two "poles"

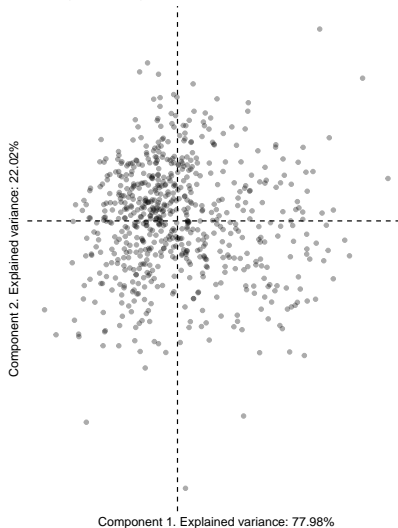


Oh, weird!

CA:
Participants Component Scores

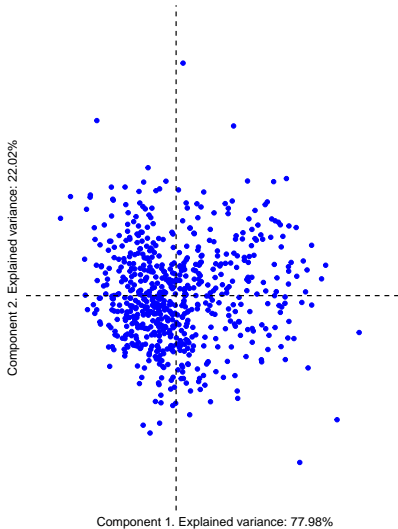


PCA:
Participants Component Scores

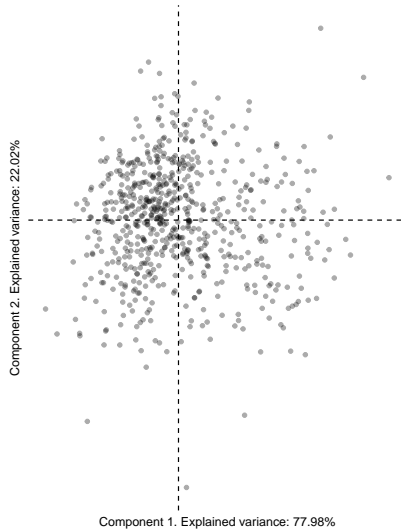


Oh, double weird!

CA:
Participants Component Scores



PCA:
Participants Component Scores



Flips: They don't matter.

	PCA Comp. 1	PCA Comp. 2
CA Comp. 1	1	0
CA Comp. 2	0	-1

Flips: They don't matter.

Escofier's Geometric Trick

- ▶ Apply PCA to continuous data or

Escofier's Geometric Trick

- ▶ Apply PCA to continuous data or
- ▶ Apply CA to “Escofier transformed” data

Thermometer

- ▶ For ordinal data

Thermometer

- ▶ For ordinal data
- ▶ Another “fuzzy” or “bipolar” coding

Thermometer

- ▶ For ordinal data
- ▶ Another “fuzzy” or “bipolar” coding
- ▶ More Escofier Geometric Magic

Thermometer

- ▶ For ordinal data
- ▶ Another “fuzzy” or “bipolar” coding
- ▶ More Escofier Geometric Magic
 - ▶ Subtract the maximum (minimum is now 0)

Thermometer

- ▶ For ordinal data
- ▶ Another “fuzzy” or “bipolar” coding
- ▶ More Escofier Geometric Magic
 - ▶ Subtract the maximum (minimum is now 0)
 - ▶ $\left[\frac{\max(x) - x}{\max} \quad \frac{x - \min(x)}{\max} \right]$

Thermometer

- ▶ For ordinal data
- ▶ Another “fuzzy” or “bipolar” coding
- ▶ More Escofier Geometric Magic
 - ▶ Subtract the maximum (minimum is now 0)
 - ▶ $\left[\frac{\max(x) - x}{\max} \quad \frac{x - \min(x)}{\max} \right]$
- ▶ Apply CA

More Geometric Magic

	PTEDUCAT	CDRSB	ADAS13	MOCA
5023	18	0.0	6	30
5026	18	1.5	8	24
5027	18	4.0	27	19
5028	16	3.5	20	19
5031	14	2.0	16	20
5037	16	5.0	35	17
5040	18	0.0	8	20
5047	16	1.0	17	24
5054	18	3.5	22	21
5058	20	3.0	17	21
5063	14	2.5	38	16

More Geometric Magic

	PTEDUCAT+	PTEDUCAT-	CDRSB+	CDRSB-	ADAS13+	ADAS13-	MOCA+	MOCA-
5023	0.75	0.25	0.00	1.00	0.13	0.87	1.00	0.00
5026	0.75	0.25	0.27	0.73	0.17	0.83	0.57	0.43
5027	0.75	0.25	0.73	0.27	0.59	0.41	0.21	0.79
5028	0.50	0.50	0.64	0.36	0.43	0.57	0.21	0.79
5031	0.25	0.75	0.36	0.64	0.35	0.65	0.29	0.71
5037	0.50	0.50	0.91	0.09	0.76	0.24	0.07	0.93
5040	0.75	0.25	0.00	1.00	0.17	0.83	0.29	0.71
5047	0.50	0.50	0.18	0.82	0.37	0.63	0.57	0.43
5054	0.75	0.25	0.64	0.36	0.48	0.52	0.36	0.64
5058	1.00	0.00	0.55	0.45	0.37	0.63	0.36	0.64
5063	0.25	0.75	0.45	0.55	0.83	0.17	0.00	1.00

More Geometric Magic

	PTEDUCAT+	PTEDUCAT-	CDRSB+	CDRSB-	ADAS13+	ADAS13-	MOCA+	MOCA-
5023	0.75	0.25	0.00	1.00	0.13	0.87	1.00	0.00
5026	0.75	0.25	0.27	0.73	0.17	0.83	0.57	0.43
5027	0.75	0.25	0.73	0.27	0.59	0.41	0.21	0.79
5028	0.50	0.50	0.64	0.36	0.43	0.57	0.21	0.79
5031	0.25	0.75	0.36	0.64	0.35	0.65	0.29	0.71
5037	0.50	0.50	0.91	0.09	0.76	0.24	0.07	0.93
5040	0.75	0.25	0.00	1.00	0.17	0.83	0.29	0.71
5047	0.50	0.50	0.18	0.82	0.37	0.63	0.57	0.43
5054	0.75	0.25	0.64	0.36	0.48	0.52	0.36	0.64
5058	1.00	0.00	0.55	0.45	0.37	0.63	0.36	0.64
5063	0.25	0.75	0.45	0.55	0.83	0.17	0.00	1.00

- ▶ Row sums are total number of *original* variables

More Geometric Magic

	PTEDUCAT+	PTEDUCAT-	CDRSB+	CDRSB-	ADAS13+	ADAS13-	MOCA+	MOCA-
5023	0.75	0.25	0.00	1.00	0.13	0.87	1.00	0.00
5026	0.75	0.25	0.27	0.73	0.17	0.83	0.57	0.43
5027	0.75	0.25	0.73	0.27	0.59	0.41	0.21	0.79
5028	0.50	0.50	0.64	0.36	0.43	0.57	0.21	0.79
5031	0.25	0.75	0.36	0.64	0.35	0.65	0.29	0.71
5037	0.50	0.50	0.91	0.09	0.76	0.24	0.07	0.93
5040	0.75	0.25	0.00	1.00	0.17	0.83	0.29	0.71
5047	0.50	0.50	0.18	0.82	0.37	0.63	0.57	0.43
5054	0.75	0.25	0.64	0.36	0.48	0.52	0.36	0.64
5058	1.00	0.00	0.55	0.45	0.37	0.63	0.36	0.64
5063	0.25	0.75	0.45	0.55	0.83	0.17	0.00	1.00

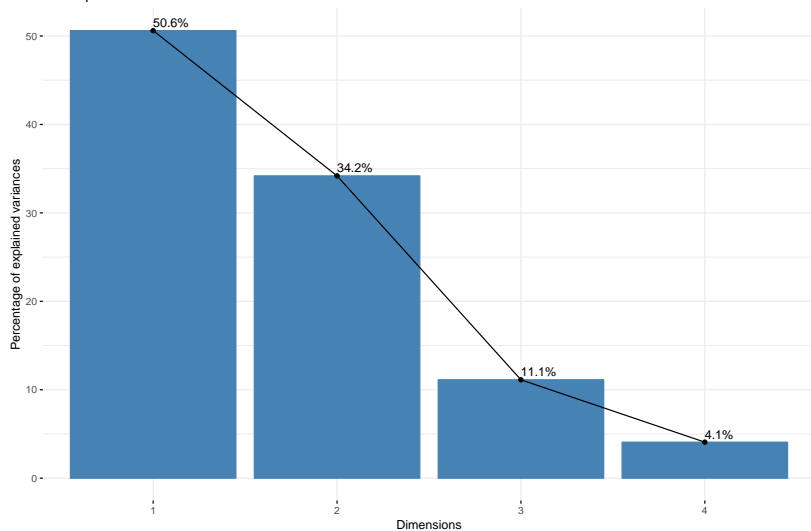
- ▶ Row sums are total number of *original* variables
- ▶ Sum within a variable (e.g. EDU) is total number of rows

More Geometric Magic

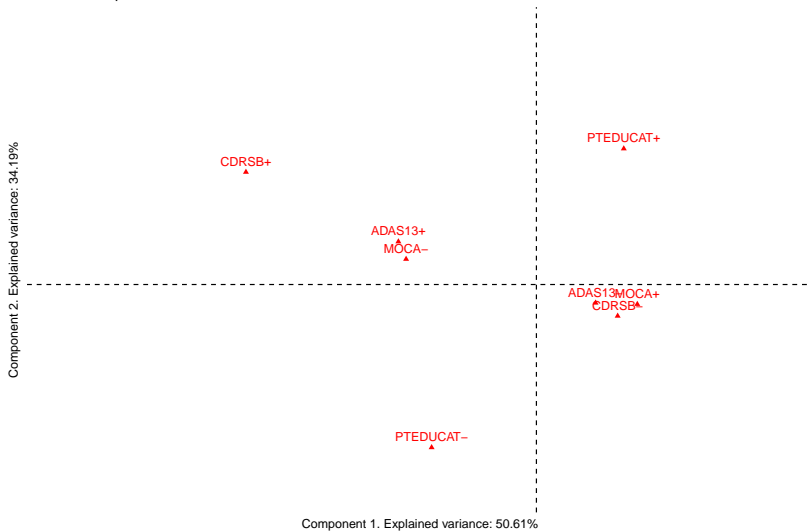
	PTEDUCAT+	PTEDUCAT-	CDRSB+	CDRSB-	ADAS13+	ADAS13-	MOCA+	MOCA-
5023	0.75	0.25	0.00	1.00	0.13	0.87	1.00	0.00
5026	0.75	0.25	0.27	0.73	0.17	0.83	0.57	0.43
5027	0.75	0.25	0.73	0.27	0.59	0.41	0.21	0.79
5028	0.50	0.50	0.64	0.36	0.43	0.57	0.21	0.79
5031	0.25	0.75	0.36	0.64	0.35	0.65	0.29	0.71
5037	0.50	0.50	0.91	0.09	0.76	0.24	0.07	0.93
5040	0.75	0.25	0.00	1.00	0.17	0.83	0.29	0.71
5047	0.50	0.50	0.18	0.82	0.37	0.63	0.57	0.43
5054	0.75	0.25	0.64	0.36	0.48	0.52	0.36	0.64
5058	1.00	0.00	0.55	0.45	0.37	0.63	0.36	0.64
5063	0.25	0.75	0.45	0.55	0.83	0.17	0.00	1.00

- ▶ Row sums are total number of *original* variables
- ▶ Sum within a variable (e.g. EDU) is total number of rows
- ▶ Sum of the table is rows \times columns

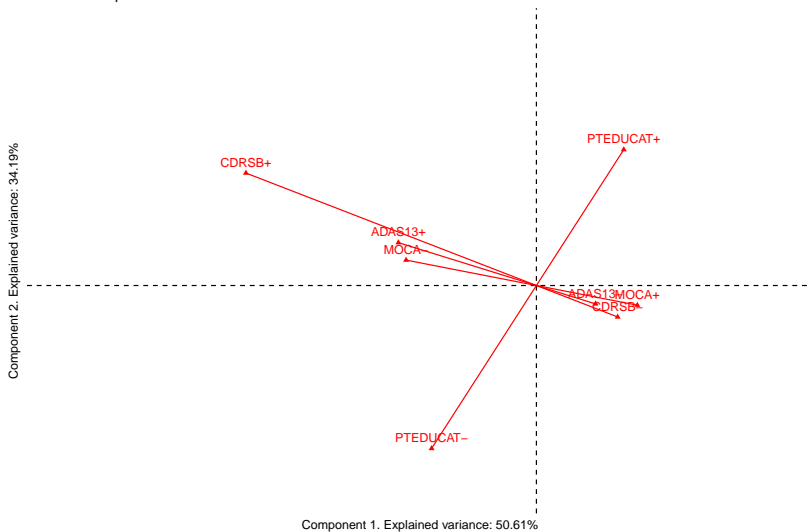
CA:
Scree plot



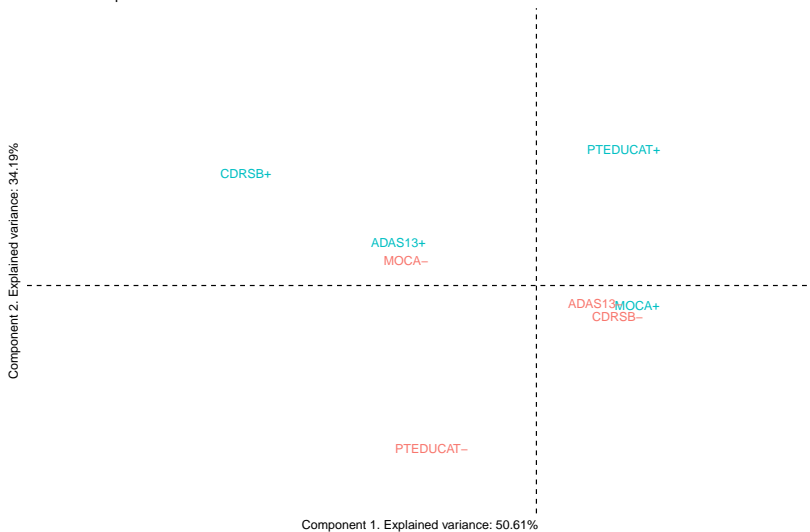
CA:
Variable Component Scores



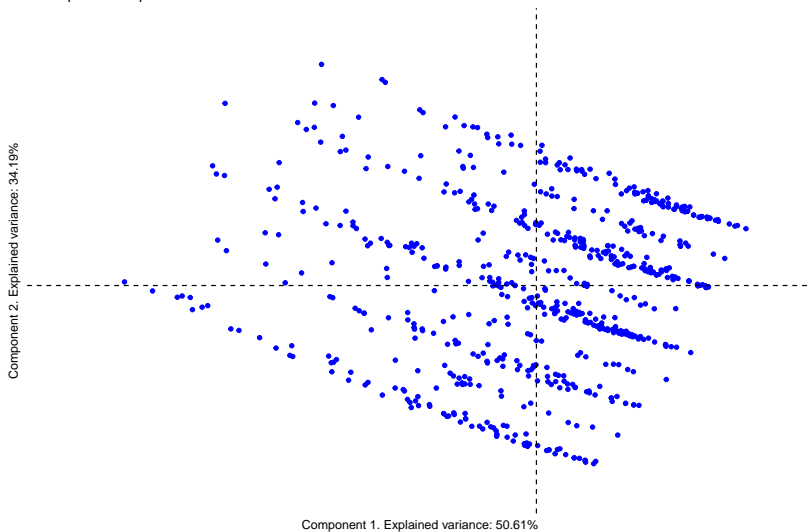
CA:
Variable Component Scores



CA:
Variable Component Scores

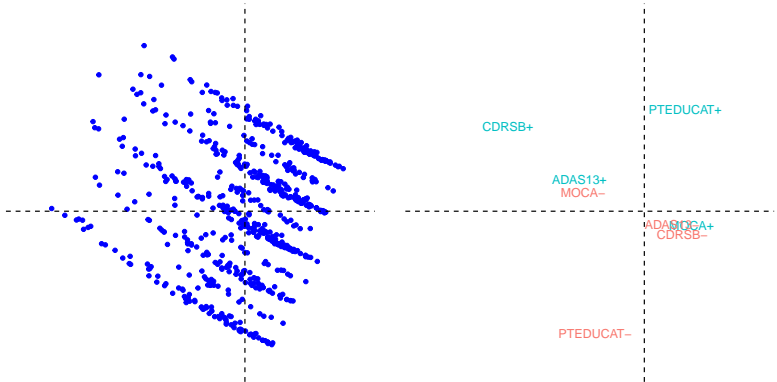


CA:
Participants Component Scores



CA

Component 2. Explained variance: 34.19%



Component 1. Explained variance: 50.61%

Thermometer vs. Disjunctive

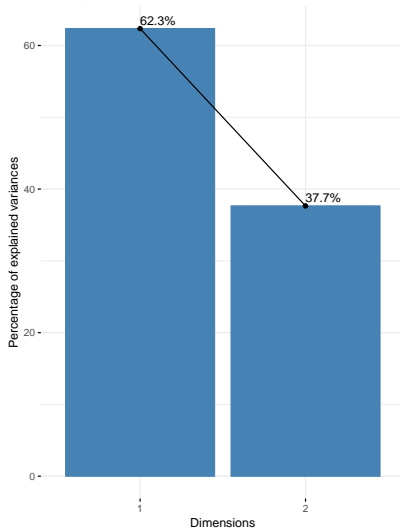
- ▶ Sometimes data could be either

Thermometer vs. Disjunctive

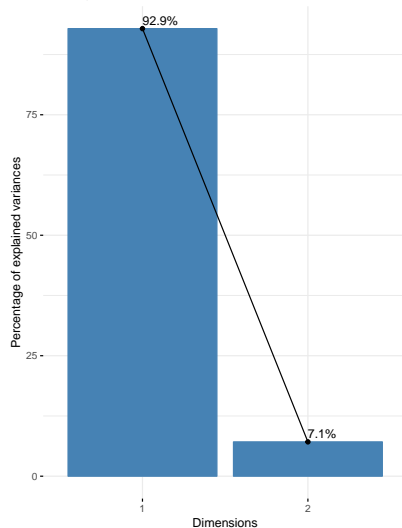
- ▶ Sometimes data could be either
- ▶ Let's analyze it both ways

	APOE4	HMSCORE
5023	0	0
5026	1	1
5027	0	1
5028	2	1
5031	0	1
5037	1	1
5040	0	1
5047	2	1
5054	1	0
5058	0	0
5063	1	1

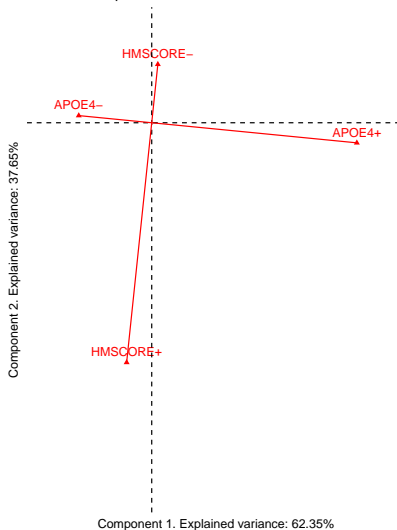
CA (thermometer):
Scree plot



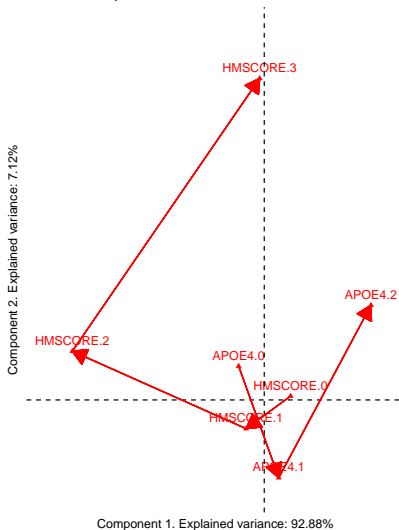
MCA (disjunctive):
Scree plot



CA (thermometer):
Variable Component Scores



MCA (disjunctive):
Variable Component Scores



Thermometer vs. Disjunctive

- ▶ For a small (reasonable) number of levels: disjunctive

Thermometer vs. Disjunctive

- ▶ For a small (reasonable) number of levels: disjunctive
- ▶ Otherwise: thermometer

Thermometer vs. Disjunctive

- ▶ For a small (reasonable) number of levels: disjunctive
- ▶ Otherwise: thermometer
- ▶ Interpretation:

Thermometer vs. Disjunctive

- ▶ For a small (reasonable) number of levels: disjunctive
- ▶ Otherwise: thermometer
- ▶ Interpretation:
 - ▶ Thermometer is “easier”

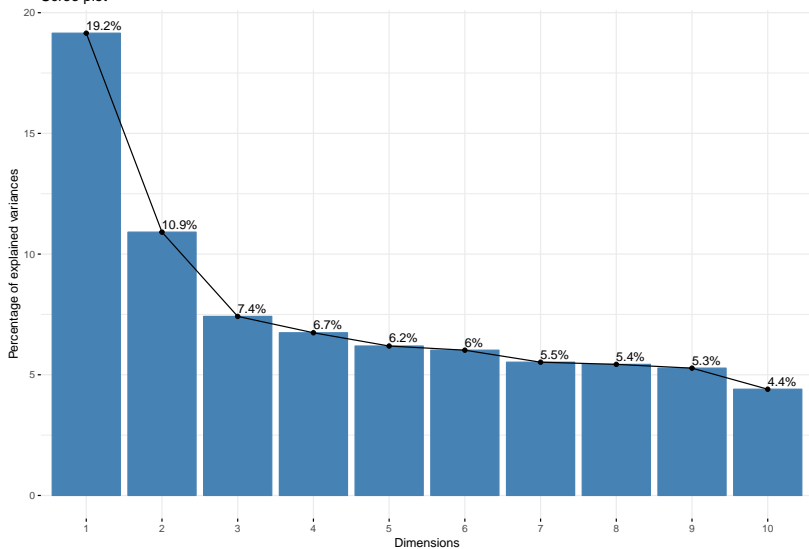
Thermometer vs. Disjunctive

- ▶ For a small (reasonable) number of levels: disjunctive
- ▶ Otherwise: thermometer
- ▶ Interpretation:
 - ▶ Thermometer is “easier”
 - ▶ Disjunctive is more informative

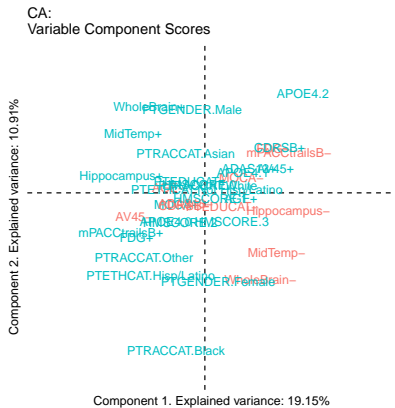
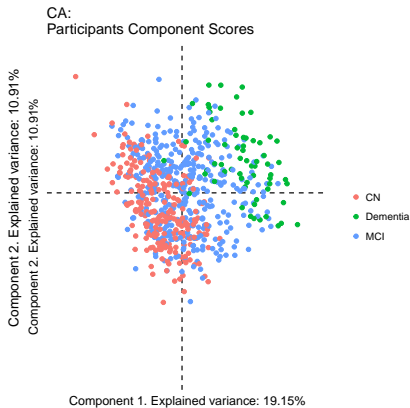
All of the data

	DX	AGE	PTGENDER	PTEDUCAT	PTETHCAT	PTRACCAT	APOE4	FDG	AV45	CDRSB	ADAS13	MOCA	WholeBrain	Hippocampus	MidTemp	mPACtrailsB	HMSCORE
5023	CN	63.9	Female	18	Not Hisp/Latino	Asian	0	1.29	1.03	0.0	6	30	1057351.0	7904	21306	1.81	0
5026	MCI	70.5	Female	18	Not Hisp/Latino	White	1	1.08	1.44	1.5	8	24	1023057.3	8051	16501	-1.45	1
5027	Dementia	75.5	Male	18	Not Hisp/Latino	White	0	1.06	1.44	4.0	27	19	986723.7	6534	17437	-17.27	1
5028	Dementia	61.9	Male	16	Not Hisp/Latino	White	2	1.13	1.38	3.5	20	19	1182704.6	7481	20797	-11.50	1
5031	MCI	80.2	Female	14	Hisp/Latino	White	0	1.14	1.52	2.0	16	20	908133.9	5040	19032	-8.21	1
5037	Dementia	67.3	Male	16	Not Hisp/Latino	Black	1	0.98	1.21	5.0	35	17	1161499.6	5831	21428	-12.80	1
5040	CN	75.9	Female	18	Not Hisp/Latino	Black	0	1.24	1.01	0.0	8	20	943160.6	7994	16634	0.94	1
5047	MCI	68.8	Female	16	Not Hisp/Latino	Black	2	1.70	1.48	1.0	17	24	1070406.1	7920	22043	-4.90	1
5054	Dementia	74.0	Female	18	Not Hisp/Latino	White	1	1.12	1.43	3.5	22	21	1138040.1	6580	20836	-7.63	0
5058	Dementia	61.8	Male	20	Not Hisp/Latino	Asian	0	0.97	1.54	3.0	17	21	1195549.3	7318	22757	-9.18	0
5063	Dementia	71.5	Female	14	Not Hisp/Latino	White	1	0.92	1.61	2.5	38	16	817421.2	5364	12542	-15.03	1

Scree plot



CA:
Everything!



Component 1. Explained variance: 19.15%

Resampling

FUCK