

Statistical learning - Unsupervised learning

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Unsupervised learning

Unsupervised learning is a set of tools to explore possible structure in a set of n observation of p variables.

- ▶ There is no outcome variable - no predictions.
- ▶ There is no way to check how well the algorithm works.
- ▶ Often part of an exploratory data analysis.
 - ▶ Aiming at visualizing the data in informing ways - PCA.
 - ▶ Aiming at finding subgroups in the data - clustering.

Principal component analysis

Problem: One has a set of n observation of p variables X_1, X_2, \dots, X_p . How to visualize / understand the data?

- ▶ Plot all combinations of 2 or 3 dimensional plots.
Unfeasible for large p !
- ▶ Find a low-representation of the data that captures as much as the information as possible.

Principal component analysis (PCA):

- ▶ Finds a set of dimensions that are as interesting as possible.
- ▶ Interesting: a large variation of the data is on that dimension.

Principal components

Example in 2 dimensions:

- ▶ 1st principal component - direction through the data that explains the most variance
- ▶ 2nd principal component - direction orthogonal to that of the 1st component, explaining the next greatest amount of variance

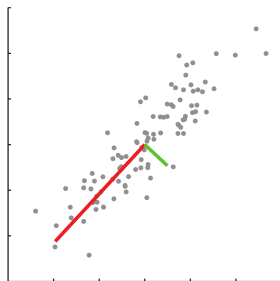


Figure adapted from Poldrack et al. 2011

Each component is a linear combination of the original variables.

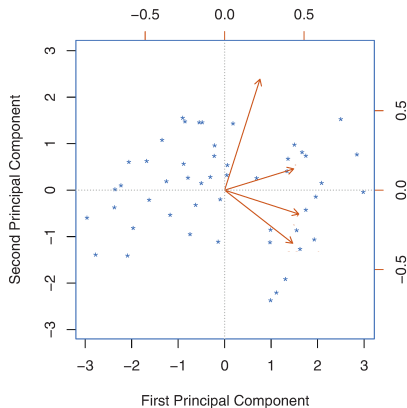
First principal component:

$$Z_1 = \phi_{11}X_1 + \phi_{21}X_2 + \cdots + \phi_{p1}X_p, \quad \text{with} \quad \sum_{j=1}^p \phi_{j1}^2 = 1$$

ϕ s are the loadings of the first principal component.

Visualizing the data

- ▶ 50 observations of 4 variables
- ▶ Blue dots: Scores of the observations in the first two components.
- ▶ Orange arrows: The first two principal components vectors of loadings.



Further remarks

- ▶ Variables should be centered and scaled before PCA.
- ▶ How many principal components shall one retain?
 - ▶ Proportion of explained variance by the first components
 - ▶ Scree plots

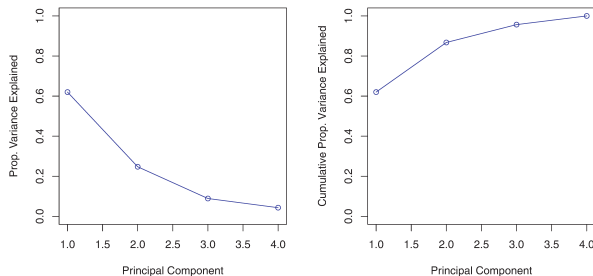


Figure adapted from Jones et al. 2013

- ▶ One chooses the smallest amount of components to retain a large amount of the total variance.



Contents lists available at ScienceDirect

Neuropsychologia

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Principal component analysis of behavioural individual differences suggests that particular aspects of visual working memory may relate to specific aspects of attention

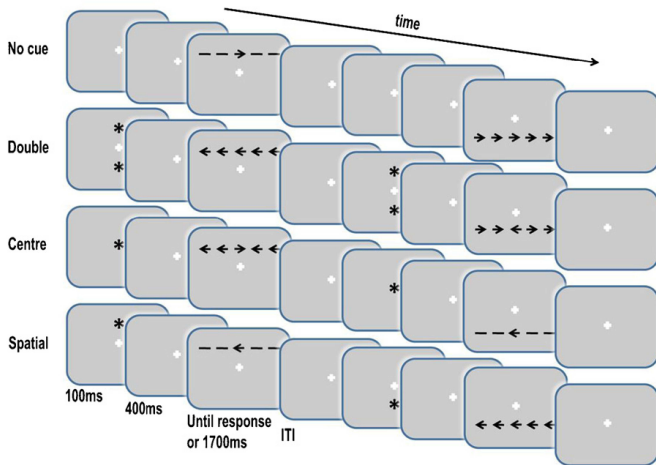
Maro G. Machizawa^{a,b,*}, Jon Driver^{a,b,c}

^a UCL Institute of Cognitive Neuroscience, University College London, United Kingdom

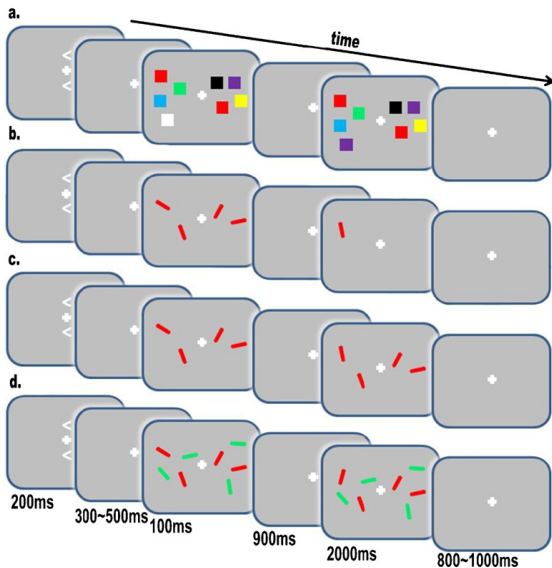
^b UCL Institute of Neurology, University College London, United Kingdom

^c Wellcome Trust Centre for Neuroimaging at UCL, University College London, United Kingdom

Example - attention tasks



Example - working-memory tasks



Example - results

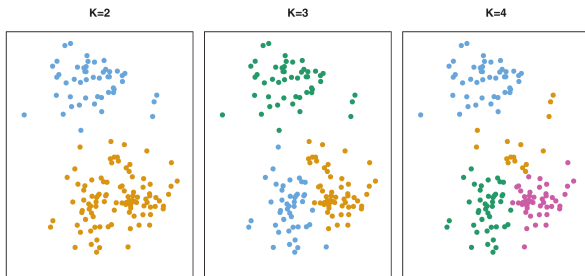
- ▶ 50 subjects
- ▶ 3 measures of attention: alerting score, orienting score, conflict score
- ▶ 3 measures of visual working-memory: capacity, precision, filtering efficiency

	Components		
	1	2	3
WM capacity	.76	.08	.17
ANT alerting	.70	-.06	-.10
WM precision	.34	.80	.17
ANT orienting	.31	-.82	.16
WM filtering	.20	-.04	.74
ANT executive	-.14	.04	.82

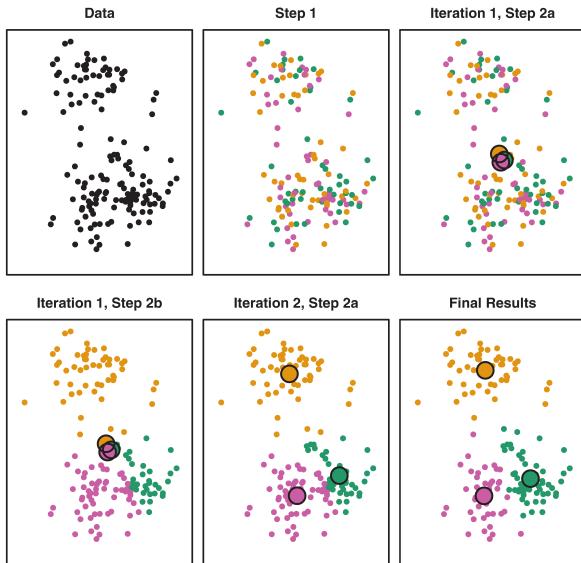
Clustering - K -means clustering

Aim: separating the observation into K clusters.

- ▶ Each observation will be assigned to one and only one cluster - no overlapping.
- ▶ Clusters are determined so that the within cluster variation is as small as possible.
- ▶ Variation is defined using a distance - usually euclidean distance.
- ▶ The number K of clusters is pre-specified.



K-means clustering - one algorithm illustration



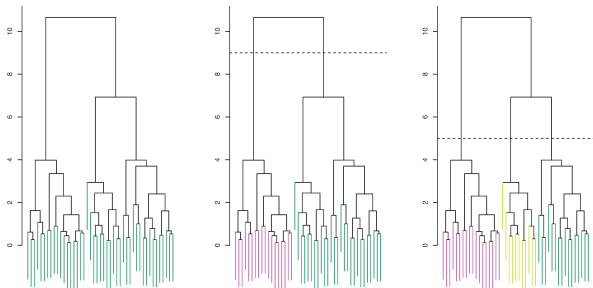
Local optimum

- ▶ The final solution is a local and not a global optimum.
- ▶ One runs several times and selects the best solution.



Hierarchical clustering

- ▶ Agglomerative clustering: clusters are fused, a pair at a time, based on similarity.
- ▶ The resulting dendrogram can be cut at different levels.
- ▶ A measure of distance is defined - usually euclidean distance.
- ▶ A measure of cluster similarity is defined. For example: complete linkage or average linkage.



Hierarchical clustering

