Training in ade4 in R - Module II: Advanced methods

Two-table methods

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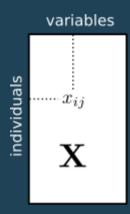
2025-10-19

Introduction

```
## List of 4
## $ env :'data.frame': 30 obs. of 11 variables:
## $ fish :'data.frame': 30 obs. of 27 variables:
## $ xy :'data.frame': 30 obs. of 2 variables:
## $ species:'data.frame': 27 obs. of 4 variables:
```

- Species table: abundance of 27 fish species recorded for 30 sites on the Doubs river
- Environmental table: 11 environmental variables for the same sites
- Spatial coordinates

Introduction

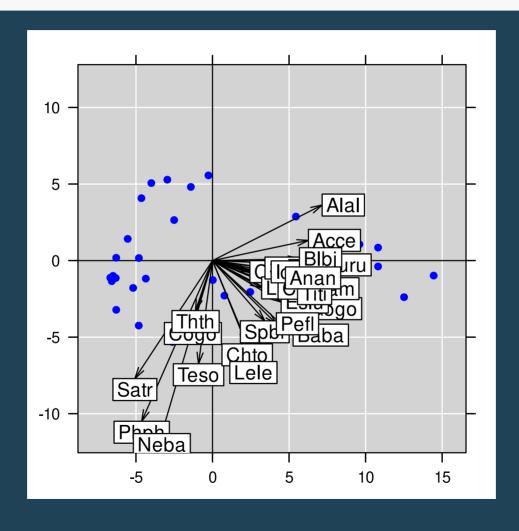


One table with p variables measured on n individuals

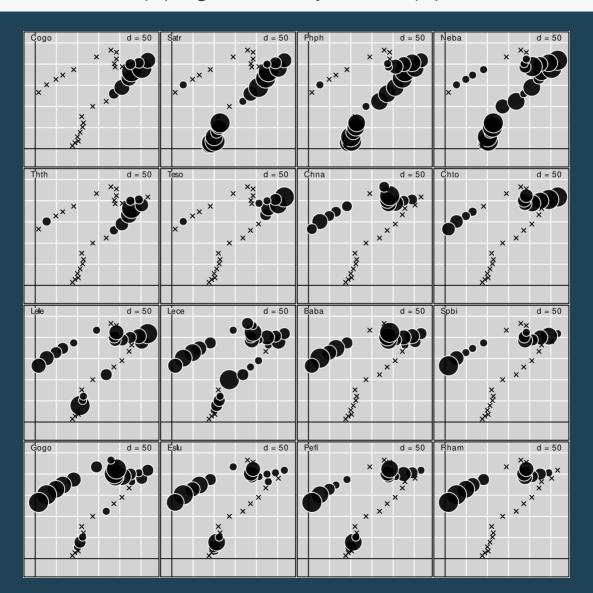
- quantitative (dudi.pca)
- categorical (dudi.coa or dudi.acm)
- both (dudi.mix or dudi.hillsmith)

Describe the information contained in the table:

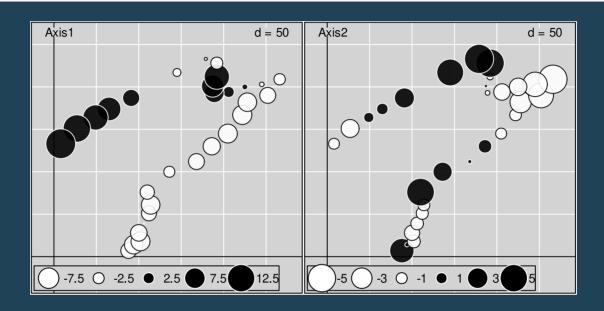
- Identify which variables are the most linked
- Identify the differences/similarities between individuals



```
s.value(doubs$xy, doubs$fish[, 1:16], centerpar = TRUE,
    symbol = "circle", plegend.drawKey = FALSE, paxes.draw = FALSE)
```

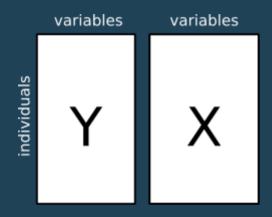


```
s.value(doubs$xy, pca_fish$li, symbol = "circle",
    paxes.draw = FALSE)
```



Which factors can explain these structures?

Two tables



One table with p variables measured on n individuals

One table with *m* variables measured on the same individuals

Identify what is the information common to both tables:

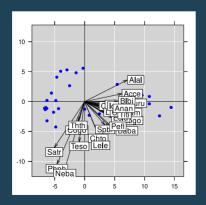
- Identify which variables are the most linked
- Identify how this link varies for individuals

But how?

Indirect ordination



Summarize by a simple ordination method

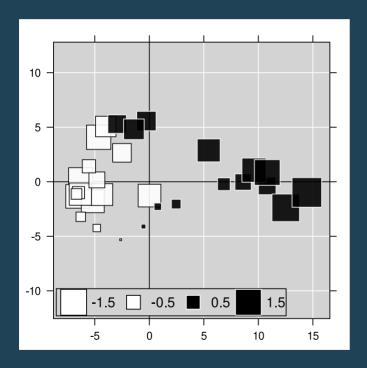




and interpret the structures with the second table using simple tools

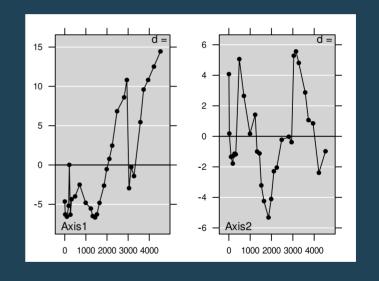
- Graphical interpretation
- Correlation
- Regression

Graphics



Correlation

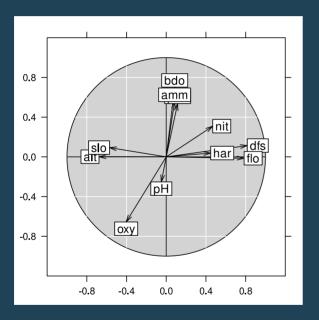
```
s1d.curve(pca_fish$li,
    p1.horizontal = FALSE,
    at = doubs$env$dfs)
```



cor(pca_fish\$li, doubs\$env\$dfs)

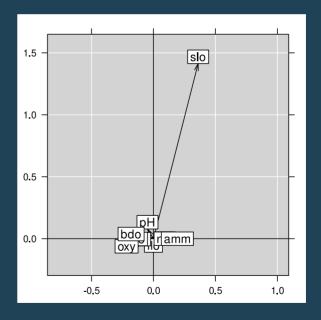
```
## [,1]
## Axis1 0.8169072
## Axis2 0.1136704
```

Correlation

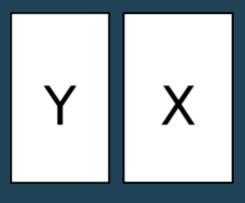


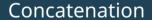
Regression

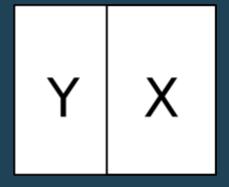
```
lm1 <- lm(as.matrix(pca_fish$li)
    as.matrix(doubs$env))
s.arrow(coefficients(lm1)[-1,
    ], labels = names(doubs$env))</pre>
```



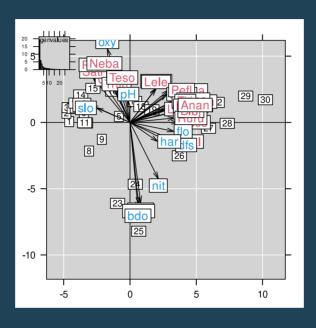
Analysis of the concanated table



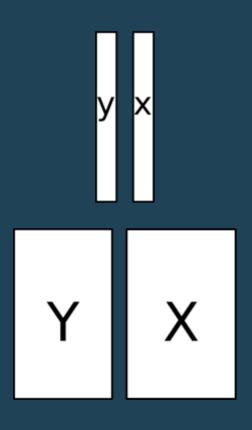




Simple ordination



From two variables to two tables



- Canonical Correlation Analysis (correlation)
- Co-Inertia Analysis (covariance)
- Analysis on instrumental variables (regression)

Linear combinations

PCA

Find a vector of coefficients $\mathbf{a}=[a_1,\cdots,a_p]^ op$ maximizing $\|\mathbf{X}\mathbf{Q}\mathbf{a}\|_{\mathbf{D}}^2$ with $\|\mathbf{a}\|_{\mathbf{O}}=1$

Linear regression

Find a vector of coefficients $\mathbf{a} = [a_1, \cdots, a_p]^ op$ maximizing $\|\mathbf{X}\mathbf{a}\mathbf{y}\|_{\mathbf{D}}^2$

Two-table methods

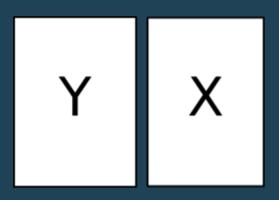
Define two vectors of coefficients ${f a}$ and ${f b}$ to build two linear combinations ${f XQa}$ and ${f YMb}$

Canonical correlation analysis



- function stats:cancor
- ullet maximization of $cor(\mathbf{Xa},\mathbf{Yb})$

Co-inertia analysis

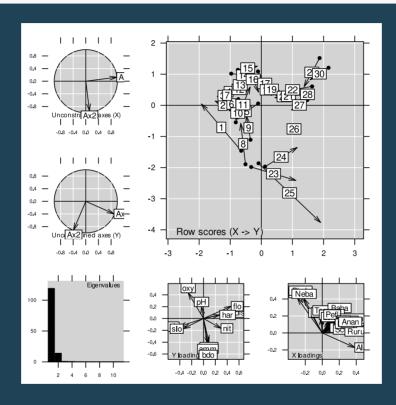


- function ade4::coinertia
- maximization of $cov(\mathbf{XQa}, \mathbf{YMb})$

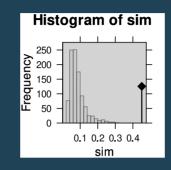
A compromise between canonical correlation analysis, and the two PCAs:

$$cov(\mathbf{XQa}, \mathbf{YMb}) = cor(\mathbf{XQa}, \mathbf{YMb}) \cdot \|\mathbf{XQa}\|_{\mathbf{D}} \cdot \|\mathbf{YMb}\|_{\mathbf{D}}$$

pca_env <- dudi.pca(doubs\$env, scannf = FALSE)
coi <- coinertia(pca_fish, pca_env, scannf = FALSE)
plot(coi)</pre>

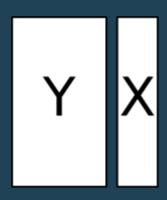


```
rt.coi <- randtest(coi)
plot(rt.coi)</pre>
```



Try summary(coi)

Analysis on instrumental variables



- function ade4::pcaiv
- maximization of $\|\widehat{\mathbf{Y}}\mathbf{Qa}\|_{\mathbf{D}}^2$

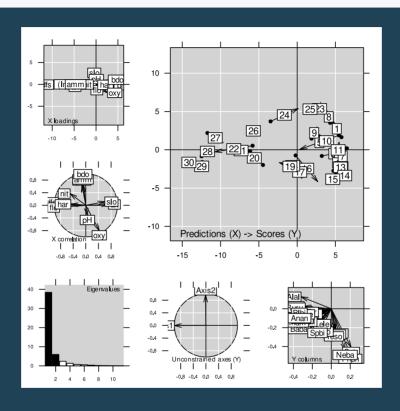
This framework encompasses:

- Redundancy Analysis (RDA)
- Canonical Correspondence Analysis (CCA)

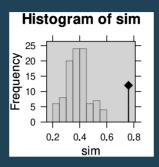
In practice, it corresponds to the PCA (for RDA) or CA (for CCA) of the predicted table $\widehat{\mathbf{Y}}$ containing the prediction of the linear models of \mathbf{Y} by \mathbf{X} .

In vegan, use functions rda and cca with a formula interface.

rda1 <- pcaiv(pca_fish, doubs\$env, scannf = FALSE)
plot(rda1)</pre>



rt.rda <- randtest(rda1)
plot(rt.rda)</pre>



Try summary(rda1)

When a PCA is applied on the response table, the method is called Redundancy Analysis

Try to apply a correspondence analysis (dudi.coa) instead of a PCA on doubs\$fish. You obtain Canonical Correspondence Analysis.

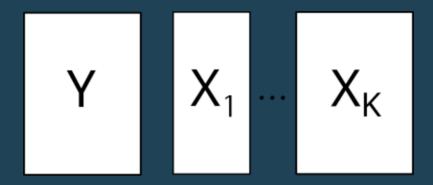
Partial analyses

In some circumstances, it is useful to remove an effect corresponding to covariables (e.g., sampling constraints) to identify structures that are independent to this effect.

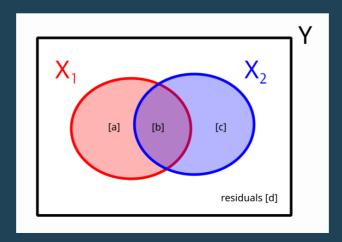
Partial analysis is implemented in function orthopcaiv which focuses on the analysis of residual table ${f E}={f Y}-\widehat{{f Y}}$.

In vegan, this is implemented by Condition() in the formula framework.

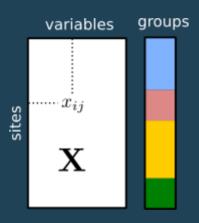
Variation partitioning



When multiple sets of explanatory variables are considered, variation partitioning can be applied to identify their additive contribution to the structuring of the response table (see varipart or more complete vegan::varpart).



One particular case



The second table contains only one categorical variable

The aim is to maximize the separation between the groups

- cancor-like method is Discriminant Analysis (ade4::discrimin)
- pcaiv-like method is Between-Class Analaysis (ade4::bca)