

# Vegan: an introduction to ordination

Jari Oksanen

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## Abstract

The document describes typical, simple work pathways of vegetation ordination. Unconstrained ordination uses as examples detrended correspondence analysis and non-metric multidimensional scaling, and shows how to interpret their results by fitting environmental vectors and factors or smooth environmental surfaces to the graph. The basic plotting command, and more advanced plotting commands for congested plots are also discussed, as well as adding items such as ellipses, convex hulls, and other items for classes. The constrained ordination uses constrained (canonical) correspondence analysis as an example. It is first shown how a model is defined, then the document discusses model building and significance tests of the whole analysis, single constraints and axes.

## Contents

<b>1</b>	<b>Ordination</b>	<b>2</b>
1.1	Detrended correspondence analysis . . . . .	2
1.2	Non-metric multidimensional scaling . . . . .	2
<b>2</b>	<b>Ordination graphics</b>	<b>3</b>
2.1	Cluttered plots . . . . .	4
2.2	Adding items to ordination plots . . . . .	5
<b>3</b>	<b>Fitting environmental variables</b>	<b>6</b>
<b>4</b>	<b>Constrained ordination</b>	<b>7</b>
4.1	Significance tests . . . . .	9
4.2	Conditioned or partial ordination . . . . .	10

**Vegan** is a package for community ecologists. This documents explains how the commonly used ordination methods can be performed in **vegan**. The document only is a very basic introduction. Another document (*vegan tutorial*) (<http://cc.oulu.fi/~jarioksa/opetus/method/vegantutor.pdf>) gives a longer and more detailed introduction to ordination. The current document only describes a small part of all **vegan** functions. For most functions, the canonical references are the **vegan** help pages, and some of the most important additional functions are listed at this document.

# 1 Ordination

The **vegan** package contains all common ordination methods: Principal component analysis (function **rda**, or **prcomp** in the base R), correspondence analysis (**cca**), detrended correspondence analysis (**decorana**) and a wrapper for non-metric multidimensional scaling (**metaMDS**). Functions **rda** and **cca** mainly are designed for constrained ordination, and will be discussed later. In this chapter I describe functions **decorana** and **metaMDS**.

## 1.1 Detrended correspondence analysis

Detrended correspondence analysis (DCA) is done like this:

```
> library(vegan)
> data(dune)
> ord <- decorana(dune)
```

This saves ordination results in **ord**:

```
> ord
```

Call:

```
decorana(veg = dune)
```

Detrended correspondence analysis with 26 segments.

Rescaling of axes with 4 iterations.

	DCA1	DCA2	DCA3	DCA4
Eigenvalues	0.5117	0.3036	0.12125	0.14267
Decorana values	0.5360	0.2869	0.08136	0.04814
Axis lengths	3.7004	3.1166	1.30055	1.47888

The display of results is very brief: only eigenvalues and used options are listed. Actual ordination results are not shown, but you can see them with command **summary(ord)**, or extract the scores with command **scores**. The **plot** function also automatically knows how to access the scores.

## 1.2 Non-metric multidimensional scaling

Function **metaMDS** is a bit special case. The actual ordination is performed by function **vegan** function **monoMDS** (or alternatively using **isoMDS** of the **MASS** package). Function **metaMDS** is a wrapper to perform non-metric multidimensional scaling (NMDS) like recommended in community ordination: it uses adequate dissimilarity measures (function **vegdist**), then it runs NMDS several times with random starting configurations, compares results (function **procrustes**), and stops after finding twice a similar minimum stress solution. Finally it scales and rotates the solution, and adds species scores to the configuration as weighted averages (function **wascores**):

```
> ord <- metaMDS(dune)

Run 0 stress 0.1192678
Run 1 stress 0.1886532
Run 2 stress 0.1183186
... New best solution
```

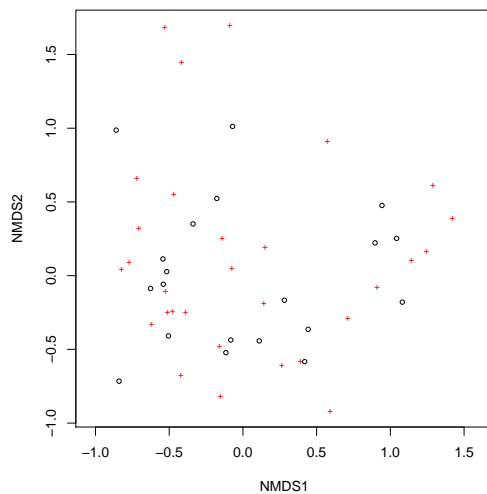


Figure 1: Default ordination plot.

```
... procustes: rmse 0.02026887  max resid 0.06495011
Run 3 stress 0.1192678
Run 4 stress 0.1183186
... procustes: rmse 6.471967e-05  max resid 0.000210315
*** Solution reached

> ord

Call:
metaMDS(comm = dune)

global Multidimensional Scaling using monoMDS

Data:      dune
Distance: bray

Dimensions: 2
Stress:     0.1183186
Stress type 1, weak ties
Two convergent solutions found after 4 tries
Scaling: centring, PC rotation, halfchange scaling
Species: expanded scores based on 'dune'
```

## 2 Ordination graphics

Ordination is nothing but a way of drawing graphs, and it is best to inspect ordinations only graphically (which also implies that they should not be taken too seriously).

All ordination results of **vegan** can be displayed with a `plot` command (Fig. 1):

```
> plot(ord)
```

Default `plot` command uses either black circles for sites and red pluses for species, or black and red text for sites and species, resp. The choices depend on

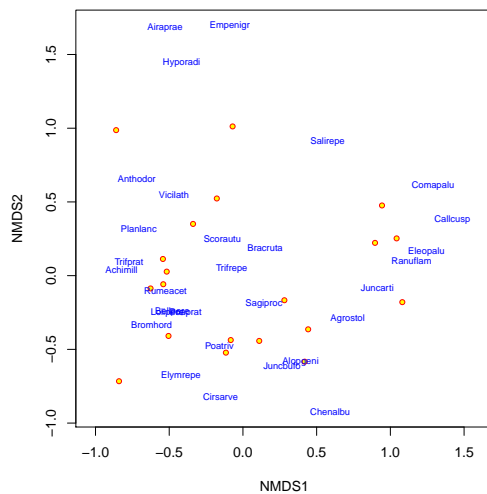


Figure 2: A more colourful ordination plot where sites are points, and species are text.

the number of items in the plot and ordination method. You can override the default choice by setting `type = "p"` for points, or `type = "t"` for text. For a better control of ordination graphics you can first draw an empty plot (`type = "n"`) and then add species and sites separately using `points` or `text` functions. In this way you can combine points and text, and you can select colours and character sizes freely (Fig. 2):

```
> plot(ord, type = "n")
> points(ord, display = "sites", cex = 0.8, pch=21, col="red", bg="yellow")
> text(ord, display = "spec", cex=0.7, col="blue")
```

All **vegan** ordination methods have a specific `plot` function. In addition, **vegan** has an alternative plotting function `ordiplot` that also knows many non-**vegan** ordination methods, such as `prcomp`, `cmdscale` and `isoMDS`. All **vegan** plot functions return invisibly an `ordiplot` object, so that you can use `ordiplot` support functions with the results (`points`, `text`, `identify`).

Function `ordirgl` (requires **rgl** package) provides dynamic three-dimensional graphics that can be spun around or zoomed into with your mouse. Function **ordiplot3d** (requires package `scatterplot3d`) displays simple three-dimensional scatterplots.

## 2.1 Cluttered plots

Ordination plots are often congested: there is a large number of sites and species, and it may be impossible to display all clearly. In particular, two or more species may have identical scores and are plotted over each other. **Vegan** does not have (yet?) automatic tools for clean plotting in these cases, but here some methods you can try:

- Zoom into graph setting axis limits `xlim` and `ylim`. You must typically set both, because **vegan** will maintain equal aspect ratio of axes.
- Use points and add label only some points with `identify` command.

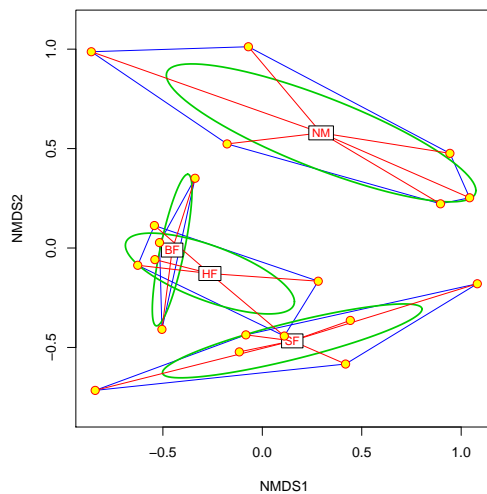


Figure 3: Convex hull, standard error ellipse and a spider web diagram for Management levels in ordination.

- Use `select` argument in `ordination text` and `points` functions to only show the specified items.
- Use `ordilabel` function that uses opaque background to the text: some text labels will be covered, but the uppermost are readable.
- Use automatic `orditorp` function that uses text only if this can be done without overwriting previous labels, but points in other cases.
- Use automatic `ordipointlabel` function that uses both points and text labels, and tries to optimize the location of the text to avoid overwriting.
- Use interactive `orditkplot` function that draws both points and labels for ordination scores, and allows you to drag labels to better positions. You can export the results of the edited graph to encapsulated `postscript`, `pdf`, `png` or `jpeg` files, or copy directly to encapsulated `postscript`, or return the edited positions to R for further processing.

## 2.2 Adding items to ordination plots

**Vegan** has a group of functions for adding information about classification or grouping of points onto ordination diagrams. Function `ordihull` adds convex hulls, `ordiellipse` adds ellipses of standard deviation, standard error or confidence areas, and `ordispider` combines items to their centroid (Fig. 3):

```
> data(dune.env)
> attach(dune.env)

> plot(ord, disp="sites", type="n")
> ordihull(ord, Management, col="blue")
> ordiellipse(ord, Management, col=3,lwd=2)
> ordispider(ord, Management, col="red", label = TRUE)
> points(ord, disp="sites", pch=21, col="red", bg="yellow", cex=1.3)
```

In addition, you can overlay a cluster dendrogram from `hclust` using `ordicluster` or a minimum spanning tree from `spantree` with its `lines` function. Segmented

arrows can be added with `ordiarrows`, lines with `ordisegments` and regular grids with `ordigrid`.

### 3 Fitting environmental variables

**Vegan** provides two functions for fitting environmental variables onto ordination:

- `envfit` fits vectors of continuous variables and centroids of levels of class variables (defined as `factor` in R). The arrow shows the direction of the (increasing) gradient, and the length of the arrow is proportional to the correlation between the variable and the ordination.
- `ordisurf` (which requires package **mgcv**) fits smooth surfaces for continuous variables onto ordination using thinplate splines with cross-validated selection of smoothness.

Function `envfit` can be called with a `formula` interface, and it optionally can assess the “significance” of the variables using permutation tests:

```
> ord.fit <- envfit(ord ~ A1 + Management, data=dune.env, perm=999)
> ord.fit
```

```
***VECTORS
```

```
      NMDS1  NMDS2    r2 Pr(>r)
A1 0.96473 0.26325 0.3649 0.017 *
```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Permutation: free
```

```
Number of permutations: 999
```

```
***FACTORS:
```

```
Centroids:
```

```
      NMDS1  NMDS2
ManagementBF -0.4534 -0.0103
ManagementHF -0.2635 -0.1282
ManagementNM  0.2957  0.5790
ManagementSF  0.1506 -0.4670
```

```
Goodness of fit:
```

```
      r2 Pr(>r)
Management 0.4134 0.009 **
```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Permutation: free
```

```
Number of permutations: 999
```

The result can be drawn directly or added to an ordination diagram (Fig. 4):

```
> plot(ord, dis="site")
> plot(ord.fit)
```

Function `ordisurf` directly adds a fitted surface onto ordination, but it returns the result of the fitted thinplate spline `gam` (Fig. 4):

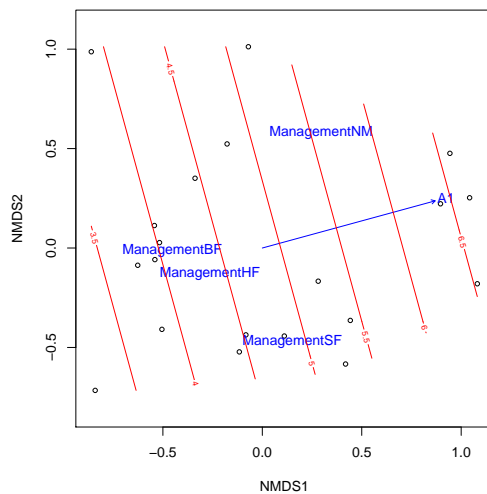


Figure 4: Fitted vector and smooth surface for the thickness of A1 horizon (A1, in cm), and centroids of Management levels.

```
> ordisurf(ord, A1, add=TRUE)

Family: gaussian
Link function: identity

Formula:
y ~ s(x1, x2, k = 10, bs = "tp", fx = FALSE)
<environment: 0x6e6fa00>

Estimated degrees of freedom:
1.59 total = 2.59

REML score: 41.58727
```

## 4 Constrained ordination

**Vegan** has three methods of constrained ordination: constrained or “canonical” correspondence analysis (function `cca`), redundancy analysis (function `rda`) and distance-based redundancy analysis (function `capscale`). All these functions can have a conditioning term that is “partialled out”. I only demonstrate `cca`, but all functions accept similar commands and can be used in the same way.

The preferred way is to use `formula` interface, where the left hand side gives the community data frame and the right hand side lists the constraining variables:

```
> ord <- cca(dune ~ A1 + Management, data=dune.env)
> ord

Call: cca(formula = dune ~ A1 + Management, data = dune.env)

              Inertia Proportion Rank
Total              2.1153      1.0000
Constrained        0.7798      0.3686    4
Unconstrained      1.3355      0.6314   15
```

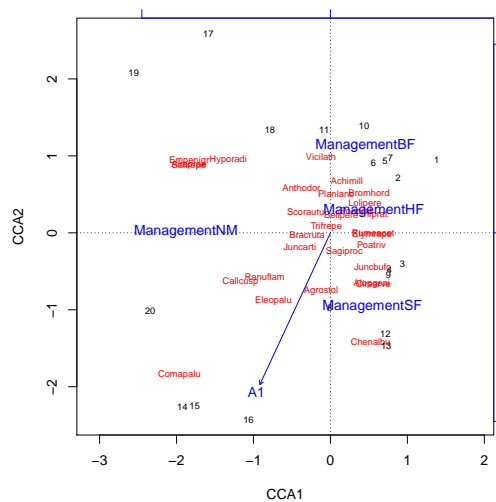


Figure 5: Default plot from constrained correspondence analysis.

Inertia is mean squared contingency coefficient

Eigenvalues for constrained axes:

CCA1	CCA2	CCA3	CCA4
0.3187	0.2372	0.1322	0.0917

Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8	CA9	CA10
0.3620	0.2029	0.1527	0.1345	0.1110	0.0800	0.0767	0.0553	0.0444	0.0415
CA11	CA12	CA13	CA14	CA15					
0.0317	0.0178	0.0116	0.0087	0.0047					

The results can be plotted with (Fig. 5):

```
> plot(ord)
```

There are three groups of items: sites, species and centroids (and biplot arrows) of environmental variables. All these can be added individually to an empty plot, and all previously explained tricks of controlling graphics still apply.

It is not recommended to perform constrained ordination with all environmental variables you happen to have: adding the number of constraints means slacker constraint, and you finally end up with solution similar to unconstrained ordination. In that case it is better to use unconstrained ordination with environmental fitting. However, if you really want to do so, it is possible with the following shortcut in formula:

```
> cca(dune ~ ., data=dune.env)
```

```
Call: cca(formula = dune ~ A1 + Moisture + Management + Use +
Manure, data = dune.env)
```

	Inertia	Proportion	Rank
Total	2.1153	1.0000	
Constrained	1.5032	0.7106	12
Unconstrained	0.6121	0.2894	7

Inertia is mean squared contingency coefficient

Some constraints were aliased because they were collinear (redundant)



Eigenvalues for constrained axes:

CCA1	CCA2	CCA3	CCA4	CCA5	CCA6	CCA7	CCA8	CCA9	CCA10
0.4671	0.3410	0.1761	0.1532	0.0953	0.0703	0.0589	0.0499	0.0318	0.0260
CCA11	CCA12								
0.0228	0.0108								

Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7
0.27237	0.10876	0.08975	0.06305	0.03489	0.02529	0.01798

## 4.1 Significance tests

**vegan** provides permutation tests for the significance of constraints. The test mimics standard analysis of variance function (`anova`), and the default test analyses all constraints simultaneously:

```
> anova(ord)
```

Permutation test for cca under reduced model

Permutation: free

Number of permutations: 999

```
Model: cca(formula = dune ~ A1 + Management, data = dune.env)
```

	Df	ChiSquare	F	Pr(>F)
Model	4	0.77978	2.1896	0.001 ***
Residual	15	1.33549		

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

The function actually used was `anova.cca`, but you do not need to give its name in full, because R automatically chooses the correct `anova` variant for the result of constrained ordination.

It is also possible to analyse terms separately:

```
> anova(ord, by="term", permutations=199)
```

Permutation test for cca under reduced model

Terms added sequentially (first to last)

Permutation: free

Number of permutations: 199

```
Model: cca(formula = dune ~ A1 + Management, data = dune.env)
```

	Df	ChiSquare	F	Pr(>F)
A1	1	0.22476	2.5245	0.025 *
Management	3	0.55502	2.0780	0.010 **
Residual	15	1.33549		

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

This test is sequential: the terms are analysed in the order they happen to be in the model. You can also analyse significances of marginal effects ("Type III effects"):

```
> anova(ord, by="mar", permutations=199)
```

```

Permutation test for cca under reduced model
Marginal effects of terms
Permutation: free
Number of permutations: 199

Model: cca(formula = dune ~ A1 + Management, data = dune.env)
      Df ChiSquare      F Pr(>F)
A1      1  0.17594 1.9761  0.06 .
Management 3  0.55502 2.0780  0.01 **
Residual 15  1.33549
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Moreover, it is possible to analyse significance of each axis:

> anova(ord, by="axis", permutations=499)

Permutation test for cca under reduced model
Marginal tests for axes
Permutation: free
Number of permutations: 499

Model: cca(formula = dune ~ A1 + Management, data = dune.env)
      Df ChiSquare      F Pr(>F)
CCA1    1  0.31875 3.5801  0.002 **
CCA2    1  0.23718 2.6640  0.004 **
CCA3    1  0.13217 1.4845  0.102
CCA4    1  0.09168 1.0297  0.390
Residual 15  1.33549
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## 4.2 Conditioned or partial ordination

All constrained ordination methods can have terms that are partialled out from the analysis before constraints:

```

> ord <- cca(dune ~ A1 + Management + Condition(Moisture), data=dune.env)
> ord

```

```

Call: cca(formula = dune ~ A1 + Management +
Condition(Moisture), data = dune.env)

```

	Inertia	Proportion	Rank
Total	2.1153	1.0000	
Conditional	0.6283	0.2970	3
Constrained	0.5109	0.2415	4
Unconstrained	0.9761	0.4615	12

Inertia is mean squared contingency coefficient

Eigenvalues for constrained axes:

CCA1	CCA2	CCA3	CCA4
0.24932	0.12090	0.08160	0.05904

Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8	CA9
-----	-----	-----	-----	-----	-----	-----	-----	-----

```

0.30637 0.13191 0.11516 0.10947 0.07724 0.07575 0.04871 0.03758 0.03106
  CA10    CA11    CA12
0.02102 0.01254 0.00928

```

This partials out the effect of **Moisture** before analysing the effects of **A1** and **Management**. This also influences the significances of the terms:

```

> anova(ord, by="term", permutations=499)

Permutation test for cca under reduced model
Terms added sequentially (first to last)
Permutation: free
Number of permutations: 499

Model: cca(formula = dune ~ A1 + Management + Condition(Moisture), data = dune.env)
      Df ChiSquare      F Pr(>F)
A1      1   0.11543 1.4190 0.122
Management 3   0.39543 1.6205 0.012 *
Residual 12   0.97610
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

If we had a designed experiment, we may wish to restrict the permutations so that the observations only are permuted within levels of **Moisture**. Restricted permutation is based on the powerful **permute** package. Function **how()** can be used to define permutation schemes. In the following, we set the levels with **plots** argument:

```

> how <- how(nperm=499, plots = Plots(strata=dune.env$Moisture))
> anova(ord, by="term", permutations = how)

Permutation test for cca under reduced model
Terms added sequentially (first to last)
Plots: dune.env$Moisture, plot permutation: none
Permutation: free
Number of permutations: 499

Model: cca(formula = dune ~ A1 + Management + Condition(Moisture), data = dune.env)
      Df ChiSquare      F Pr(>F)
A1      1   0.11543 1.4190 0.242
Management 3   0.39543 1.6205 0.002 **
Residual 12   0.97610
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```