

ADVANCED COMMUNITY DATA ANALYSIS USING VEGAN

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CONSTRAINED ORDINATION

CCA is the constrained form of CA; fitted using `cca()`.

Two interfaces for specifying models

- basic; `cca1 <- cca(X = varespec, Y = varechem)`
- formula; `cca1 <- cca(varespec ~ ., data = varechem)`

Formula interface is the more powerful — *recommended*

CANONICAL CORRESPONDENCE ANALYSIS

```
cca1 <- cca(varespec ~ ., data = varechem)
cca1
```

```
Call: cca(formula = varespec ~ N + P + K + Ca + Mg + S + Al + Fe +
Mn + Zn + Mo + Baresoil + Humdepth + pH, data = varechem)
```

	Inertia	Proportion	Rank
Total	2.0832	1.0000	
Constrained	1.4415	0.6920	14
Unconstrained	0.6417	0.3080	9

Inertia is mean squared contingency coefficient

Eigenvalues for constrained axes:

CCA1	CCA2	CCA3	CCA4	CCA5	CCA6	CCA7	CCA8	CCA9	CCA10
0.4389	0.2918	0.1628	0.1421	0.1180	0.0890	0.0703	0.0584	0.0311	0.0133
CCA11	CCA12	CCA13	CCA14						
0.0084	0.0065	0.0062	0.0047						

Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8	CA9
0.19776	0.14193	0.10117	0.07079	0.05330	0.03330	0.01887	0.01510	0.00949

REDUNDANCY ANALYSIS

RDA is the constrained form of PCA; fitted using `rda()`.

```
rda1 <- rda(varespec ~ ., data = varechem)
rda1
```

```
Call: rda(formula = varespec ~ N + P + K + Ca + Mg + S + Al + Fe +
Mn + Zn + Mo + Baresoil + Humdepth + pH, data = varechem)
```

	Inertia	Proportion	Rank
Total	1825.7000	1.0000	
Constrained	1459.9000	0.7997	14
Unconstrained	365.8000	0.2003	9

Inertia is variance

Eigenvalues for constrained axes:

RDA1	RDA2	RDA3	RDA4	RDA5	RDA6	RDA7	RDA8	RDA9	RDA10	RDA11	RDA12
820.1	399.3	102.6	47.6	26.8	24.0	19.1	10.2	4.4	2.3	1.5	0.9
RDA13	RDA14										
0.7	0.3										

Eigenvalues for unconstrained axes:

PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
186.19	88.46	38.19	18.40	12.84	10.55	5.52	4.52	1.09

THE `cca.object`

- Objects of class "`cca`" are complex with many components
- Entire class described in `?cca.object`
- Depending on what analysis performed some components may be `NULL`
- Used for (C)CA, PCA, RDA, and CAP (`capscale()`)

THE `cca`.object

`cca1` has a large number of components

- **`$call`** how the function was called
- **`$grand.total`** in (C)CA sum of 'rowsum'
- **`$rowsum`** the row sums
- **`$colsum`** the column sums
- **`$tot.chi`** total inertia, sum of Eigenvalues
- **`$pCCA`** Conditioned (partialled out) components
- **`$CCA`** Constrained components
- **`$CA`** Unconstrained components
- **`$method`** Ordination method used
- **`$inertia`** Description of what inertia is

THE `cca`.object

Depending on how one called `cca()` etc some of these components will be **NULL**

`$pCCA` is only filled in if a *partial* constrained ordination fitted

`rda()` returns objects with classes "**rda**" and "**cca**", but in most cases those objects work like those of class "**cca**"

The Eigenvalues and axis scores are now spread about the `$CA` and `$CCA` components (also `$pCCA` if a *partial* CCA)

Thankfully we can use *extractor* functions to get at such things

Use `eigenvals()` to extract Eigenvalues from a fitted ordination object

```
eigenvals(cca1)
```

CCA1	CCA2	CCA3	CCA4	CCA5	CCA6	CCA7
0.4388704	0.2917753	0.1628465	0.1421302	0.1179519	0.0890291	0.0702945
CCA8	CCA9	CCA10	CCA11	CCA12	CCA13	CCA14
0.0583592	0.0311408	0.0132944	0.0083644	0.0065385	0.0061563	0.0047332
CA1	CA2	CA3	CA4	CA5	CA6	CA7
0.1977645	0.1419256	0.1011741	0.0707868	0.0533034	0.0332994	0.0188676
CA8	CA9					
0.0151044	0.0094876					

To extract a range of scores from a fitted ordination use `scores()`

- takes an ordination object as the first argument
- `choices` — which axes? Defaults to `c(1,2)`
- `display` — which type(s) of scores to return
 - `"sites"` or `"wa"`: scores for samples in response matrix
 - `"species"`: scores for variables/columns in response
 - `"lc"`: linear combination site scores
 - `"bp"`: biplot scores (coords of arrow tip)
 - `"cn"`: centroid scores (coords of factor centroids)

EXTRACTING AXIS SCORES

```
str(scores(cca1, choices = 1:4, display = c("species", "sites")), max = 1)
```

List of 2

```
$ species: num [1:44, 1:4] 0.0753 -0.1813 -1.0535 -1.2774 -0.1526 ...  
..- attr(*, "dimnames")=List of 2  
$ sites : num [1:24, 1:4] 0.178 -0.97 -1.28 -1.501 -0.598 ...  
..- attr(*, "dimnames")=List of 2
```

```
head(scores(cca1, choices = 1:2, display = "sites"))
```

	CCA1	CCA2
18	0.1784733	-1.0598842
15	-0.9702382	-0.1971387
24	-1.2798478	0.4764498
27	-1.5009195	0.6521559
23	-0.5980933	-0.1840362
19	-0.1102881	0.7143142

SCALINGS...

When we draw the results of many ordinations we display 2 or more sets of data

Can't display all of these and maintain relationships between the scores

Solution scale one set of scores relative to the other via the **scaling** argument

- **scaling** = 1 — Focus on sites, scale site scores by λ_i
- **scaling** = 2 — Focus on species, scale species scores by λ_i
- **scaling** = 3 — Symmetric scaling, scale both scores by $\sqrt{\lambda_i}$
- **scaling** = -1 — As above, but
- **scaling** = -2 — For `cca()` multiply results by $\sqrt{(1/(1 - \lambda_i))}$
- **scaling** = -3 — this is Hill's scaling
- **scaling** < 0 — For `rda()` divide species scores by species' σ
- **scaling** = 0 — raw scores

```
scores(cca1, choices = 1:2, display = "species", scaling = 3)
```

Partial constrained ordinations remove the effect of one or more variables *then* fit model of interest

Argument **Z** is used for a data frame of variables to partial out

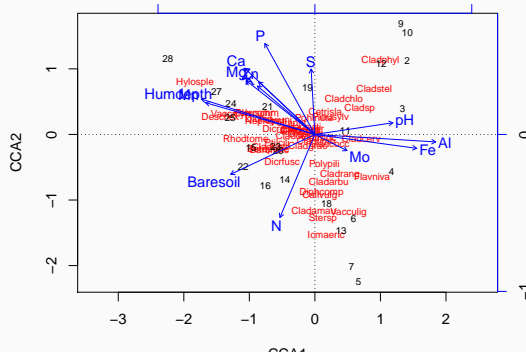
Or with the formula interface use the **Condition()** function

```
pcca <- cca(X = varespec,  
            Y = varechem[, "Ca", drop = FALSE],  
            Z = varechem[, "pH", drop = FALSE])  
pcca <- cca(varespec ~ Ca + Condition(pH), data = varechem) ## easier!
```

TRIPLOTS

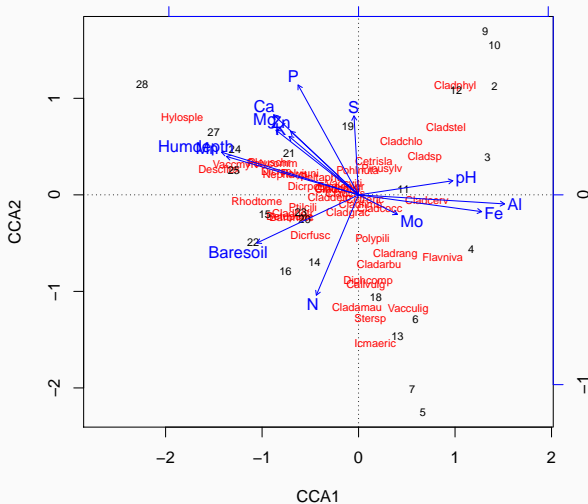
Triplots will generally produce a mess; we can really only display a couple of bits approximately anyway Trying to cram three things in is a recipe for a mess... but we can do it

```
plot(cca1)
```



TRIPLLOTS

```
plot(cca1)
```



If we don't want to think it's easy to fit a poor model with many constraints

That's what we just did with `cca1` and `rda1`

Remember, CCA and RDA are *just regression methods* — everything you know about regression applies here

A better approach is to *think* about the important variables and include only those

The formula interface allows you to create interaction or quadratic terms easily (though be careful with latter)

It also handles factor or class constraints automatically unlike the basic interface

BUILDING CONSTRAINED ORDINATION MODELS

```
vare.cca <- cca(varespec ~ Al + P*(K + Baresoil), data = varechem)
vare.cca
```

```
Call: cca(formula = varespec ~ Al + P * (K + Baresoil), data =
varechem)
```

	Inertia	Proportion	Rank
Total	2.083	1.000	
Constrained	1.046	0.502	6
Unconstrained	1.038	0.498	17

Inertia is mean squared contingency coefficient

Eigenvalues for constrained axes:

CCA1	CCA2	CCA3	CCA4	CCA5	CCA6
0.3756	0.2342	0.1407	0.1323	0.1068	0.0561

Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
0.27577	0.15411	0.13536	0.11803	0.08887	0.05511	0.04919	0.03781

(Showed only 8 of all 17 unconstrained eigenvalues)

For CCA we have little choice but to do

1. Fit well-chosen set of candidate models & compare, or
2. Fit a *full* model of well-chosen variables & then do stepwise selection

But automatic approaches to model building should be used cautiously!

The standard `step()` function can be used as **vegan** provides two helper methods, `deviance()` and `extractAIC()`, used by `step()`

Vegan also provides methods for class `"cca"` for `add1()` and `drop1()`

Linear dependencies between constraints can be investigated via the *variance inflation factor* or VIF

VIF is a measure of how much the variance of $\hat{\beta}_j$ is inflated by presence of other covariates

Lots of rules of thumb

- VIF ≥ 20 indicates *strong collinearity* in constraints
- VIF ≥ 10 potentially of concern & should be looked at

Computed via `vif.cca()`

`step()` uses AIC which is a fudge for RDA/CCA. Alternatively use function `ordistep()`

1. Define an upper and lower model scope, say the full model and the null model
2. To step from the lower scope or null model we use

```
upr <- cca(varespec ~ ., data = varechem)
lwr <- cca(varespec ~ 1, data = varechem)
set.seed(1)
mods <- ordistep(lwr, scope = formula(upr), trace = 0)
```

`trace = 0` is used here to turn off printing of progress

Permutation tests are used (more on these later); the theory for an AIC for ordination is somewhat loose

STEPWISE SELECTION IN CCA

The object returned by `step()` is a standard "cca" object with an extra component `$anova`

The `$anova` component contains a summary of the steps involved in automatic model building

```
mods
```

```
Call: cca(formula = varespec ~ A1 + P + K, data = varechem)
```

	Inertia	Proportion	Rank
Total	2.0832	1.0000	
Constrained	0.6441	0.3092	3
Unconstrained	1.4391	0.6908	20

Inertia is mean squared contingency coefficient

Eigenvalues for constrained axes:

CCA1	CCA2	CCA3
0.3616	0.1700	0.1126

Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
0.3500	0.2201	0.1851	0.1551	0.1351	0.1003	0.0773	0.0537

(Showed only 8 of all 20 unconstrained eigenvalues)

The `$anova` component contains a summary of the steps involved in automatic model building

```
mods$anova
```

```
      Df    AIC      F Pr(>F)
+ Al   1 128.61 3.6749 0.005 **
+ P    1 127.91 2.5001 0.005 **
+ K    1 127.44 2.1688 0.035 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

STEPWISE SELECTION IN CCA

Step-wise model selection is fairly fragile; if we start from the full model we won't end up with the same final model

```
mods2 <- step(upr, scope = list(lower = formula(lwr), upper = formula(upr)), trace = 0,  
              test = "perm")  
mods2
```

```
Call: cca(formula = varespec ~ P + K + Mg + S + Mn + Mo + Baresoil  
+ Humdepth, data = varechem)
```

	Inertia	Proportion	Rank
Total	2.0832	1.0000	
Constrained	1.1165	0.5360	8
Unconstrained	0.9667	0.4640	15

Inertia is mean squared contingency coefficient

Eigenvalues for constrained axes:

CCA1	CCA2	CCA3	CCA4	CCA5	CCA6	CCA7	CCA8
0.4007	0.2488	0.1488	0.1266	0.0875	0.0661	0.0250	0.0130

Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8	CA9
0.25821	0.18813	0.11927	0.10204	0.08791	0.06085	0.04461	0.02782	0.02691
CA10	CA11	CA12	CA13	CA14	CA15			
0.01646	0.01364	0.00823	0.00655	0.00365	0.00238			

ADJUSTED r^2 FOR LINEAR MODELS

As with ordinary R^2 , that of an RDA is biased for the same reasons as for a linear regression

- adding a variable to constraints will increase R^2
- the larger the number of constraints in the model the larger R^2 is due to random correlations

Can attempt to account for this bias via an *adjusted* R^2 measure

$$R_{adj}^2 = 1 - \frac{n-1}{n-m-1}(1-R^2)$$

- n is number of samples m is number of constraints (model degrees of freedom)
- Can be used up to $\sim M > n/2$ before becomes too conservative
- Can be negative
- Compute using `RsquareAdj()`

STEPWISE SELECTION VIA ADJUSTED r^2

The problems with stepwise selection in regression models are myriad. Affects RDA, CCA, etc as well

Blanchet, Legendre, and Borcard (2008) proposed a two-step solution for models where R^2_{adj} makes sense

- *Global test* of all constraints
 - Proceed **only** if this test is significant
 - Helps prevent inflation of overall type I error
- Proceed with forward selection, but with *two* stopping rules
 - Usual significance threshold α
 - The global R^2_{adj}
 - Stop if next candidate model is non-significant or if R^2_{adj} exceeds the global R^2_{adj}

Available in `ordiR2step()`

PERMUTATION TESTS

RDA has lots of theory behind it, CCA not as much. However, ecological/environmental data invariably violate what little theory we have

Instead we use permutation tests to assess the *importance* of fitted models — the data are shuffled in some way and the model refitted to derive a Null distribution under some hypothesis of *no effect*

What is shuffled and *how* is of **paramount** importance for the test to be valid

- No conditioning (partial) variables then rows of the species data are permuted
- With conditioning variables, two options are available, both of which *permute residuals* from model fits
 - The *full model* uses residuals from model $Y = X + Z + \varepsilon$
 - The *reduced model* uses residuals from model $Y = X + Z + \varepsilon$
- In **vegan** which is used can be set via argument **model** with "**direct**", "~~full~~", and "**reduced**" respectively
- In current **vegan** option **method** = "**full**" is disabled

A test statistic is required, computed for observed model & each permuted model
vegan uses a pseudo- F statistic

$$F = \frac{\chi^2_{model}/df_{model}}{\chi^2_{resid}/df_{resid}}$$

Evaluate whether F is unusually large relative to the null (permutation) distribution of F

PERMUTATION TESTS IN VEGAN: `anova()`

- The main user function is the `anova()` method
- It is an interface to the lower-level function `permutest.cca()`
- At its most simplest, the `anova()` method tests whether the “model” as a whole is significant

$$F = \frac{1.4415/14}{0.6417/9} = 1.4441$$

```
set.seed(42)
(perm <- anova(cca1))
```

```
Permutation test for cca under reduced model
Permutation: free
Number of permutations: 999
```

```
Model: cca(formula = varespec ~ N + P + K + Ca + Mg + S + Al + Fe + Mn + Zn + Mo + Baresoil + Humdepth + pH, data = varechem)
      Df ChiSquare      F Pr(>F)
Model   14   1.44148  1.4441 0.041 *
Residual 9   0.64171
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

PERMUTATION TESTS IN VEGAN: `anova()`

- `anova.cca()` has a number of arguments

```
args(anova.cca)
```

```
function (object, ..., permutations = how(nperm = 999), by = NULL,  
      model = c("reduced", "direct", "full"), parallel = getOption("mc.cores"),  
      strata = NULL, cutoff = 1, scope = NULL)  
NULL
```

- **alpha** is the desired p value threshold (Type I error rate)
- **beta** is the Type II error rate
- Permuting stops if the result is different from **alpha** for the given **beta**
- This is evaluated every **step** permutations
- **perm.max** sets a limit on the number of permutations
- **by** determines what is tested; the default is to test the model
- More direct control can be achieved via `permutest.cca()`

A number of types of test can be envisaged

- Testing the overall significance of the model
- Testing constrained (canonical) axes
- Testing individual model terms *sequentially*
- The *marginal* effect of a single variable

The first is the default in `anova()`

The other three can be selected via the argument `method`

PERMUTATION TESTS | TESTING CANONICAL AXES

- The constrained (canonical) axes can be individually tests by specifying `by = "axis"`
- The first axis is tested in terms of variance explained compared to residual variance
- The second axis is tested after partialling out the first axis... and so on

```
set.seed(1)
anova(mods, by = "axis")
```

```
Permutation test for cca under reduced model
Marginal tests for axes
Permutation: free
Number of permutations: 999
```

```
Model: cca(formula = varespec ~ A1 + P + K, data = varechem)
      Df ChiSquare      F Pr(>F)
CCA1    1   0.36156 5.0249 0.001 ***
CCA2    1   0.16996 2.3621 0.011 *
CCA3    1   0.11262 1.5651 0.124
Residual 20   1.43906
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

PERMUTATION TESTS | TESTING TERMS SEQUENTIALLY

- The individual terms in the model can be tested using `by = "terms"`
- The terms are assessed in the order they were specified in the model, sequentially from first to last
- Test is of the additional variance explained by adding the k th variable to the model
- **Ordering of the terms** will affect the results

```
set.seed(5)
anova(mods, by = "terms")
```

```
Permutation test for cca under reduced model
Terms added sequentially (first to last)
Permutation: free
Number of permutations: 999
```

```
Model: cca(formula = varespec ~ A1 + P + K, data = varechem)
      Df ChiSquare    F Pr(>F)
A1      1   0.29817 4.1440 0.001 ***
P       1   0.18991 2.6393 0.011 *
K       1   0.15605 2.1688 0.024 *
Residual 20   1.43906
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

PERMUTATION TESTS | TESTING TERMS MARGINAL EFFECTS

- The marginal *effect* of a model term can be assessed using `by = "margin"`
- The marginal *effect* is the effect of a particular term when all other model terms are included in the model

```
set.seed(10)
anova(mods, by = "margin")
```

```
Permutation test for cca under reduced model
Marginal effects of terms
Permutation: free
Number of permutations: 999
```

```
Model: cca(formula = varespec ~ A1 + P + K, data = varechem)
      Df ChiSquare      F Pr(>F)
A1      1   0.31184 4.3340 0.001 ***
P       1   0.16810 2.3362 0.012 *
K       1   0.15605 2.1688 0.025 *
Residual 20   1.43906
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Example & data taken from Leps & Smilauer, Case Study 2

Spring fen meadow vegetation in westernmost Carpathian mountains

```
## load vegan
library("vegan")

## load the data
spp <- read.csv("data/meadow-spp.csv", header = TRUE, row.names = 1)
env <- read.csv("data/meadow-env.csv", header = TRUE, row.names = 1)
```

CONSTRAINED ORDINATION WORKED EXAMPLE | SPRING MEADOW VEGETATION

CCA a reasonable starting point as the gradient is long here (check with `decorana()` if you want)

```
m1 <- cca(spp ~ ., data = env)
set.seed(32)
anova(m1)
```

Permutation test for cca under reduced model

Permutation: free

Number of permutations: 999

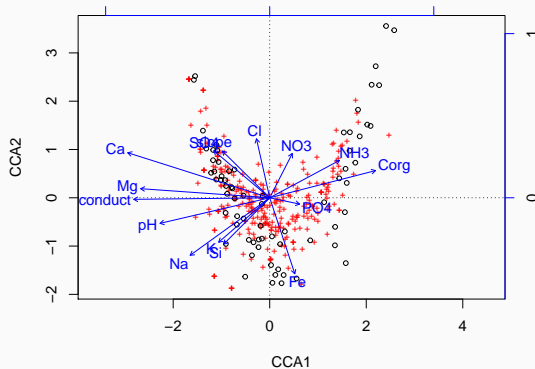
Model: `cca(formula = spp ~ Ca + Mg + Fe + K + Na + Si + SO4 + PO4 + NO3 + NH3 + Cl + Corg + pH + conduct + slope,`

	Df	ChiSquare	F	Pr(>F)
Model	15	1.5597	1.497	0.001 ***
Residual	54	3.7509		

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

CONSTRAINED ORDINATION WORKED EXAMPLE | SPRING MEADOW VEGETATION

```
plot(m1)
```



CONSTRAINED ORDINATION WORKED EXAMPLE | SPRING MEADOW VEGETATION

```
set.seed(67)
lwr <- cca(spp ~ 1, data = env)
m2 <- ordistep(lwr, scope = formula(m1), trace = FALSE)
```

m2

Call: cca(formula = spp ~ Ca + conduct + Corg + Na + NH3 + Fe + pH, data = env)

	Inertia	Proportion	Rank
Total	5.3110	1.0000	
Constrained	0.9900	0.1864	7
Unconstrained	4.3210	0.8136	62

Inertia is mean squared contingency coefficient

Eigenvalues for constrained axes:

CCA1	CCA2	CCA3	CCA4	CCA5	CCA6	CCA7
0.4268	0.1447	0.1116	0.0936	0.0760	0.0719	0.0652

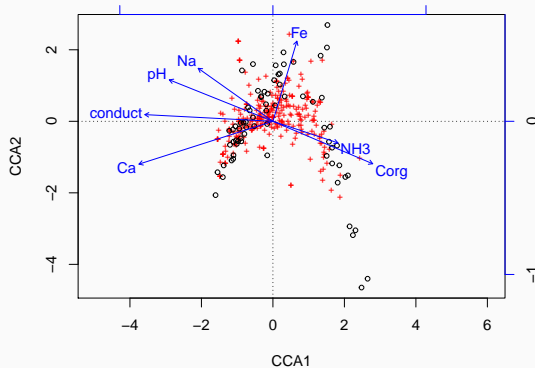
Eigenvalues for unconstrained axes:

CA1	CA2	CA3	CA4	CA5	CA6	CA7	CA8
0.27251	0.19518	0.16703	0.14993	0.14606	0.14168	0.13292	0.12154

(Showed only 8 of all 62 unconstrained eigenvalues)

CONSTRAINED ORDINATION WORKED EXAMPLE | SPRING MEADOW VEGETATION

```
plot(m2)
```



CONSTRAINED ORDINATION WORKED EXAMPLE | SPRING MEADOW VEGETATION

```
m2$anova
```

	Df	AIC	F	Pr(>F)	
+ Ca	1	453.14	4.7893	0.005	**
+ conduct	1	453.29	1.7915	0.005	**
+ Corg	1	453.61	1.6011	0.005	**
+ Na	1	453.93	1.5827	0.005	**
+ NH3	1	454.36	1.4507	0.020	*
+ Fe	1	454.89	1.3386	0.015	*
+ pH	1	455.46	1.2756	0.015	*

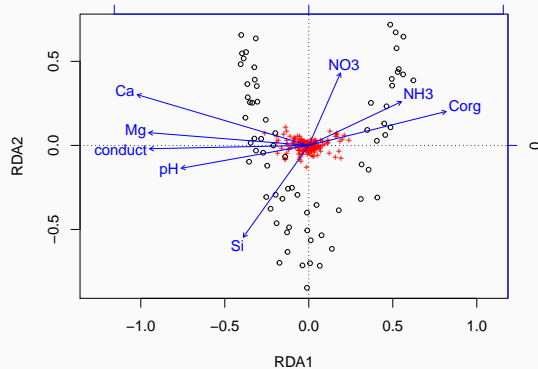
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Alternative is RDA with a transformation

```
spph <- decostand(spp, method = "hellinger")  
m3 <- rda(spph ~ ., data = env)  
lwr <- rda(spph ~ 1, data = env)  
m4 <- ordistep(lwr, scope = formula(m3), trace = FALSE)
```

CONSTRAINED ORDINATION WORKED EXAMPLE | SPRING MEADOW VEGETATION

```
plot(m4)
```



CONSTRAINED ORDINATION WORKED EXAMPLE | SPRING MEADOW VEGETATION

Stepwise using R^2_{adj}

```
m5 <- ordiR2step(lwr, scope = formula(m3), trace = FALSE)
m5$anova
```

	R2.adj	Df	AIC	F	Pr(>F)	
+ Ca	0.12588	1	-41.779	10.9370	0.002	**
+ NH3	0.14628	1	-42.468	2.6242	0.002	**
+ conduct	0.16322	1	-42.925	2.3570	0.002	**
+ Si	0.17711	1	-43.164	2.1136	0.002	**
+ Corg	0.18518	1	-42.940	1.6442	0.006	**
+ NO3	0.19257	1	-42.680	1.5853	0.018	*
+ pH	0.19966	1	-42.417	1.5583	0.010	**
<All variables>	0.20332					

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

vegan provides a series of diagnostics to help assess the model fit

- `goodness()`
- `inertcomp()`
- `spenvcor()`
- `intersetcor()`
- `vif.caa()`

`goodness()` computes two goodness of fit statistics for species or sites

Which goodness of fit measure is returned is controlled by argument `statistic`

- `statistic = "explained"` (default) gives the cumulative proportion of variance explained by each axis
- `statistic = "distance"` gives the residual distance between the “fitted” location in constrained ordination space and the location in the full dimensional space

```
head(goodness(mods))
```

	CCA1	CCA2	CCA3
Callvulg	0.0062471656	0.318907619	0.8254657
Empenigr	0.1164701677	0.137604904	0.1953245
Rhodtome	0.0999089739	0.169697909	0.1824153
Vaccmyrt	0.2361482843	0.240516323	0.2406730
Vaccviti	0.1523704591	0.156502301	0.2110550
Pinusylv	0.0009244423	0.004802076	0.0060096

```
head(goodness(mods, summarize = TRUE))
```

Callvulg	Empenigr	Rhodtome	Vaccmyrt	Vaccviti	Pinusylv
0.8254657	0.1953245	0.1824153	0.2406730	0.2110550	0.0060096

DIAGNOSTICS FOR CONSTRAINED ORDINATIONS | INERTIA DECOMPOSITION

`inertcomp()` decomposes the variance in samples or species in partial, constrained, and unconstrained components

Same two types of measure available by argument `statistic`

- `statistic = "explained"` (default) gives the decomposition in terms of variance
- `statistic = "distance"` gives decomposition in terms of the the residual distance
- Can output as proportions of total via `proportion = TRUE`

```
head(inertcomp(mods, proportional = TRUE))
```

	CCA	CA
Callvulg	0.8254657	0.1745343
Empenigr	0.1953245	0.8046755
Rhodtome	0.1824153	0.8175847
Vaccmyrt	0.2406730	0.7593270
Vaccviti	0.2110550	0.7889450
Pinusylv	0.0060096	0.9939904

`spenvcor()` returns the species-environment correlation

The (weighted) correlation between the weighted average-based and the linear combination-based sets of site scores

A *poor* measure of goodness of fit. Sensitive to

- outliers (like all correlations)
- overfitting (using too many constraints)

Better models can have poorer species-environment correlations

```
spenvcor(mods)
```

CCA1	CCA2	CCA3
0.8554808	0.8132873	0.8792797

DIAGNOSTICS FOR CONSTRAINED ORDINATIONS | INTERSET CORRELATIONS

`intersetcor()` returns the interset correlations; the (weighted) correlation between the weighted average-based site scores and each constraint variable

Another *poor* diagnostic

- correlation based
- focuses on a single constraint-axis combination at a time

Vector fitting (`envfit()`) or biplot scores (`scores(model, display = "bp")`) are better alternatives

```
intersetcor(mods)
```

	CCA1	CCA2	CCA3
Al	0.7356151	-0.1302334	0.4259623
P	-0.3589749	-0.6110772	0.4478933
K	-0.3768462	-0.1339192	0.7760441

RESTRICTED PERMUTATION TESTS

RESTRICTED PERMUTATION TESTS

What is shuffled and *how* is of **paramount** importance for the test to be valid

Complete randomisation (default in **vegan**) assumes a null hypothesis where all observations are *independent*

Ecological / environmental data often aren't independent

- Temporal or spatial correlation
- Clustering, repeated measures
- Nested sampling designs (Split-plots designs)
- Blocks
- ...

Permutation *must* give null distribution of the test statistic whilst preserving the *dependence* between observations

Trick is to shuffle the data whilst preserving that dependence

Canoco has had restricted permutations for a *long* time. **vegan** has only recently caught up & we're not (quite) there yet

vegan still only knows how to completely randomise data or completely randomise within blocks (called **strata** in **vegan**)

The newish package **permute** grew out of initial code in the **vegan** repository to generate the sorts of restricted permutations available in Canoco

We have fully integrated **permute** into **vegan**...

vegan depends on **permute** so you should have it already installed & loaded when using **vegan**

permute follows Canoco closely — at the chiding of Cajo ter Braak when it didn't do what he wanted !

Samples can be thought of as belonging to three levels of a hierarchy

- the *sample* level; how are individual samples permuted
- the *plot* level; how are samples grouped at an intermediate level
- the *block* level; how are samples grouped at the outermost level

Blocks define groups of plots, each of which can contain groups of samples

RESTRICTED PERMUTATIONS WITH PERMUTE

Blocks are *never* permuted; if defined, only plots or samples *within* the blocks get shuffled & samples never swapped between blocks

Plots or samples within plots, or both can be permuted following one of four simple permutation types

1. Free permutation (randomisation)
2. Time series or linear transect, equal spacing
3. Spatial grid designs, equal regular spacing
4. Permutation of plots (groups of samples)
5. Fixed (no permutation)

Multiple plots per block, multiple samples per plot; plots could be arranged in a spatial grid and samples within each of the plots form a time series

Blocks are a random factor that does not interact with factors that vary within blocks

Blocks form groups of samples that are never permuted between blocks, only within blocks

Using blocks you can achieve what the **strata** argument does now in **vegan**; needs to be a factor variable

The variation *between* blocks should be excluded from the test; **permute** doesn't do this for you!

Use + **Condition(blocks)** in the model formula where **blocks** is a factor containing the block membership for each observation

Can link *randomly* starting point of one series to any time point of another series if series are stationary under null hypothesis that the series are unrelated

Achieve this via cyclic shift permutations — wrap series into a circle by joining start and end points

Works OK if there are no trends or cyclic pattern — autocorrelation structure only broken at the end points *if* series are stationary

Can detrend to make series stationary but not if you want to test significance of a trend

```
shuffle(10, control = how(within = Within(type = "series")))
```

```
[1]  9 10  1  2  3  4  5  6  7  8
```

- The trick of cyclic shifts can be extended to two dimensions for a regular spatial grid arrangement of points

- Now shifts are *toroidal* as we join the end point in the x direction together and in the y direction together

```
matrix(perm, ncol = 3)
```

	[,1]	[,2]	[,3]
[1,]	6	9	3
[2,]	4	7	1
[3,]	5	8	2

Split-plot designs are hierarchical with two levels of units

1. **whole-plots** , which contain
2. **split-plots** (the samples)

Can permute one or both of these but whole-plots must be of equal size

Essentially allows more than one error stratum to be analyzed

Test effect of constraints that vary *between* whole plots by permuting the whole-plots whilst retaining order of split-plots (samples) within the whole-plots

Test effect of constraints that vary *within* whole-plots by permuting the split-plots within whole-plots without permuting the whole-plots

Whole-plots or split-plots can be time series, linear transects or rectangular grids in which case the appropriate restricted permutation is used

If the split-plots are parallel time series & **time** is an autocorrelated error component affecting all series then the same cyclic shift can be applied to each time series (within each whole-plot) (**constant** = **TRUE**)

(Without wanting to get *too* technical) Mirroring in restricted permutations allows for isotropy in dependences by reflecting the ordering of samples in time or spatial dimensions

For a linear transect, technically the autocorrelation at lag h is equal to that at lag $-h$ (also in a trend-free time series)

Hence the series (1, 2, 3, 4) and (4, 3, 2, 1) are equivalent from this point of view & we can draw permutations from either version

Similar argument can be made for spatial grids

Using `mirror = TRUE` then can double (time series, linear transects) or quadruple (spatial grids) the size of the set of permutations

RESTRICTED PERMUTATIONS WITH PERMUTE | THE SET OF PERMUTATIONS

Using restricted permutations can severely reduce the size of the set of allowed permutations

As the minimum p value obtainable is $1/np$ where np is number of allowed permutations (including the observed) this can impact the ability to detect signal/pattern

If we don't want mirroring

- in a time series of 20 samples the minimum p is $1/20$ (0.05)
- in a time series of 100 samples the minimum p is $1/100$ (0.01)
- in a data set with 10 time series each of 20 observations (200 total), if we assume an autocorrelated error component over all series (**constant** = **TRUE**) then there are only 20 permutations of the data and minimum p is 0.05

When the set of permutations is small it is better to switch to an exact test & evaluate all permutations in the set rather than randomly sample from the set

In `permute`, we set up a permutation scheme with `how()`

We sample from the permutation scheme with

- `shuffle()`, which gives a single draw from scheme, or
- `shuffleSet()`, which returns a set of `n` draws from the scheme

`allPerms()` can generate the entire set of permutations — **note** this was designed for small sets of permutations & is slow if you request it for a scheme with many thousands of permutations!

`how()` has three main arguments

1. `within` — takes input from helper `Within()`
2. `plots` — takes input from helper `Plots()`
3. `blocks` — takes a factor variable as input

```
plt <- gl(3, 10)
h <- how(within = Within(type = "series"), plots = Plots(strata = plt))
```


Helper functions make it easy to change one or a few aspects of permutation scheme, rest left at defaults

`args(Within)`

```
function (type = c("free", "series", "grid", "none"), constant = FALSE,  
          mirror = FALSE, ncol = NULL, nrow = NULL)  
NULL
```

`args(Plots)`

```
function (strata = NULL, type = c("none", "free", "series", "grid"),  
          mirror = FALSE, ncol = NULL, nrow = NULL)  
NULL
```

`how()` has additional arguments, many of which control the heuristics that kick in to stop you shooting yourself in the foot and demanding 9999 permutations when there are only 10

- `complete` should we enumerate the entire set of permutations?
- `minperm` lower bound on the size of the set of permutations at & below which we turn on complete enumeration

```
args(how)
```

```
function (within = Within(), plots = Plots(), blocks = NULL,  
  nperm = 199, complete = FALSE, maxperm = 9999, minperm = 99,  
  all.perms = NULL, make = TRUE, observed = FALSE)  
NULL
```

Time series within 3 plots, 10 observation each

```
plt <- gl(3, 10)
h <- how(within = Within(type = "series"), plots = Plots(strata = plt))
set.seed(4)
p <- shuffle(30, control = h)
do.call("rbind", split(p, plt)) ## look at perms in context
```

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]
1	7	8	9	10	1	2	3	4	5	6
2	12	13	14	15	16	17	18	19	20	11
3	24	25	26	27	28	29	30	21	22	23

Time series within 3 plots, 10 observation each, same permutation within each

```
plt <- gl(3, 10)
h <- how(within = Within(type = "series", constant = TRUE), plots = Plots(strata = plt))
set.seed(4)
p <- shuffle(30, control = h)
do.call("rbind", split(p, plt)) ## look at perms in context
```

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]
1	7	8	9	10	1	2	3	4	5	6
2	17	18	19	20	11	12	13	14	15	16
3	27	28	29	30	21	22	23	24	25	26

Here by dragons

```
## Analyse the Ohraz data Case study 5 of Leps & Smilauer

## load vegan
library("vegan")

## load the data
spp <- read.csv("data/ohraz-spp.csv", header = TRUE, row.names = 1)
env <- read.csv("data/ohraz-env.csv", header = TRUE, row.names = 1)
molinia <- spp[, 1]
spp <- spp[, -1]

## Year as numeric
env <- transform(env, year = as.numeric(as.character(year)))
```

RESTRICTED PERMUTATIONS WITH PERMUTE | WORKED EXAMPLE WITH VEGAN

```
## hypothesis 1
c1 <- rda(spp ~ year + year:mowing + year:fertilizer +
         year:removal + Condition(plotid), data = env)

h <- how(within = Within(type = "none"),
        plots = Plots(strata = env$plotid, type = "free"))
set.seed(42)

anova(c1, permutations = h, model = "reduced")
```

```
Permutation test for rda under reduced model
Plots: env$plotid, plot permutation: free
Permutation: none
Number of permutations: 199
```

```
Model: rda(formula = spp ~ year + year:mowing + year:fertilizer + year:removal + Condition(plotid), data = env)
      Df Variance      F Pr(>F)
Model    4   158.85 6.4247 0.005 **
Residual 90   556.30
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(c1, permutations = h, model = "reduced", by = "axis")
```

```
Permutation test for rda under reduced model
Marginal tests for axes
Plots: env$plotid, plot permutation: free
Permutation: none
Number of permutations: 199
```

RESTRICTED PERMUTATIONS WITH PERMUTE | WORKED EXAMPLE WITH VEGAN

```
## hypothesis 2
c2 <- rda(spp ~ year:mowing + year:fertilizer + year:removal +
          Condition(year + plotid), data = env)
anova(c2, permutations = h, model = "reduced")
```

Permutation test for rda under reduced model
Plots: env\$plotid, plot permutation: free
Permutation: none
Number of permutations: 199

```
Model: rda(formula = spp ~ year:mowing + year:fertilizer + year:removal + Condition(year + plotid), data = env)
      Df Variance      F Pr(>F)
Model    3    99.24 5.3517 0.005 **
Residual 90   556.30
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(c2, permutations = h, model = "reduced", by = "axis")
```

Permutation test for rda under reduced model
Marginal tests for axes
Plots: env\$plotid, plot permutation: free
Permutation: none
Number of permutations: 199

```
Model: rda(formula = spp ~ year:mowing + year:fertilizer + year:removal + Condition(year + plotid), data = env)
      Df Variance      F Pr(>F)
RDA1    1    54.14 8.7595 0.005 **
RDA2    1    34.28 5.5458 0.005 **
RDA3    1    10.82 1.7499 0.440
```

Blanchet, F Guillaume, Pierre Legendre, and Daniel Borcard. 2008. "Forward Selection of Explanatory Variables." *Ecology* 89 (9). Eco Soc America: 2623–32.