partial RDA

Pablo E. Gutiérrez-Fonseca

11/17/2021

```
library(ggplot2)
library(dplyr)
library(vegan)
```

Primer paso: cargar las librerias que necesitas.

```
species=read.csv("data/RDA_species.csv", header=T, row.names=NULL, sep=",")
env=read.csv("data/RDA_environmetal_standart.csv", header=T, row.names=NULL, sep=",")
```

Segundo paso: cargar los datos.

```
species_1 <- select(species, -site)
env_1 <- select(env, -site)
```

Remover la columna de sitos.

Transformar datos. Hellinger es una transformacion recomendada por Legendre & Callagher (2001) en datos de abundancia y con una respuesta lineal

```
species_2 <- decostand(species_1, method = "hellinger")
```

```
partial_rda_all = rda(species_2 ~., data= env_1, scale=F)
partial_rda_env = rda(species_2 ~ temperature + oxygen + pH + conductivity,
                      data= env_1, scale=F)
partial_rda_phy = rda(species_2 ~ plants + land_use + margin,
                      data= env_1, scale=F)
partial_rda_season = rda(species_2 ~ season, data= env_1, scale=F)
```

Vamos a construir los modelos: combinados e individuales

```
RsquareAdj (partial_rda_all)
```

Ver los R2adj de cada uno

```
## $r.squared
## [1] 0.6423136
##
## $adj.r.squared
## [1] 0.5567799
```

```
RsquareAdj (partial_rda_env)
```

```
## $r.squared
## [1] 0.1834995
##
## $adj.r.squared
## [1] 0.1218768
```

```
RsquareAdj(partial_rda_phy)
```

```
## $r.squared
## [1] 0.5749283
##
## $adj.r.squared
## [1] 0.5249199
```

```
RsquareAdj(partial_rda_season)
```

```
## $r.squared
## [1] 0.01787828
##
## $adj.r.squared
## [1] 0.0003403971
```

```
varp <- varpart(species_2, ~ temperature + oxygen + pH + conductivity,
                ~ plants + land_use + margin, ~season, data = env_1)
varp
```

Vamos a correr un RDA con las matrices (diferentes factores) separadas.

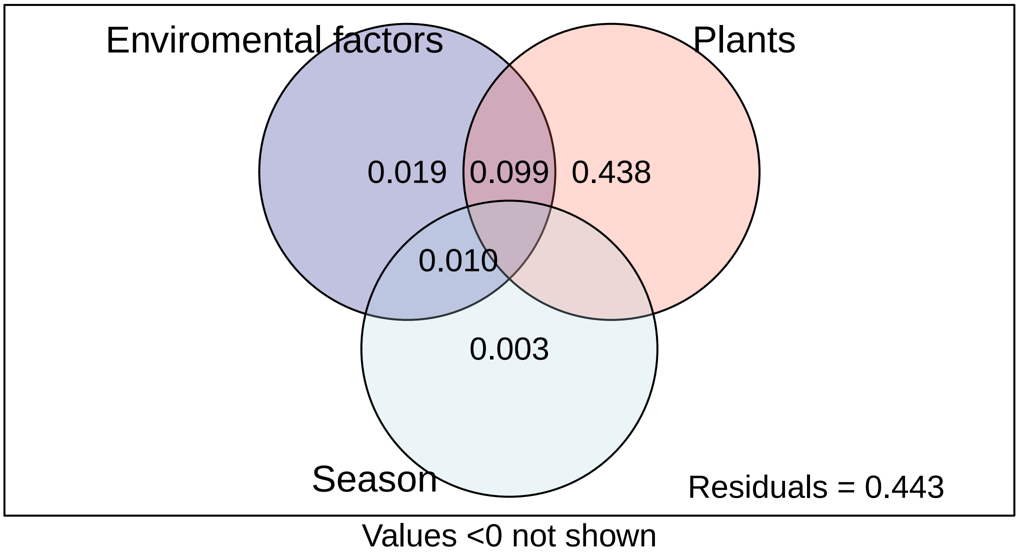
```
##
## Partition of variance in RDA
##
## Call: varpart(Y = species_2, X = ~temperature + oxygen + pH +
## conductivity, ~plants + land_use + margin, ~season, data = env_1)
##
```

```
## Explanatory tables:
## X1:  ~temperature + oxygen + pH + conductivity
## X2:  ~plants + land_use + margin
## X3:  ~season
##
## No. of explanatory tables: 3
## Total variation (SS): 34.967
##             Variance: 0.61346
## No. of observations: 58
##
## Partition table:
##                       Df R.square Adj.R.square Testable
## [a+d+f+g] = X1         4  0.18350      0.12188     TRUE
## [b+d+e+g] = X2         6  0.57493      0.52492     TRUE
## [c+e+f+g] = X3         1  0.01788      0.00034     TRUE
## [a+b+d+e+f+g] = X1+X2 10  0.63213      0.55386     TRUE
## [a+c+d+e+f+g] = X1+X3  5  0.19602      0.11871     TRUE
## [b+c+d+e+f+g] = X2+X3  7  0.59442      0.53764     TRUE
## [a+b+c+d+e+f+g] = All 11  0.64231      0.55678     TRUE
## Individual fractions
## [a] = X1 | X2+X3       4               0.01914     TRUE
## [b] = X2 | X1+X3       6               0.43807     TRUE
## [c] = X3 | X1+X2       1               0.00292     TRUE
## [d]                    0               0.09923    FALSE
## [e]                    0              -0.00608    FALSE
## [f]                    0               0.00980    FALSE
## [g]                    0              -0.00630    FALSE
## [h] = Residuals                        0.44322    FALSE
## Controlling 1 table X
## [a+d] = X1 | X3        4               0.11837     TRUE
## [a+f] = X1 | X2        4               0.02894     TRUE
## [b+d] = X2 | X3        6               0.53730     TRUE
## [b+e] = X2 | X1        6               0.43198     TRUE
## [c+e] = X3 | X1        1              -0.00316     TRUE
## [c+f] = X3 | X2        1               0.01272     TRUE
## ---
## Use function 'rda' to test significance of fractions of interest
```

Legendre (2008) [doi: 10.1093/jpe/rtm001] argued that "Negative values of Ra2 are interpreted as zeros; they correspond to cases where the explanatory variables explain less variation than random normal variables would."

Plot the results The plot shows the adjusted R2 values associated with each partition or for overlapping partitions.

```
plot(varp, digits = 2, Xnames = c('Enviromental factors', 'Plants', "Season"),
     bg = c('navy', 'tomato', "lightblue"))
```




```r
## Show values for all partitions by putting 'cutoff' low enough:
#plot(varp, cutoff = -Inf, cex = 0.7, bg=2:5)
```

```r
# significance of partition from Environment (physicochemical variables)
anova(rda(species_2 ~ temperature + oxygen + pH + conductivity +
          Condition(plants + land_use + margin) +
          Condition(season), data=env_1))
```

Then we can test the significance of each individual component.

```
## Permutation test for rda under reduced model
## Permutation: free
## Number of permutations: 999
##
## Model: rda(formula = species_2 ~ temperature + oxygen + pH + conductivity + Condition(plants + land_u
##          Df Variance      F Pr(>F)
## Model     4  0.02938 1.5398  0.027 *
## Residual 46  0.21943
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Significance of partition from Physical characteristics
anova(rda(species_2 ~ plants + land_use + margin +
          Condition(temperature + oxygen + pH + conductivity) +
          Condition(season), data=env_1))
```

```
## Permutation test for rda under reduced model
## Permutation: free
## Number of permutations: 999
##
## Model: rda(formula = species_2 ~ plants + land_use + margin + Condition(temperature + oxygen + pH + c
##          Df Variance      F Pr(>F)
## Model     6  0.27378 9.5659  0.001 ***
## Residual 46  0.21943
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Significance of partition from Season
anova(rda(species_2 ~ season +
          Condition(plants + land_use + margin) +
          Condition(temperature + oxygen + pH + conductivity),
          data=env_1))
```

```
## Permutation test for rda under reduced model
## Permutation: free
## Number of permutations: 999
##
## Model: rda(formula = species_2 ~ season + Condition(plants + land_use + margin) + Condition(temperatu
##          Df Variance      F Pr(>F)
## Model     1 0.006247 1.3096  0.201
## Residual 46 0.219425
```

Physicochemical and Physical characteriscs are all statistically significant in their contributions to Odonata community composition, even though the amount of variation explained by Physicochemistry is small. There was no statistically significant of season in Odonata composition independent of these other measured drivers.