Modeling Dune Data

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Begin by installing the necessary packages and the data about the dunes

```
#install.packages("vegan")
library(vegan)

## Loading required package: permute

## Loading required package: lattice

## This is vegan 2.3-3

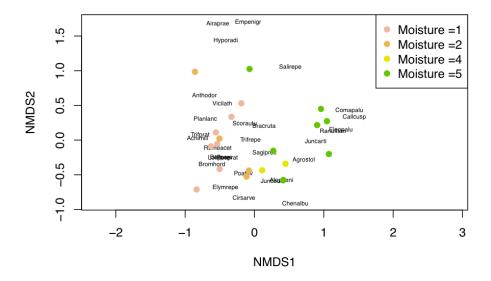
#install.packages("dummies")
library(dummies)

## dummies-1.5.6 provided by Decision Patterns

library(vegan)
data(dune)
data(dune)
data(dune.env)
?dune
```

Begin by conducting an indirect ordination on the dune plant community using the metaMDS function. Furthermore we plot the values and see the significance

```
#making a MDS analysis thing
dune_mds=metaMDS(dune)
## Run 0 stress 0.1192678
## Run 1 stress 0.2075713
## Run 2 stress 0.119268
## ... procrustes: rmse 0.000264736 max resid 0.0008142103
## *** Solution reached
#making a plot
plot(dune_mds, type='n')
text(dune_mds, 'sp', cex=.5)
# generate vector of colors
color_vect = rev(terrain.colors(6))[-1]
points(dune_mds, 'sites', pch=19,
      col=color_vect[dune.env$Moisture])
legend('topright', paste("Moisture =", c(1,2,4,5), sep=''), #fixed it holla originally 1:5
    col=color_vect, pch=19)
```



```
#how to zoom like a pleb plot(nmds, xlim=c(-10, -5), ylim)
```

Lower moisture ones are all clumped together in with lower ds1 and ds2 and the higher moisture ones are also fairly clumped but are a lil more spread apart.

CCA Testing

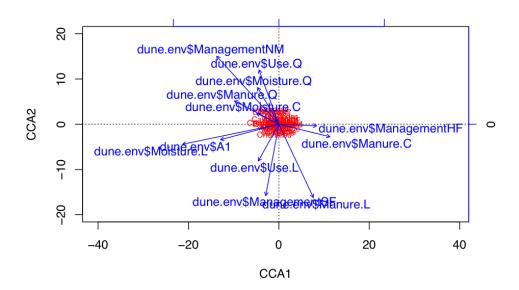
A CCA model is created so that it can later be prepared to the first RDA model. Begins by including all of the possible variables and is graphed and testing is done.

```
#creating the dune model using the cca method where it accounts for the variables a1, moisture, managem
cca_dune=cca(dune ~ dune.env$A1 + dune.env$Moisture + dune.env$Management + dune.env$Use +
#teachers board writing stuff
#anova(dune_cca) "overall model signifigance"
#anova(cca_objm[some variable], by="margin")

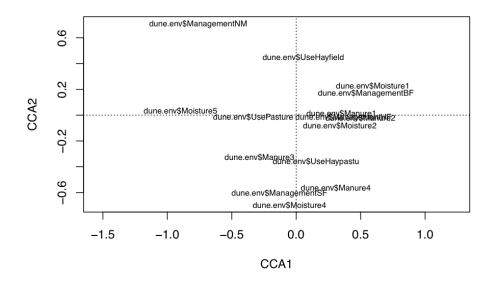
#gives the eigenvalues and more info
cca_dune

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

```
Inertia Proportion Rank
## Total
                            1.0000
                 2.1153
## Constrained
                 1.5032
                            0.7106
                            0.2894
                                     7
## Unconstrained 0.6121
## 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:
                                      CA5
##
             CA2
                     CA3
                              CA4
                                              CA6
                                                      CA7
      CA1
## 0.27237 0.10876 0.08975 0.06305 0.03489 0.02529 0.01798
#plot it
plot(cca_dune, ylim=c(-20, 20), display=c('sp','bp'), scaling=1)
\#give\ it\ a\ name\ really,\ nothing\ different\ bp=biplot
plotdune=plot(cca_dune, ylim=c(-20, 20), display=c('sp','bp'), scaling=1)
```



#a different kind of graph visual using centroids
plot(cca_dune, display=c('cn'), scaling=1)



#gives some info plotdune

```
## $species
                  CCA1
                              CCA2
## Achimill 1.25492690 0.84738144
## Agrostol -1.09878179 -0.87403204
## Airaprae -1.15089656 3.16359412
## Alopgeni -0.43420117 -1.68765705
## Anthodor 0.53600745 1.79675824
## Bellpere 1.03459795 0.11336963
## Bromhord 1.24856529 -0.04479289
## Chenalbu -0.98364433 -2.18450268
## Cirsarve 0.56489830 -1.59685273
## Comapalu -2.94874909 0.17888829
## Eleopalu -2.21751679 -0.05256048
## Elymrepe 0.89316528 -1.13280574
## Empenigr -2.01741224 2.59304832
## Hyporadi -0.95892895 2.56615801
## Juncarti -1.38768935 -0.32693579
## Juncbufo -0.09421348 -1.73961870
## Lolipere 0.88842733 -0.16927281
## Planlanc 1.17109230 1.32933035
## Poaprat 0.69015643 -0.23626637
## Poatriv 0.44468395 -0.85789652
## Ranuflam -2.02508840 0.20056138
```

```
## Rumeacet 1.15737841 0.22350748
## Sagiproc -0.42541431 -0.89284485
## Salirepe -1.30209055 2.73397355
## Scorautu -0.01439415 0.65009249
## Trifprat 1.54265121 0.97154141
## Trifrepe 0.02150547 0.19497917
## Vicilath 0.74828555 1.51704976
## Bracruta -0.21606507 0.47854617
## Callcusp -2.59465145 0.95131127
##
## $biplot
                             CCA1
## dune.env$A1
                       -0.5522284 -0.14625614
## dune.env$Moisture.L -0.9119085 -0.18984518
## dune.env$Moisture.Q -0.2019396 0.34771164
## dune.env$Moisture.C -0.2096150 0.10180106
## dune.env$ManagementHF 0.3578911 -0.01529945
## dune.env$ManagementNM -0.5893380 0.64373816
## dune.env$ManagementSF -0.1243145 -0.67611508
## dune.env$Use.L -0.1947790 -0.34791425
## dune.env$Use.Q
                       -0.1882986 0.51499752
## dune.env$Manure.L
                        0.3272520 -0.69453755
                       -0.4201628 0.22075154
## dune.env$Manure.Q
## dune.env$Manure.C
                        0.4843232 -0.11872035
## attr(,"arrow.mul")
## [1] 23.32487
## attr(,"class")
## [1] "ordiplot"
#do some permutations
anova(cca_dune, by='margin', permutations = 10)
## Permutation test for cca under reduced model
## Marginal effects of terms
## Permutation: free
## Number of permutations: 10
##
## Model: cca(formula = dune ~ dune.env$A1 + dune.env$Moisture + dune.env$Management + dune.env$Use + du
##
                    Df ChiSquare F Pr(>F)
                      1 0.11070 1.2660 0.09091 .
## dune.env$A1
## dune.env$Moisture 3 0.31587 1.2041 0.27273
## dune.env$Management 2 0.15882 0.9081 0.63636
## dune.env$Use 2 0.13010 0.7439 0.36364
## dune.env$Manure 3 0.25490 0.9717 0.54545
                     7 0.61210
## Residual
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
#tells us what variables are significant
anova(cca_dune)
```

```
## Permutation: free
## Number of permutations: 999
## Model: cca(formula = dune ~ dune.env$A1 + dune.env$Moisture + dune.env$Management + dune.env$Use + du
##
            Df ChiSquare
                              F Pr(>F)
## Model
            12
                  1.5032 1.4325 0.017 *
## Residual 7
                  0.6121
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
none of the variables have strong partial effect but the model itself has marginal significance moisture was
important somewhere up higher, what about doin a cca with just moisture?
summary(cca_dune)
                                                                                         dune.env$Use + dune
```

```
##
## Call:
## cca(formula = dune ~ dune.env$A1 + dune.env$Moisture + dune.env$Management +
## Partitioning of mean squared contingency coefficient:
##
                Inertia Proportion
## Total
                 2.1153
                            1.0000
                            0.7106
## Constrained
                 1.5032
## Unconstrained 0.6121
                           0.2894
## Eigenvalues, and their contribution to the mean squared contingency coefficient
##
## Importance of components:
                          CCA1 CCA2
                                        CCA3
                                                CCA4
                        0.4671 0.3410 0.17606 0.15317 0.09528 0.07027
## Eigenvalue
## Proportion Explained 0.2208 0.1612 0.08323 0.07241 0.04504 0.03322
## Cumulative Proportion 0.2208 0.3821 0.46529 0.53770 0.58275 0.61596
                          CCA7
                                 CCA8
                                        CCA9 CCA10 CCA11 CCA12
                        0.05887 0.04993 0.03183 0.02596 0.02282 0.01082
## Eigenvalue
## Proportion Explained 0.02783 0.02360 0.01505 0.01227 0.01079 0.00511
## Cumulative Proportion 0.64379 0.66740 0.68245 0.69472 0.70551 0.71063
##
                          CA1 CA2 CA3 CA4 CA5
                        0.2724\ 0.10876\ 0.08975\ 0.06305\ 0.03489\ 0.02529
## Proportion Explained 0.1288 0.05142 0.04243 0.02981 0.01649 0.01196
## Cumulative Proportion 0.8394 0.89081 0.93324 0.96305 0.97954 0.99150
##
                           CA7
## Eigenvalue
                        0.01798
## Proportion Explained 0.00850
## Cumulative Proportion 1.00000
## Accumulated constrained eigenvalues
## Importance of components:
                                CCA2 CCA3 CCA4
                                                      CCA5
                                                              CCA6
##
                         CCA1
## Eigenvalue
                        0.4671 0.3410 0.1761 0.1532 0.09528 0.07027 0.05887
## Proportion Explained 0.3108 0.2269 0.1171 0.1019 0.06339 0.04674 0.03916
## Cumulative Proportion 0.3108 0.5376 0.6548 0.7567 0.82005 0.86679 0.90595
                          CCA8 CCA9 CCA10 CCA11 CCA12
## Eigenvalue
                        0.04993 0.03183 0.02596 0.02282 0.01082
```

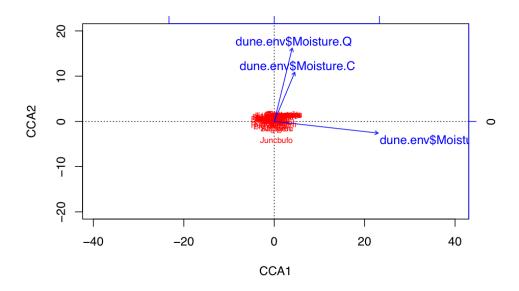
```
## Proportion Explained 0.03322 0.02118 0.01727 0.01518 0.00720
## Cumulative Proportion 0.93917 0.96035 0.97762 0.99280 1.00000
## Scaling 2 for species and site scores
## * Species are scaled proportional to eigenvalues
\#\# * Sites are unscaled: weighted dispersion equal on all dimensions
##
##
## Species scores
##
##
                CCA1
                        CCA2
                                 CCA3
                                           CCA4
                                                     CCA5
                                                              CCA6
## Achimill 0.857707 0.49484 -0.045074 -0.057950 0.670679 0.056946
## Agrostol -0.750987 -0.51041 -0.001514 -0.006522 0.110328 -0.113279
## Airaprae -0.786606 1.84744 0.777309 1.068417 0.558936 -0.142093
## Alopgeni -0.296764 -0.98554 0.015875 0.454024 0.295335 0.124614
## Anthodor 0.366346 1.04925 -0.217724 0.412435 0.563903 -0.226744
## Bellpere 0.707119 0.06620 0.500239 -0.369709 0.592272 -0.330213
## Bromhord 0.853359 -0.02616 0.335626 -0.427024 0.865565 -0.093885
## Chenalbu -0.672293 -1.27568 -0.417041 0.994310 0.640906 0.521336
## Cirsarve 0.386092 -0.93251 0.963978 -0.468823 0.239146 -0.908823
## Comapalu -2.015388 0.10446 -1.185954 -1.972940 -0.083546 -0.219456
## Eleopalu -1.515611 -0.03069 -0.455387 -0.508862 0.111183 -0.132850
## Elymrepe 0.610453 -0.66152 0.628614 -0.124262 -0.491387 -0.510855
## Empenigr -1.378845 1.51426 1.387645 0.973499 -0.434196 -0.642379
## Hyporadi -0.655401 1.49855 0.738512 0.362909 -0.104564 0.310460
## Juncarti -0.948447 -0.19092 -0.028958 0.148431 -0.292973 -0.155408
## Juncbufo -0.064392 -1.01588 -0.297937 1.118684 -0.196979 0.823725
## Lolipere 0.607215 -0.09885 0.262228 -0.409402 -0.312573 0.082660
## Planlanc 0.800409 0.77629 -0.606615 -0.038048 -0.021902 0.152465
## Poaprat 0.471703 -0.13797 0.252857 -0.205726 -0.176841 0.061944
## Poatriv 0.303929 -0.50098 -0.033488 0.157680 0.180752 -0.110423
## Ranuflam -1.384091 0.11712 -0.129524 -0.120128 0.041536 -0.207804
## Rumeacet 0.791036 0.13052 -1.100806 0.537567 -0.416656 -0.396323
## Sagiproc -0.290759 -0.52139 0.288191 0.373446 -0.109281 0.193977
## Salirepe -0.889942 1.59655 1.182347 0.817665 -0.457263 -0.271421
## Scorautu -0.009838 0.37963 0.098333 -0.075560 0.001781 0.125526
## Trifprat 1.054359 0.56735 -1.455764 0.398295 -0.539708 -0.564846
## Trifrepe 0.014698 0.11386 -0.184205 -0.244273 0.089510 0.207091
## Vicilath 0.511432 0.88591 0.273760 -1.050861 -0.335122 1.591159
## Bracruta -0.147674  0.27946 -0.137684  0.084272 -0.210685  0.147748
## Callcusp -1.773372 0.55553 -0.188876 -0.426816 -0.097141 -0.008786
##
## Site scores (weighted averages of species scores)
##
         CCA1
                  CCA2
                           CCA3
                                  CCA4
                                           CCA5
## 1
      1.19460 -0.71633 1.656429 -1.4249 -2.23242 -1.09183
## 2
      0.86805 -0.35777 0.934868 -0.9242 1.33133 -0.48738
## 3
      ## 4
      0.25095 -0.99294 1.237259 -0.4411 0.35593 -1.14729
## 5
      1.11991 0.45932 -1.022763 0.2895 0.27912 -1.76102
      0.99305 0.73388 -2.001441 0.3758 -1.04277 -0.73162
## 6
## 7 1.03098 0.34363 -1.083231 0.2079 -0.14394 0.29945
## 8 -0.66671 -0.71037 0.004385 -0.1742 -0.10923 0.07552
```

```
## 9 0.09269 -1.09341 0.218954 0.9201 -1.32966 0.09022
## 10 0.95315 0.58996 0.146744 -0.9667 1.81728 0.84400
## 11 0.47318 0.74856 0.535395 -1.0620 -1.51667 3.25324
## 12 -0.27934 -1.30695 -0.512852 2.0022 0.26928 1.96951
## 13 -0.37400 -1.45815 -0.153034 1.4764 1.08084 1.21481
## 14 -2.04173 0.23744 -1.448971 -2.6038 0.41722 -0.22568
## 15 -1.93799 -0.04255 -1.367867 -1.8081 -0.32644 -0.85946
## 16 -1.91272 -0.56130 -0.881308 -0.5388 0.40537 -0.81739
## 17 0.33533 2.74717 0.494859 1.7252 3.00069 0.15330
## 18 0.26805 1.23029 0.753438 -0.3018 -1.09614 1.50399
## 19 -0.75573 2.53794 2.225936 2.4221 0.13516 0.14348
## 20 -2.03905  0.80938  0.463176  0.2188 -1.15999 -1.41953
##
## Site constraints (linear combinations of constraining variables)
##
                CCA2
                         CCA3
                                  CCA4
                                          CCA5
                                                   CCA6
        CCA1
## 1
      0.7577 -1.0533 2.075818 -0.62357 -2.6193 -0.57163
## 2
    1.0307 -0.2511 0.942759 -0.72795 1.0939 0.10633
      0.3825 -0.9571 0.943652 -0.50806 0.2566 -0.92249
      0.3861 -0.9325 0.963978 -0.46882 0.2391 -0.90882
## 4
## 5
      1.0281 0.3743 -1.180481 -0.15376 0.1863 -2.04984
     1.0753 0.8100 -1.860152 0.77287 -0.9596 -0.47288
## 7
     1.0282 0.1537 -0.720078 0.01393 -0.2159 0.69023
## 8 -0.8347 -0.6324 -0.367053 -0.18633 0.2121 -0.93866
     0.2553 -0.9868  0.226845  1.11630 -1.5671  0.68393
## 9
## 10 0.8517 0.5884 0.543136 -0.45186 1.9874 0.90302
## 11 0.3961 0.6106 -0.007613 -2.01145 -1.4337 2.39468
## 12 -0.4745 -1.4349 -0.522321 1.76672 0.5542
## 13 -0.6723 -1.2757 -0.417041 0.99431 0.6409 0.52134
## 14 -2.3490 0.6722 -1.087969 -2.00082 -0.2983 -0.03446
## 15 -1.6817 -0.4633 -1.283939 -1.94506 0.1312 -0.40445
## 16 -1.4075 -0.6080 -0.607258 0.19306 0.5431 0.63171
## 17 0.1018 2.3472 -0.138197 1.21079 2.0486 0.60834
## 18 0.4019 1.7339 0.567131 0.27132 -0.4606 0.67225
## 19 -1.3788 1.5143 1.387645 0.97350 -0.4342 -0.64238
## 20 -1.3717 1.5635 1.428297 1.05197 -0.4691 -0.61505
##
## Biplot scores for constraining variables
##
                          CCA1
                                  CCA2
                                          CCA3
                                                   CCA4
                                                            CCA5
                        -0.5522 -0.1463 -0.51591 -0.29706  0.10631 -0.18332
## dune.env$A1
## dune.env$Moisture.L
                       -0.9119 -0.1898 0.03915 0.20902 0.10538 -0.03575
                       -0.2019 0.3477 -0.29349 -0.20611 -0.28362 -0.13473
## dune.env$Moisture.Q
## dune.env$Moisture.C -0.2096 0.1018 0.30630 -0.29946 0.52413 -0.28239
## dune.env$ManagementHF 0.3579 -0.0153 -0.54867 0.22163 -0.32970 -0.28950
## dune.env$ManagementNM -0.5893 0.6437 0.15687 -0.01426 -0.04765 -0.07934
## dune.env$ManagementSF -0.1243 -0.6761 0.21198 0.15451 0.10333 -0.01935
## dune.env$Use.L
                       -0.1948 -0.3479 -0.33163 -0.42684 -0.10232 0.22884
## dune.env$Use.Q
                        -0.1883 0.5150 -0.02175 -0.01096 -0.05112 0.16095
## dune.env$Manure.L
                        0.3273 -0.6945 0.04111 -0.03004 0.04278 -0.26545
                       -0.4202 0.2208 0.52839 -0.20156 -0.12699 -0.23457
## dune.env$Manure.Q
## dune.env$Manure.C
                        0.4843 -0.1187 0.31321 -0.19926 -0.15232 0.17747
```

```
##
##
## Centroids for factor constraints
##
##
                           CCA1
                                    CCA2
                                            CCA3
                                                      CCA4
                                                               CCA5
## dune.env$Moisture1
                        0.86961 0.39190 -0.30729 -0.271184 -0.42482
## dune.env$Moisture2
                        0.49529 -0.13803 0.71613 -0.298514 0.95955
                       -0.07641 -1.19047 -0.11369 1.411949 -0.60287
## dune.env$Moisture4
## dune.env$Moisture5
                       -1.31323 0.06247 -0.07829 0.008202 0.07168
## dune.env$ManagementBF 0.79133 0.29313 0.53596 -0.977522 0.73099
## dune.env$ManagementHF 0.53656 -0.02637 -0.81693 0.330865 -0.48837
## dune.env$ManagementNM -1.11223 1.21134 0.29730 -0.029662 -0.09172
## dune.env$ManagementSF -0.19081 -1.03722 0.32552 0.237132 0.15857
## dune.env$UseHayfield
                        0.08045 0.76460 0.35627
                                                  0.470345
                       0.22445 -0.61214 0.02544 0.013349 0.06101
## dune.env$UseHaypastu
## dune.env$UsePasture
                       -0.48763 -0.02094 -0.53183 -0.668114 -0.20870
## dune.env$Manure1
                        0.51300 0.02905 0.27896 -0.315483 -0.22424
## dune.env$Manure2
                        0.72919 -0.03448 -0.70675 0.367543
                        -0.41706 -0.55693 -0.52936 0.221143 0.26656
## dune.env$Manure3
## dune.env$Manure4
                        ##
                          CCA6
## dune.env$Moisture1
                        0.0229
## dune.env$Moisture2
                        -0.2087
## dune.env$Moisture4
                        0.9444
## dune.env$Moisture5
                        -0.2261
## dune.env$ManagementBF 1.0250
## dune.env$ManagementHF -0.4322
## dune.env$ManagementNM -0.1446
## dune.env$ManagementSF -0.0296
## dune.env$UseHayfield -0.1392
## dune.env$UseHaypastu -0.1916
## dune.env$UsePasture
                        0.5131
## dune.env$Manure1
                        1.2323
## dune.env$Manure2
                        -0.3713
## dune.env$Manure3
                        0.1926
## dune.env$Manure4
                        -0.8552
```

It seemed like moisture had the most significance so now we cut the model and make a new version including only the moisture variables and rerun the plot.

```
cca_dune_moisture=cca(dune ~ dune.env$Moisture)
plot(cca_dune_moisture, ylim=c(-20, 20), display=c('sp','bp'), scaling=1)
```



both of them are saying moisture is most important but in total none of it is super signifigant. The CCA model was more useful to me.