Homework 2 EEB590C

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Assignment:

Select one of the two datasets (HW2.dat1.csv or HW2.dat2.csv found in the Data Repository). Each contains a multivariate dataset and several independent (X) variables. Using the methods learned in weeks 6-10, examine patterns in the dataset. You may use one or more (or all) of the X-variables, and a variety of methods to describe the patterns.

You must use at least one method from the material learned in: Weeks 6-7, Week 8, Week 9, and Week 10

```
## Loading required package: rgl

## Loading required package: Matrix
```

```
#READ in both csv datasets
dat1<-read.csv("HW2.dat1.csv", header= TRUE)
dat2<-read.csv("HW2.dat2.csv", header = TRUE)
```

WEEK 6 MATERIAL

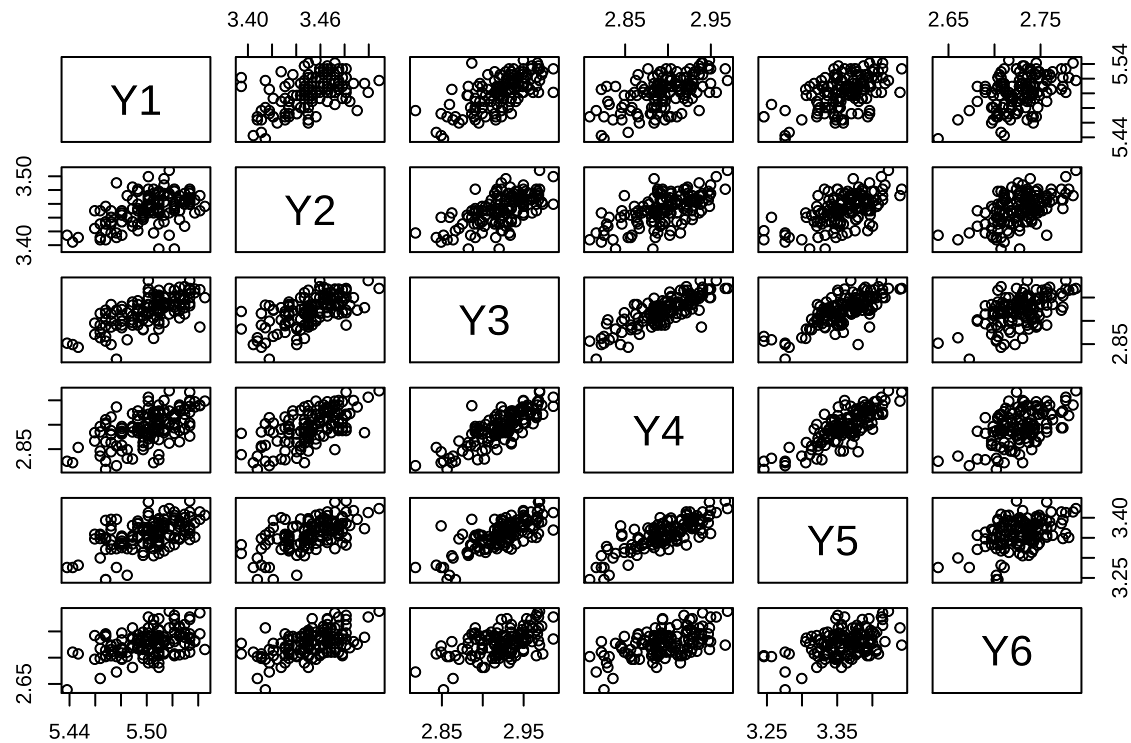
We selected dataset 1 to analyse.

```
dat1.dat<-log(as.matrix(dat1[,(4:9)]))
mydat<-rrpp.data.frame("Y"=dat1.dat,"X1"= as.factor(dat1$X1),"X2"= as.factor(dat1$X2),"X3"= dat1$X3)

cor(dat1.dat)
```

```
##           Y1        Y2        Y3        Y4        Y5        Y6
## Y1 1.0000000 0.5035656 0.6794433 0.5778571 0.5336809 0.4364807
## Y2 0.5035656 1.0000000 0.6234217 0.6163699 0.5853149 0.5347691
## Y3 0.6794433 0.6234217 1.0000000 0.8215338 0.7486924 0.5121106
## Y4 0.5778571 0.6163699 0.8215338 1.0000000 0.8107807 0.5229477
## Y5 0.5336809 0.5853149 0.7486924 0.8107807 1.0000000 0.4609773
## Y6 0.4364807 0.5347691 0.5121106 0.5229477 0.4609773 1.0000000
```

```
pairs(dat1.dat)
```




```r
var(dat1.dat)
```

```
##              Y1           Y2           Y3           Y4           Y5
## Y1 0.0005119657 0.0002543216 0.0004889894 0.0004448629 0.0004388798
## Y2 0.0002543216 0.0004982111 0.0004426031 0.0004680943 0.0004748318
## Y3 0.0004889894 0.0004426031 0.0010116995 0.0008890710 0.0008655112
## Y4 0.0004448629 0.0004680943 0.0008890710 0.0011576319 0.0010026103
## Y5 0.0004388798 0.0004748318 0.0008655112 0.0010026103 0.0013209518
## Y6 0.0002462486 0.0002976194 0.0004061418 0.0004436410 0.0004177450
##              Y6
## Y1 0.0002462486
## Y2 0.0002976194
## Y3 0.0004061418
## Y4 0.0004436410
## Y5 0.0004177450
## Y6 0.0006216936
```

```r
var(scale(dat1.dat))
```

```
##           Y1        Y2        Y3        Y4        Y5        Y6
## Y1 1.0000000 0.5035656 0.6794433 0.5778571 0.5336809 0.4364807
## Y2 0.5035656 1.0000000 0.6234217 0.6163699 0.5853149 0.5347691
## Y3 0.6794433 0.6234217 1.0000000 0.8215338 0.7486924 0.5121106
## Y4 0.5778571 0.6163699 0.8215338 1.0000000 0.8107807 0.5229477
## Y5 0.5336809 0.5853149 0.7486924 0.8107807 1.0000000 0.4609773
## Y6 0.4364807 0.5347691 0.5121106 0.5229477 0.4609773 1.0000000
```

```r
#dist(dat1.dat, method= "euclidean")
```

Single factor MANOVA

```r
#single factor MANOVA
x1<-as.factor(dat1$X1)
model1 <- lm(dat1.dat~x1)
summary(model1) #yields a set of univariate analyses
```

```
## Response Y1 :
##
## Call:
## lm(formula = Y1 ~ x1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.047855 -0.013544 -0.001324  0.015324  0.043495
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept)  5.510712   0.002068 2664.377  < 2e-16 ***
## x11         -0.024778   0.003446   -7.191 4.09e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01929 on 134 degrees of freedom
## Multiple R-squared:  0.2784, Adjusted R-squared:  0.2731
## F-statistic: 51.71 on 1 and 134 DF,  p-value: 4.089e-11
##
##
## Response Y2 :
##
## Call:
## lm(formula = Y2 ~ x1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.059680 -0.013926  0.001607  0.015340  0.060176
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept)  3.454188   0.002383 1449.525   <2e-16 ***
## x11         -0.005808   0.003970   -1.463    0.146
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02223 on 134 degrees of freedom
## Multiple R-squared:  0.01572,    Adjusted R-squared:  0.008377
## F-statistic:  2.14 on 1 and 134 DF,  p-value: 0.1458
##
##
## Response Y3 :
##
```

```
## Call:
## lm(formula = Y3 ~ x1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.108253 -0.018507  0.003394  0.020429  0.070796
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.925970   0.003379 865.827   <2e-16 ***
## x11         -0.010478   0.005630  -1.861   0.0649 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03152 on 134 degrees of freedom
## Multiple R-squared:  0.0252, Adjusted R-squared:  0.01792
## F-statistic: 3.464 on 1 and 134 DF,  p-value: 0.06492
##
##
## Response Y4 :
##
## Call:
## lm(formula = Y4 ~ x1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.088257 -0.015131 -0.000352  0.027031  0.075104
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.896828   0.003659 791.670   <2e-16 ***
## x11         -0.002451   0.006096  -0.402    0.688
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03413 on 134 degrees of freedom
## Multiple R-squared:  0.001205,   Adjusted R-squared:  -0.006248
## F-statistic: 0.1617 on 1 and 134 DF,  p-value: 0.6882
##
##
## Response Y5 :
##
## Call:
## lm(formula = Y5 ~ x1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.112349 -0.018086  0.000696  0.024309  0.083726
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.358038   0.003906  859.78   <2e-16 ***
## x11         0.003967   0.006507    0.61    0.543
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03643 on 134 degrees of freedom
## Multiple R-squared:  0.002767,   Adjusted R-squared:  -0.004675
## F-statistic: 0.3718 on 1 and 134 DF,  p-value: 0.5431
##
##
## Response Y6 :
##
## Call:
## lm(formula = Y6 ~ x1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.086408 -0.018190 -0.000752  0.015316  0.063325
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept)  2.729201   0.002675 1020.320   <2e-16 ***
## x11         -0.004065   0.004456   -0.912    0.363
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02495 on 134 degrees of freedom
## Multiple R-squared:  0.00617,   Adjusted R-squared:  -0.001246
## F-statistic: 0.8319 on 1 and 134 DF,  p-value: 0.3634
```

```
summary(manova(model1)) #does multivariate test (using Pillai's)
```

```
##            Df  Pillai approx F num Df den Df    Pr(>F)
## x1          1 0.44162   17.005      6    129 2.098e-14 ***
## Residuals 134
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(manova(model1),test="Wilks")    #does multivariate test (using Wilks)
```

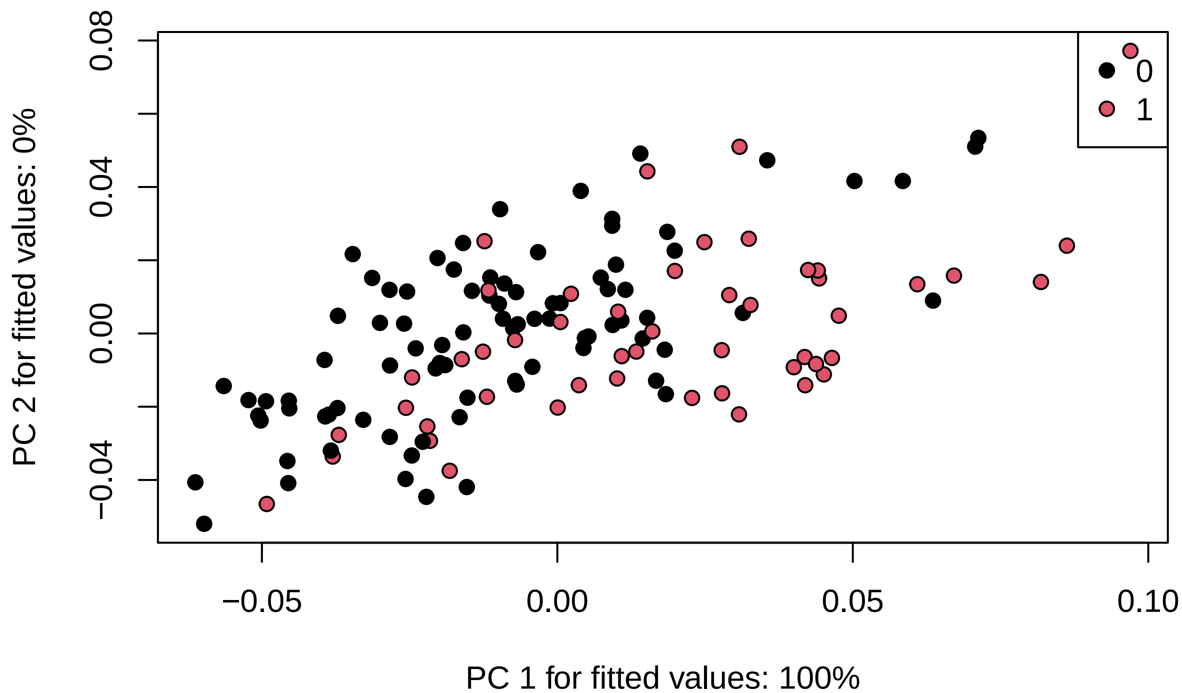
```
##            Df   Wilks approx F num Df den Df    Pr(>F)
## x1          1 0.55838   17.005      6    129 2.098e-14 ***
## Residuals 134
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##### MANOVA via RRPP
model.rrpp <- lm.rrpp(dat1.dat~x1,data = mydat, print.progress = FALSE)
anova(model.rrpp)
```

```
##
## Analysis of Variance, using Residual Randomization
## Permutation procedure: Randomization of null model residuals
## Number of permutations: 1000
## Estimation method: Ordinary Least Squares
## Sums of Squares and Cross-products: Type I
## Effect sizes (Z) based on F distributions
##
##            Df      SS        MS     Rsq      F      Z Pr(>F)
```

```
## x1           1 0.02494 0.0249429 0.03607 5.0144 2.1329  0.018 *
## Residuals 134 0.66655 0.0049742 0.96393
## Total     135 0.69149
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Call: lm.rrpp(f1 = dat1.dat ~ x1, data = mydat, print.progress = FALSE)
```

```
plot(model.rrpp, type = "PC", pch=21, bg = x1)  #PC PLOT!
legend("topright", levels(x1), pch = 21, pt.bg = 1:4)
```



Factorial MANOVA

```
#Factorial MANOVA
model2<-lm(mydat$Y~mydat$X1*mydat$X2)
summary(manova(model2))
```

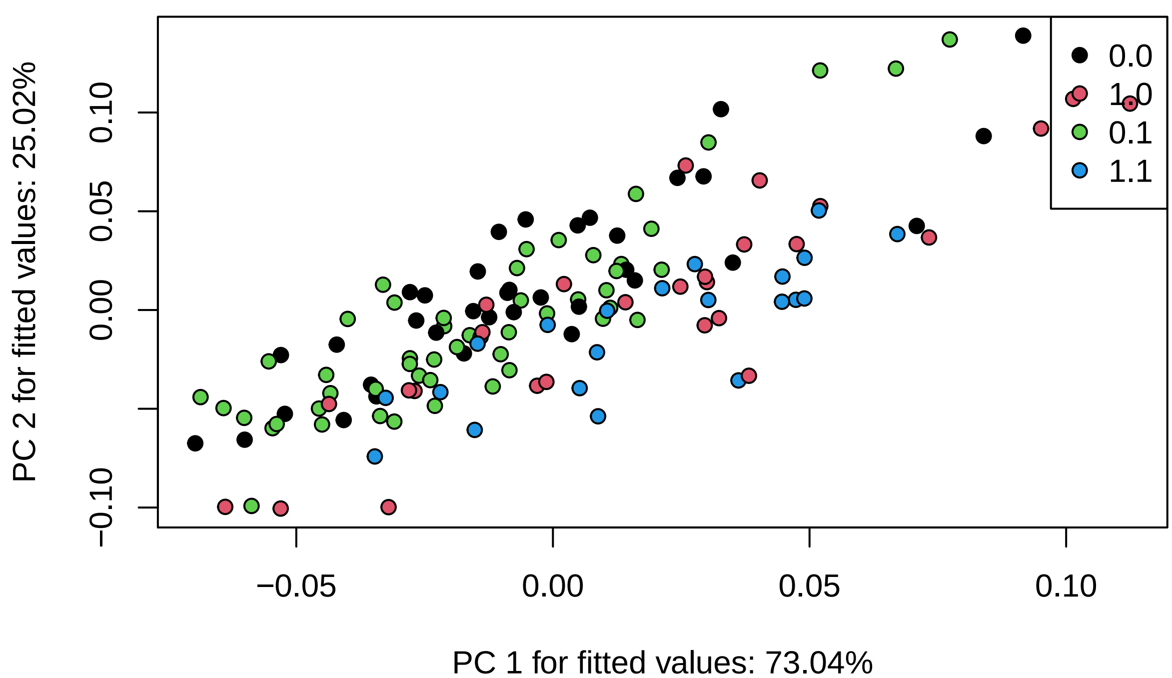
```
##                    Df  Pillai approx F num Df den Df    Pr(>F)
## mydat$X1            1 0.44815  17.1889      6    127 1.778e-14 ***
## mydat$X2            1 0.06874   1.5625      6    127    0.1634
## mydat$X1:mydat$X2   1 0.02965   0.6468      6    127    0.6926
## Residuals         132
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Factorial MANOVA via RRPP
model2.rrpp <- lm.rrpp(mydat$Y~mydat$X1*mydat$X2,data = mydat, print.progress = FALSE)
```

```r
anova(model2.rrpp)
```

```
##
## Analysis of Variance, using Residual Randomization
## Permutation procedure: Randomization of null model residuals
## Number of permutations: 1000
## Estimation method: Ordinary Least Squares
## Sums of Squares and Cross-products: Type I
## Effect sizes (Z) based on F distributions
##
##                      Df      SS        MS     Rsq      F        Z Pr(>F)
## mydat$X1              1 0.02494 0.0249429 0.03607 5.0236  2.13464  0.016 *
## mydat$X2              1 0.00955 0.0095488 0.01381 1.9232  1.10454  0.141
## mydat$X1:mydat$X2     1 0.00160 0.0015977 0.00231 0.3218 -0.68919  0.749
## Residuals           132 0.65540 0.0049652 0.94781
## Total               135 0.69149
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Call: lm.rrpp(f1 = mydat$Y ~ mydat$X1 * mydat$X2, data = mydat, print.progress = FALSE)
```

```r
groups <- interaction(mydat$X1,mydat$X2)
plot(model2.rrpp, type = "PC", pch=21, bg = groups)
legend("topright", levels(groups), pch = 21, pt.bg = 1:4)
```



Multivariate Regression

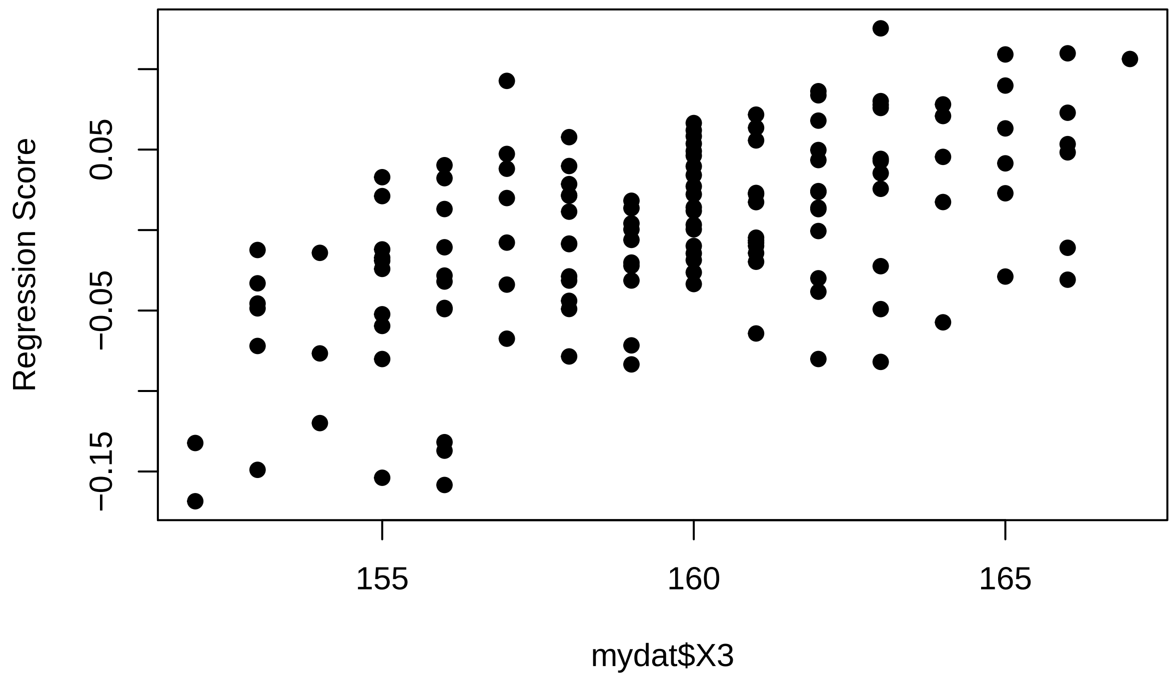
```r
#_____________________________________________________________________________#
### Multivariate Regression
summary(manova(lm(mydat$Y~mydat$X3)))
```

```
##            Df  Pillai approx F num Df den Df    Pr(>F)
## mydat$X3    1 0.51567   22.892      6    129 < 2.2e-16 ***
## Residuals 134
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
model.reg <- lm.rrpp(mydat$Y~mydat$X3, data = mydat, print.progress = FALSE)
anova(model.reg)
```

```
##
## Analysis of Variance, using Residual Randomization
## Permutation procedure: Randomization of null model residuals
## Number of permutations: 1000
## Estimation method: Ordinary Least Squares
## Sums of Squares and Cross-products: Type I
## Effect sizes (Z) based on F distributions
##
##            Df      SS       MS     Rsq      F      Z Pr(>F)
## mydat$X3    1 0.15206 0.152065 0.21991 37.775 4.6113  0.001 **
## Residuals 134 0.53943 0.004026 0.78009
## Total     135 0.69149
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Call: lm.rrpp(f1 = mydat$Y ~ mydat$X3, data = mydat, print.progress = FALSE)
```

```r
### Visualizing multivariate regression
plot(model.reg, type = "regression", reg.type = "RegScore",
     predictor = mydat$X3, pch=19)
```



MANCOVA

```
summary(manova(lm(mydat$Y~ mydat$X1*mydat$X2*mydat$X3))) #no iteraction significant, just X1 and X3 sig
```

```
##                             Df  Pillai approx F num Df den Df Pr(>F)
## mydat$X1                     1 0.53847  23.9171      6    123 <2e-16 ***
## mydat$X2                     1 0.06933   1.5271      6    123 0.1747
## mydat$X3                     1 0.52166  22.3566      6    123 <2e-16 ***
## mydat$X1:mydat$X2            1 0.07557   1.6758      6    123 0.1324
## mydat$X1:mydat$X3            1 0.07297   1.6137      6    123 0.1488
## mydat$X2:mydat$X3            1 0.03431   0.7282      6    123 0.6277
## mydat$X1:mydat$X2:mydat$X3   1 0.01441   0.2997      6    123 0.9360
## Residuals                  128
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(manova(lm(mydat$Y~ mydat$X1+mydat$X3))) # FIT COMMON SLOPE
```

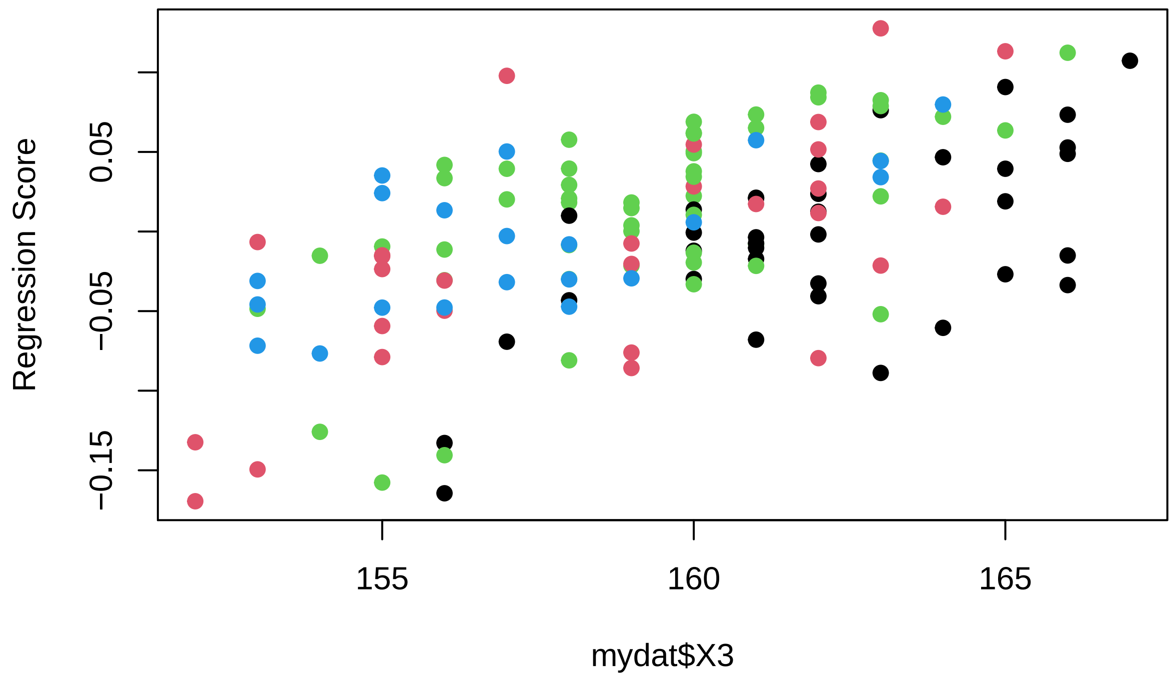
```
##              Df  Pillai approx F num Df den Df    Pr(>F)
## mydat$X1      1 0.51929   23.045      6    128 < 2.2e-16 ***
## mydat$X3      1 0.45726   17.973      6    128 4.804e-15 ***
## Residuals 133
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#MANCOVA via RRPP
model.mancova <- lm.rrpp(mydat$Y~ mydat$X1*mydat$X2*mydat$X3, data =mydat, print.progress = FALSE)
```

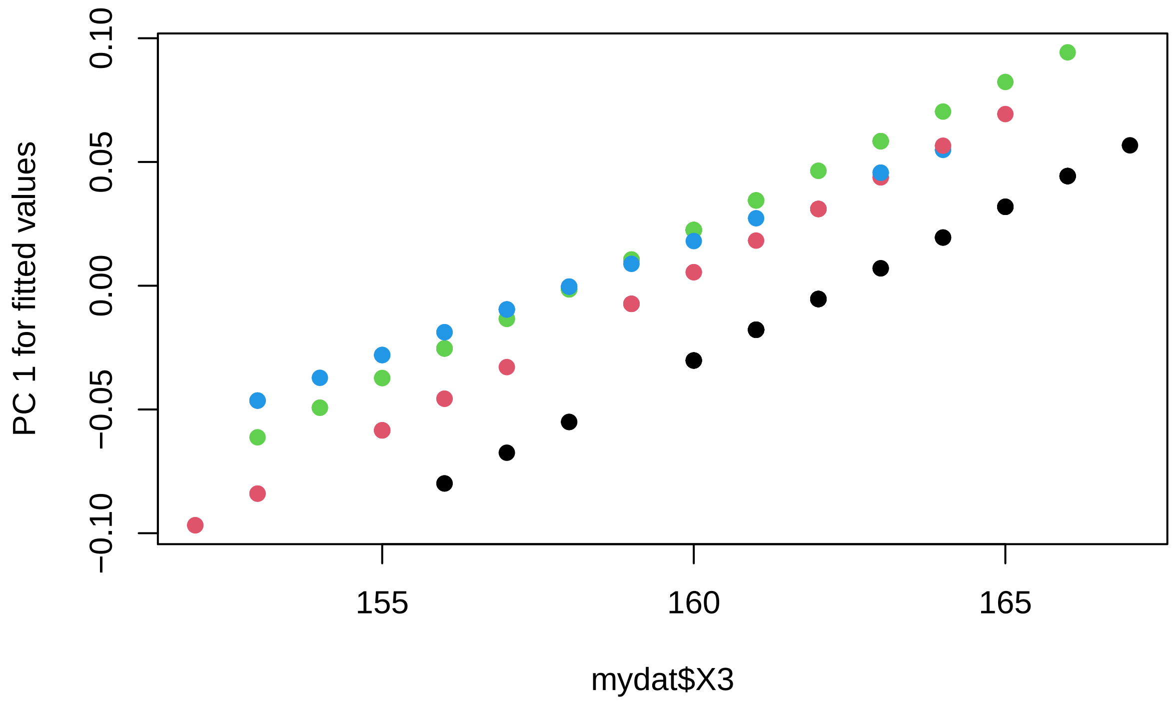
```r
anova(model.mancova)
```

```
##
## Analysis of Variance, using Residual Randomization
## Permutation procedure: Randomization of null model residuals
## Number of permutations: 1000
## Estimation method: Ordinary Least Squares
## Sums of Squares and Cross-products: Type I
## Effect sizes (Z) based on F distributions
##
##                               Df      SS       MS     Rsq       F       Z Pr(>F)
## mydat$X1                       1 0.02494 0.024943 0.03607  6.9316  2.4835  0.005
## mydat$X2                       1 0.00955 0.009549 0.01381  2.6536  1.4403  0.086
## mydat$X3                       1 0.18310 0.183096 0.26478 50.8822  4.7686  0.001
## mydat$X1:mydat$X2              1 0.00782 0.007822 0.01131  2.1738  1.4143  0.088
## mydat$X1:mydat$X3              1 0.00250 0.002501 0.00362  0.6951 -0.0430  0.508
## mydat$X2:mydat$X3              1 0.00155 0.001550 0.00224  0.4307 -0.5844  0.722
## mydat$X1:mydat$X2:mydat$X3     1 0.00143 0.001429 0.00207  0.3972 -0.6541  0.746
## Residuals                    128 0.46060 0.003598 0.66610
## Total                        135 0.69149
##
## mydat$X1                     **
## mydat$X2                     .
## mydat$X3                     **
## mydat$X1:mydat$X2            .
## mydat$X1:mydat$X3
## mydat$X2:mydat$X3
## mydat$X1:mydat$X2:mydat$X3
## Residuals
## Total
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Call: lm.rrpp(f1 = mydat$Y ~ mydat$X1 * mydat$X2 * mydat$X3, data = mydat,
##     print.progress = FALSE)
```

```r
### Visualizing MANCOVA
plot(model.mancova, type = "regression", reg.type = "RegScore",
     predictor = mydat$X3, pch=19, col = as.numeric(groups))
```




```
plot(model.mancova, type = "regression", reg.type = "PredLine",
     predictor = mydat$X3, pch=19,
     col = as.numeric(groups))
```



WEEK 8 MATERIAL

```
Y <- scale(mydat$Y, scale = FALSE) #center data
pca.dat1<-prcomp(Y) #told nothing about groups
summary(pca.dat1)
```

```
## Importance of components:
##                            PC1     PC2     PC3     PC4     PC5     PC6
## Standard deviation     0.06081 0.02151 0.01850 0.01533 0.01502 0.01260
## Proportion of Variance 0.72190 0.09036 0.06683 0.04587 0.04403 0.03102
## Cumulative Proportion  0.72190 0.81225 0.87908 0.92495 0.96898 1.00000
```

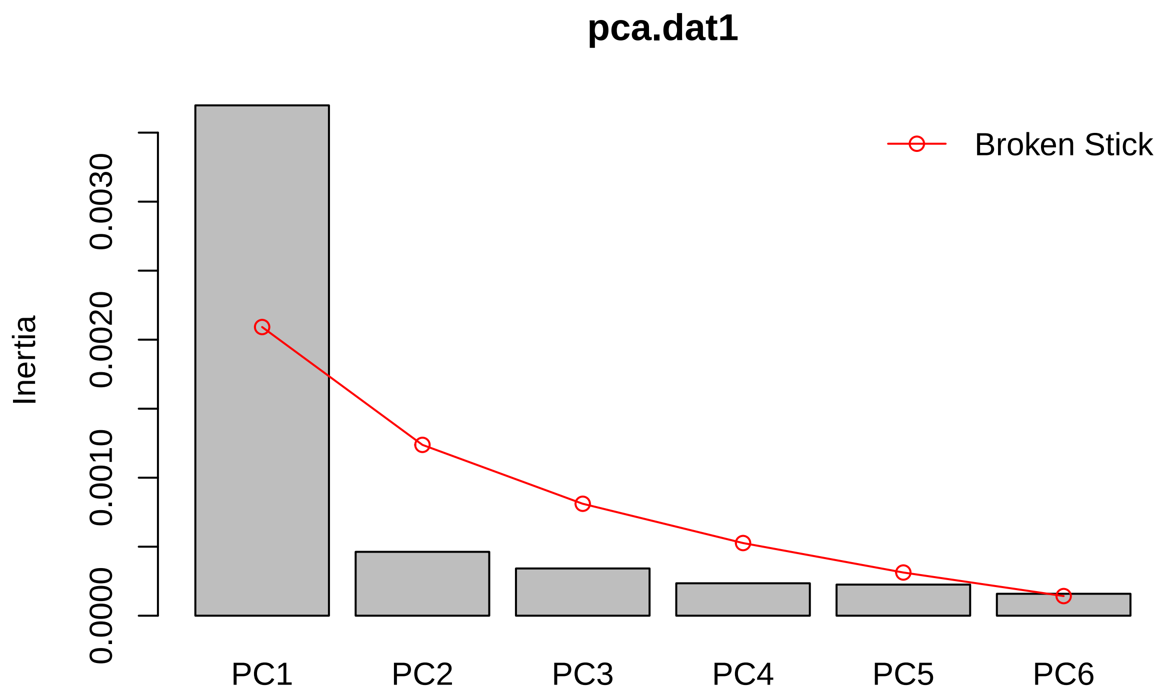
```
library(vegan)
```

```
## Loading required package: permute

## Loading required package: lattice

## This is vegan 2.5-7
```

```
screeplot(pca.dat1,bstick = TRUE)
```

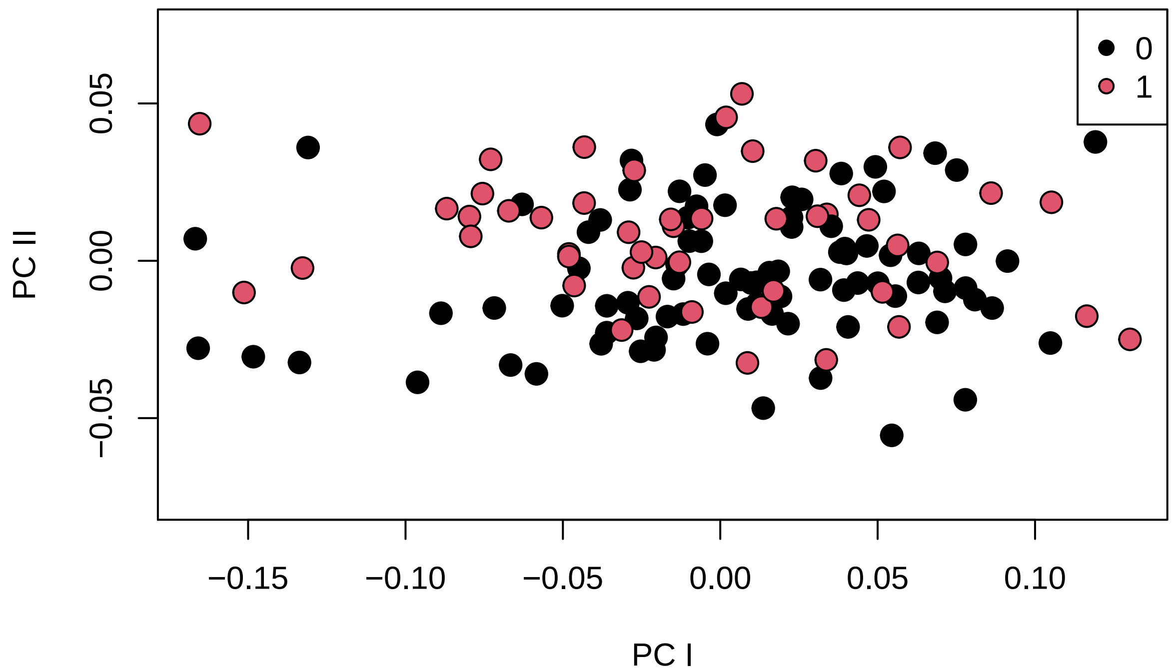



```
pca.dat1$rotation[,1]
```

```
##        Y1        Y2        Y3        Y4        Y5        Y6
## 0.2620346 0.2675598 0.4778146 0.5212309 0.5411779 0.2586263
```

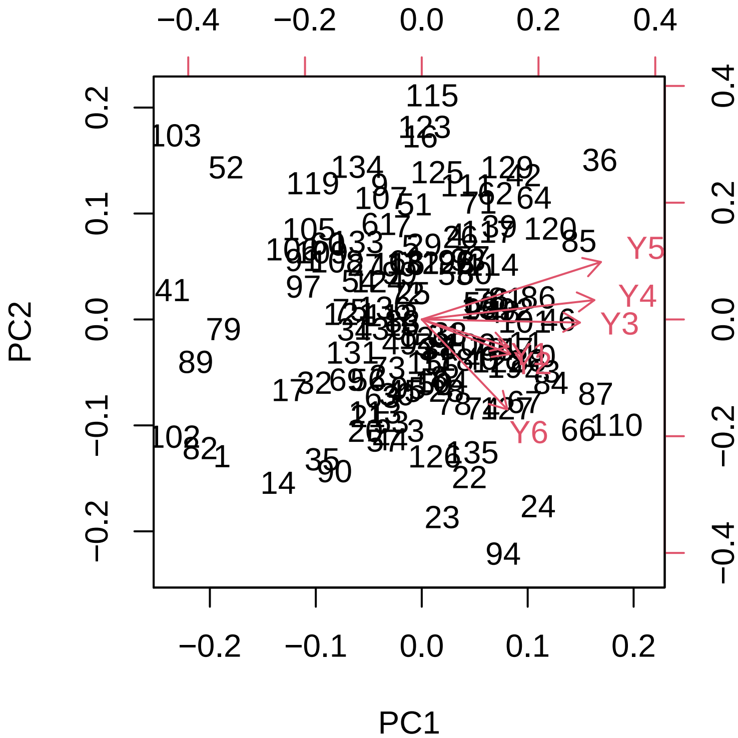
```
PC.scores<-pca.dat1$x

plot(PC.scores,xlab="PC I", ylab="PC II",asp=1,pch=21,bg=mydat$X1,cex = 1.5)
legend("topright", levels(mydat$X1), pch = 21,pt.bg=1:2)
```



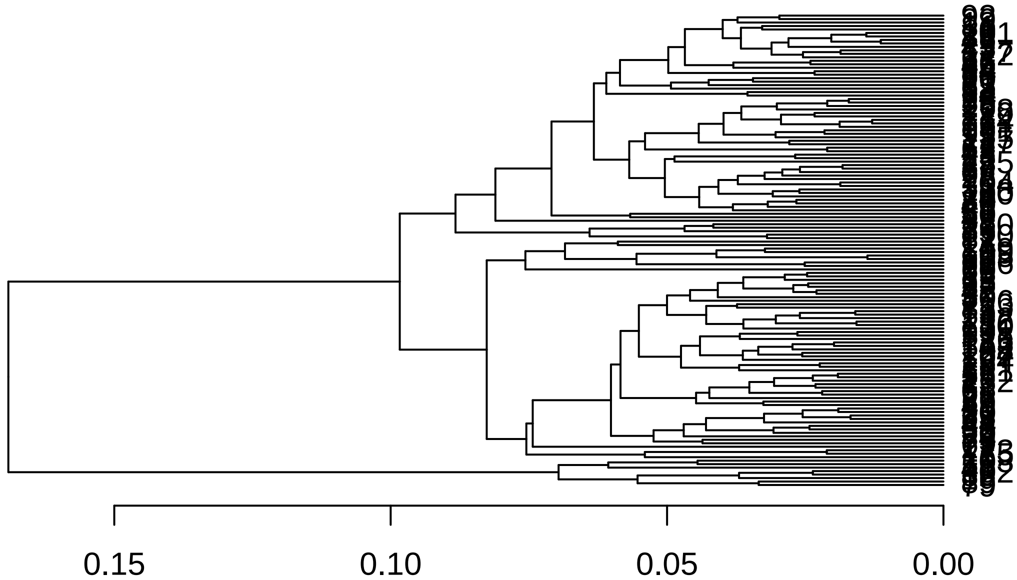
Biplot

```
#Biplot of dat1
biplot(pca.dat1)
```

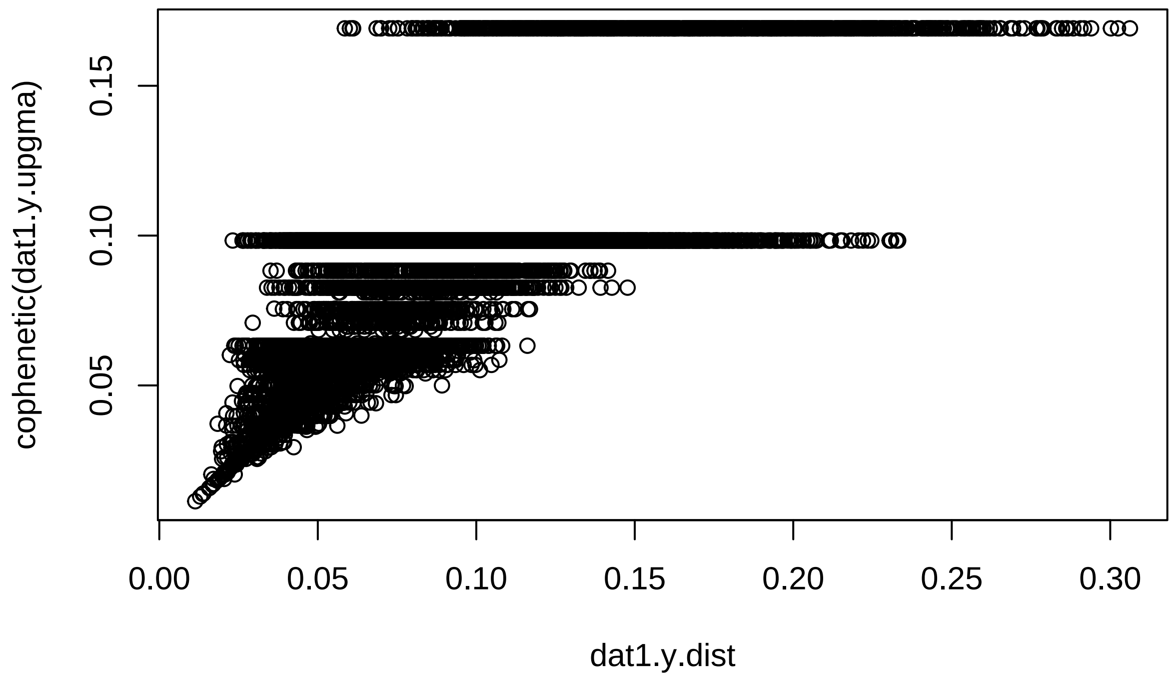


WEEK 9 MATERIAL

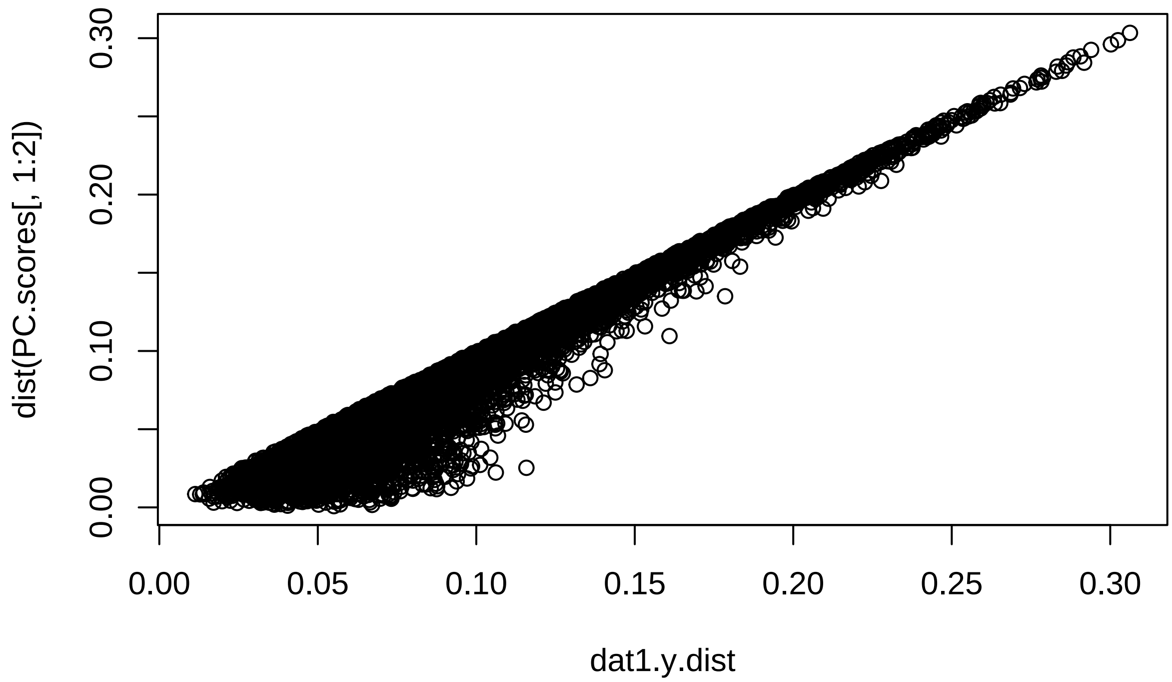
```
##UPGMA
dat1.y.dist<-dist(PC.scores)
dat1.y.upgma<-hclust(dat1.y.dist,method="average")
plot(as.dendrogram(dat1.y.upgma),horiz=TRUE,lwd=4)   #UPGMA
```



```
#PLOT of actual vs. UPGMA distances
plot(dat1.y.dist,cophenetic(dat1.y.upgma))
```



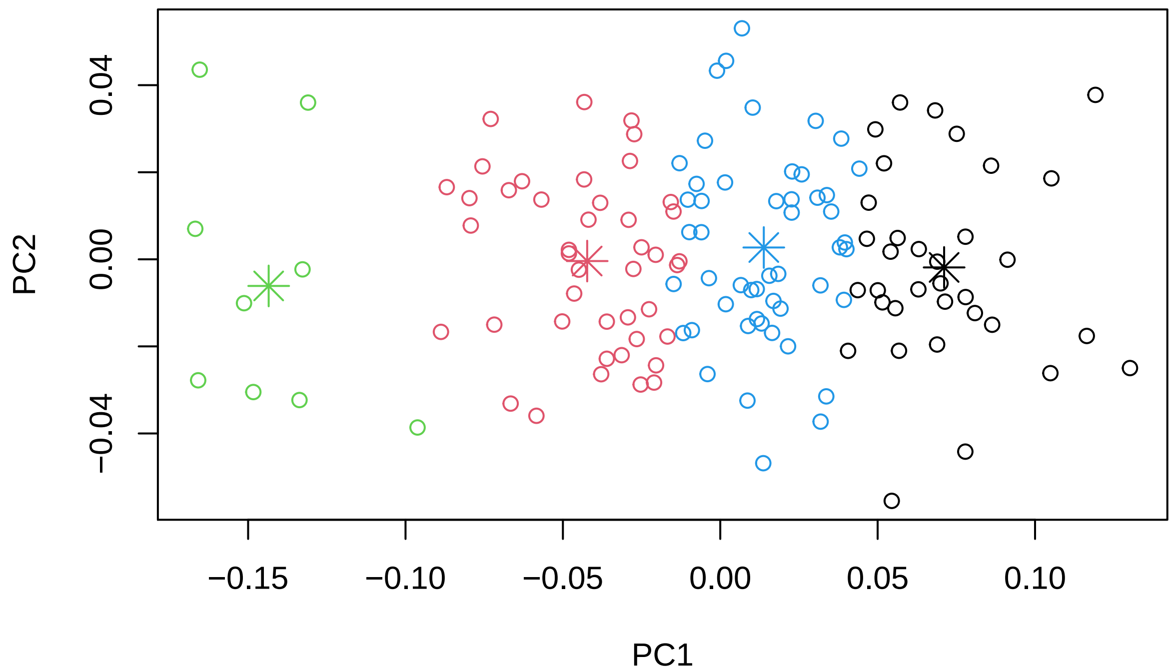

```
# SAME from PC
plot(dat1.y.dist,dist(PC.scores[,1:2]))
```



K-MEANS CLUSTERING METHODS

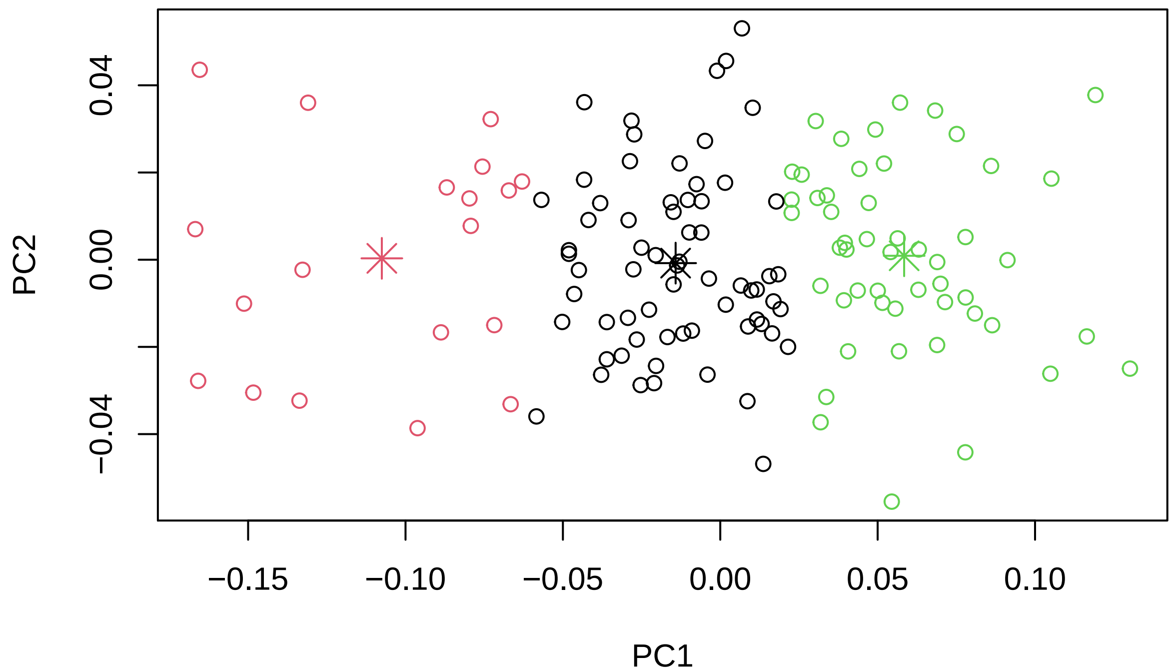
Clustering by 4

```
#K-means = 4
kclusters4<-kmeans(PC.scores,4)
plot(PC.scores[,1:2],col=kclusters4$cluster)
points(kclusters4$centers, col = 1:4, pch = 8, cex=2)
```



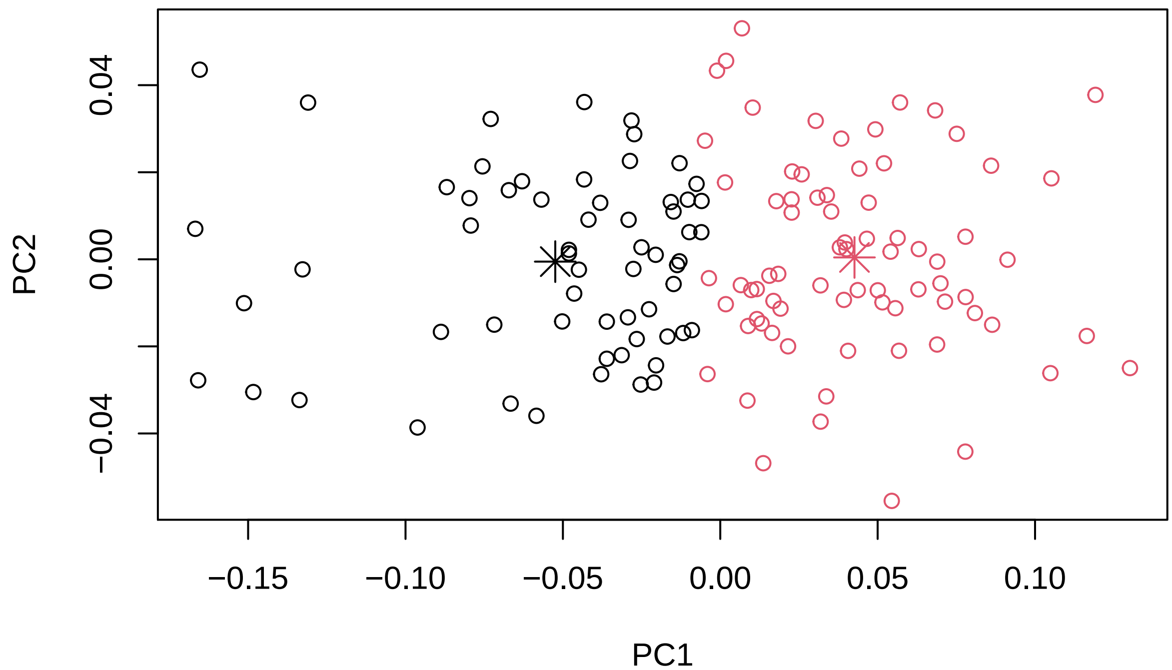
Clustering by 3

```
#K-means = 3
kclusters3<-kmeans(PC.scores,3)
plot(PC.scores[,1:2],col=kclusters3$cluster)
points(kclusters3$centers, col = 1:3, pch = 8, cex=2)
```



Clustering by 2

```
#K-means = 2
kclusters2<-kmeans(PC.scores,2)
plot(PC.scores[,1:2],col=kclusters2$cluster)
points(kclusters2$centers, col = 1:2, pch = 8, cex=2)
```

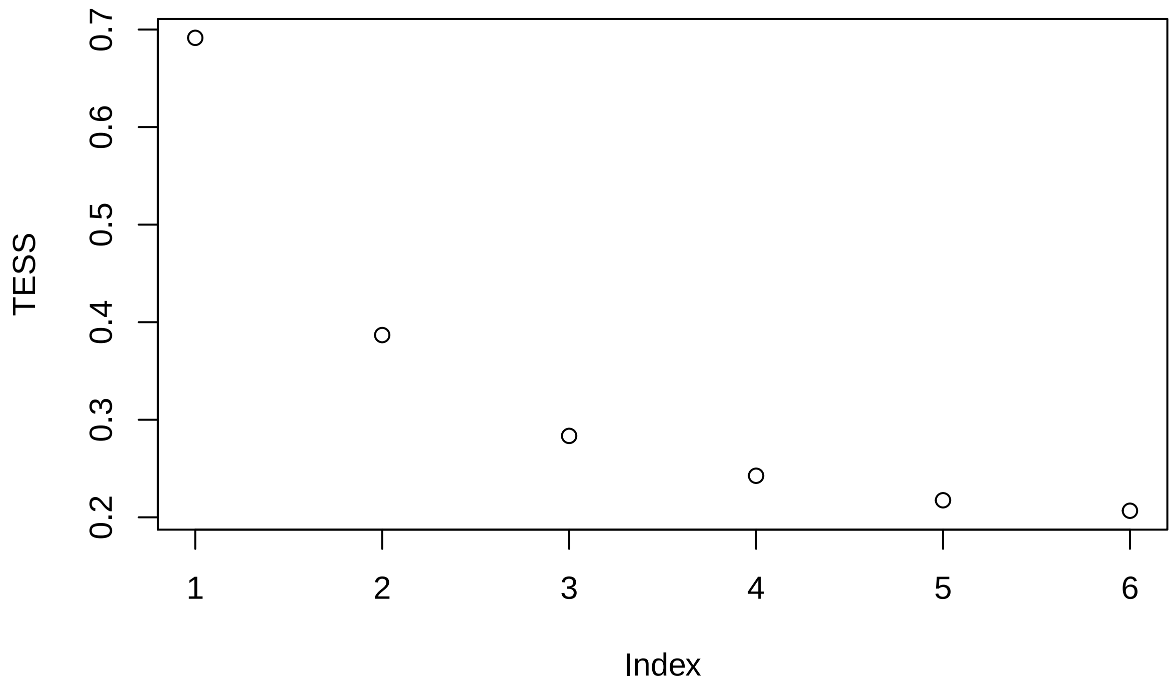



```
#NOTE: repeating k-means at a given level can lead to differing results
```

TESS: total error sums-of-squares

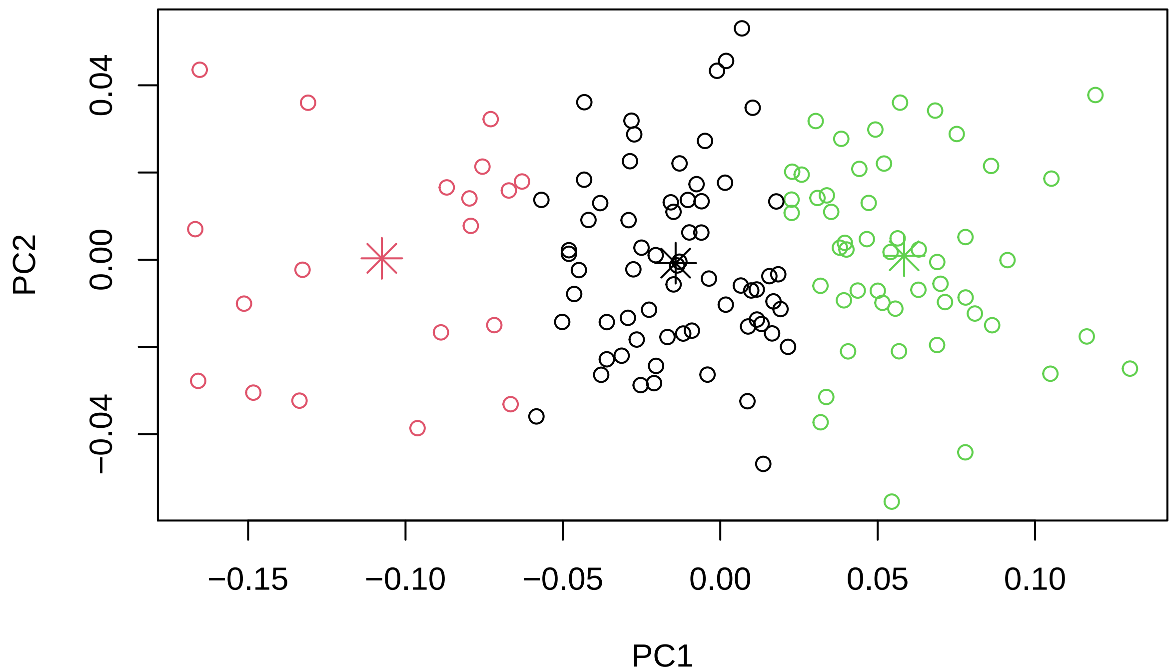
Compare the total error sums-of-squares to see which grouping results in a leveling off of the kmeans of PC scores.

```
#compare TESS
TESS<-array(NA,6)
for (i in 1:6){
  TESS[i]<-kmeans(PC.scores,i)$tot.withinss
}
plot( TESS)  #seems to bottom out at 3 groups
```



Based on the TESS results, it appears that the mean PC.scores level off at about a k grouping of 3 so we will cluster by a kmean of 3.

```
plot(PC.scores[,1:2],col=kclusters3$cluster)
points(kclusters3$centers, col = 1:3, pch = 8, cex=2)
```



WEEK 10 MATERIAL

Partial Least Squares (PLS)

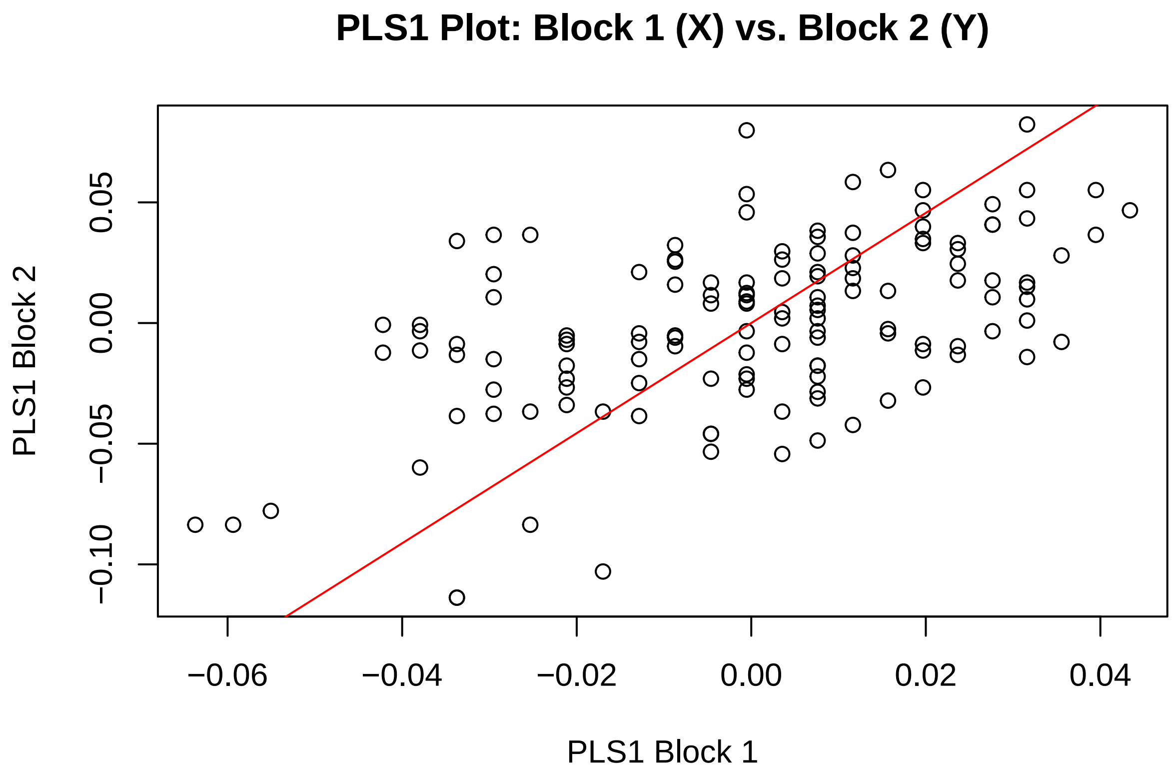
```
pls.res<-two.b.pls(mydat$Y[,1], mydat$Y[,5],print.progress = FALSE)
```

```
## Data in either A1 or A2 do not have names.  It is assumed data in both A1 and A2 are ordered the same
```

```
summary(pls.res)
```

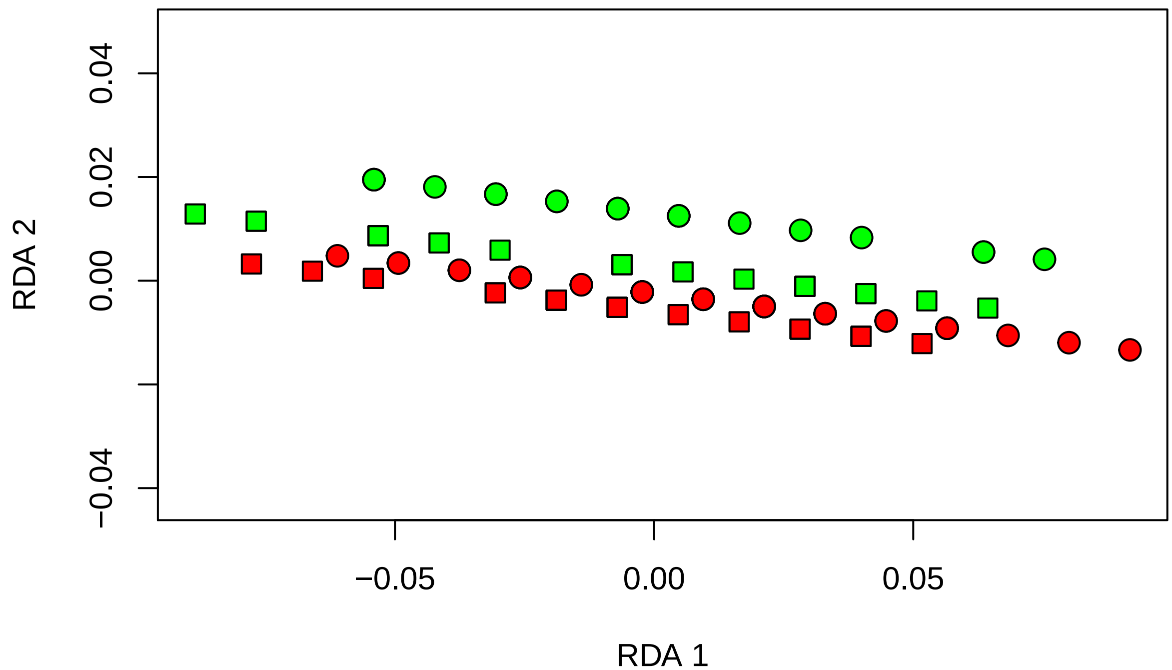
```
##
## Call:
## two.b.pls(A1 = mydat$Y[, 1], A2 = mydat$Y[, 5], print.progress = FALSE)
##
##
##
## r-PLS: 0.534
##
## Effect Size (Z): 5.7095
##
## P-value: 0.001
##
## Based on 1000 random permutations
```

```
plot(pls.res)
```



Redundancy Analysis

```
Y<-pca.dat1$x
col.gp<-rep("green",nrow(Y));   col.gp[which(mydat$X1== '0')]<-"red"
shape.gp<-rep(21,nrow(Y));   shape.gp[which(mydat$X2== '0')]<-22
rda.dat1<-rda(Y~mydat$X1+mydat$X2+mydat$X3+mydat$X1*mydat$X2)
rda.scores<-predict(rda.dat1)
plot(rda.scores,pch=shape.gp,bg=col.gp,asp=1,cex=1.5,xlab="RDA 1", ylab="RDA 2")
```


RDA 2
0.04
0.02
0.00
−0.04
−0.05
0.00
0.05
RDA 1