

STAT 501 Homework 4

Multinomial

March 2, 2018

1. (a) We choose to plot the radial visualization to see any difference between the regions and sub-regions.

```
1  #Multinomial
2  ##Problem 1
3  #a) Radial visualization
4  library(lattice)
5  require(dprep)
6  olive <-
7  ↪ read.table("http://maitra.public.iastate.edu/stat501/datasets/olive.dat",
8  ↪ header=T)
9  olive
10 colnames(olive) <- c("Regions", "CH1", "CH2", "CH3", "CH4",
11 ↪ "CH5", "CH6", "CH7", "CH8")
12 names(olive)
13 oil<- as.factor(olive$Regions)
14
15 # Use codes from Canvas
16 source("radviz2d.R")
17 # Display the radial visualization plot
18 radviz2d(dataset = cbind(olive[,-1], oil), name = "Regions")
19
20 # sub-regions R1
21 olive_R1 <- olive[olive$Regions %in% 1:4,]
22 radviz2d(dataset = cbind(olive_R1[,-1],
23 ↪ as.factor(olive_R1$Regions)), name = "R1")
24
25 # sub-region R2
26 olive_R2 <- olive[olive$Regions %in% 5:6,]
27 radviz2d(dataset = cbind(olive_R2[,-1],
28 ↪ as.factor(olive_R2$Regions)), name = "R2")
29
30 # sub-region R3
31 olive_R3 <- olive[olive$Regions %in% 7:9,]
32 radviz2d(dataset = cbind(olive_R3[,-1],
33 ↪ as.factor(olive_R3$Regions)), name = "R3")
```

The plots are shown in Figure 1 and Figure 2.

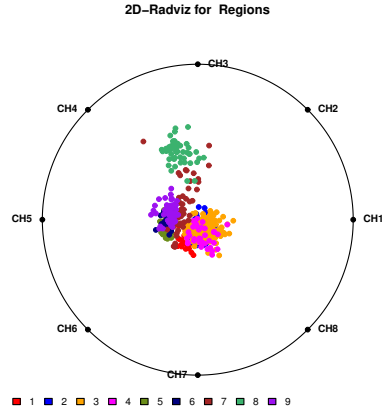


Figure 1: Radial Visualization for all regions

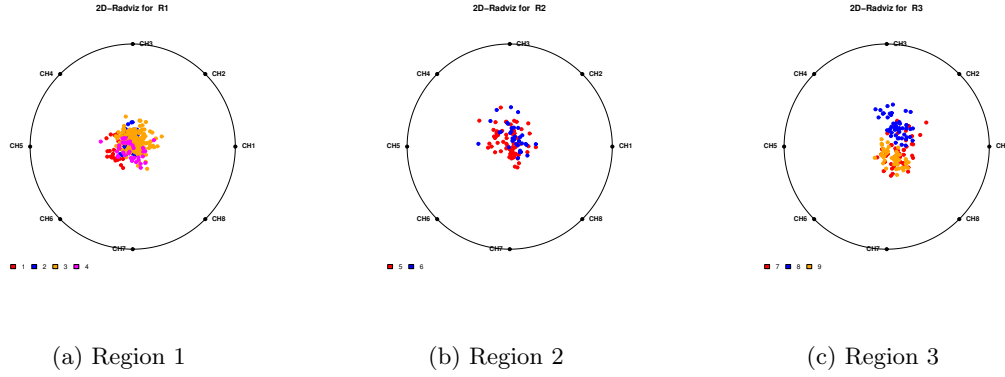


Figure 2: Radial Visualization for sub-regions

The plot that contains all nine regions does not reveal exact difference between chemical components of olive oil except component CH8. The second plot for sub-region 1 shows that all chemical components have quite same pattern. The third plot for sub-region 2 indicates much overlap of chemical components. The plot for sub-region 3 reveals the exact difference between CH8, CH7 and CH9. If we compare three sub-regions, the chemical components behave differently in each case. Among visualization methods, radial visualisation might be effective since some other methods show only overall view of the chemical components.

- (b) i. In Regions 2, we calculate the correlation matrix for each of the two sub-regions:

```

1 #b) Choose the R2
2 #i) Calculate the correlation matrix of the two sub-regions
3 cor(olive_R2[olive_R2$Regions == 5, -1])
4 cor(olive_R2[olive_R2$Regions == 6, -1])

```

The results are: For Area 5:

| | CH1 | CH2 | CH3 | CH4 | CH5 | CH6 | CH7 | CH8 | |
|---|-----|-------------|-------------|-------------|-------------|-------------|------------|-------------|-------------|
| 1 | CH1 | 1.00000000 | -0.25401254 | -0.22343243 | -0.34906506 | -0.41062951 | 0.1668259 | -0.03085139 | -0.10589148 |
| 2 | CH2 | -0.25401254 | 1.00000000 | 0.15994615 | -0.06232554 | 0.11648748 | 0.1587715 | 0.10500427 | 0.13394123 |
| 3 | CH3 | -0.22343243 | 0.15994615 | 1.00000000 | -0.24736894 | 0.08986342 | -0.3458010 | -0.29500434 | -0.04184051 |
| 4 | CH4 | -0.34906506 | -0.06232554 | -0.24736894 | 1.00000000 | -0.38972482 | 0.1767836 | 0.13928597 | 0.01336267 |
| 5 | CH5 | -0.41062951 | 0.11648748 | 0.08986342 | -0.38972482 | 1.00000000 | -0.3416671 | -0.08799411 | 0.03397236 |
| 6 | CH6 | 0.16682592 | 0.15877145 | -0.34580096 | 0.17678361 | -0.34166707 | 1.00000000 | 0.45678706 | -0.10181956 |
| 7 | CH7 | -0.03085139 | 0.10500427 | -0.29500434 | 0.13928597 | -0.08799411 | 0.4567871 | 1.00000000 | -0.03620758 |
| 8 | CH8 | -0.10589148 | 0.13394123 | -0.04184051 | 0.01336267 | 0.03397236 | -0.1018196 | -0.03620758 | 1.00000000 |

For Area 6:

| | CH1 | CH2 | CH3 | CH4 | CH5 | CH6 | CH7 | CH8 | |
|---|-----|--------------|-------------|-------------|------------|-------------|--------------|-------------|-------------|
| 1 | CH1 | 1.000000000 | 0.11900039 | 0.08786970 | -0.7994401 | 0.42188660 | -0.007466556 | 0.33270138 | 0.40508513 |
| 2 | CH2 | 0.119000387 | 1.00000000 | 0.40954913 | -0.1868781 | -0.17723037 | -0.049145339 | 0.12964611 | -0.03710676 |
| 3 | CH3 | 0.087869701 | 0.40954913 | 1.00000000 | -0.2811107 | -0.01414057 | -0.399135258 | 0.14357073 | 0.13619085 |
| 4 | CH4 | -0.799440133 | -0.18687810 | -0.28111067 | 1.00000000 | -0.79232090 | -0.151300451 | -0.60573225 | -0.36134336 |
| 5 | CH5 | 0.421886601 | -0.17723037 | -0.01414057 | -0.7923209 | 1.00000000 | -0.182269052 | 0.53905745 | 0.22800013 |
| 6 | CH6 | -0.007466556 | -0.04914534 | -0.39913526 | 0.1513005 | -0.18226905 | 1.00000000 | 0.06465175 | 0.04913952 |
| 7 | CH7 | 0.332701378 | 0.12964611 | 0.14357073 | -0.6057323 | 0.53905745 | 0.064651746 | 1.00000000 | 0.24163350 |
| 8 | CH8 | 0.405085132 | -0.03710676 | 0.13619085 | -0.3613434 | 0.22800013 | 0.049139516 | 0.24163350 | 1.00000000 |

And then we display the correlation matrix side-by-side as in Figure 3.

```

1 source("plotcorr.R")
2 par(mfrow = c(1,2))
3 plot.corr(xx = olive_R2[olive_R2$Regions == 5, -1])
4 plot.corr(xx = olive_R2[olive_R2$Regions == 6, -1])

```

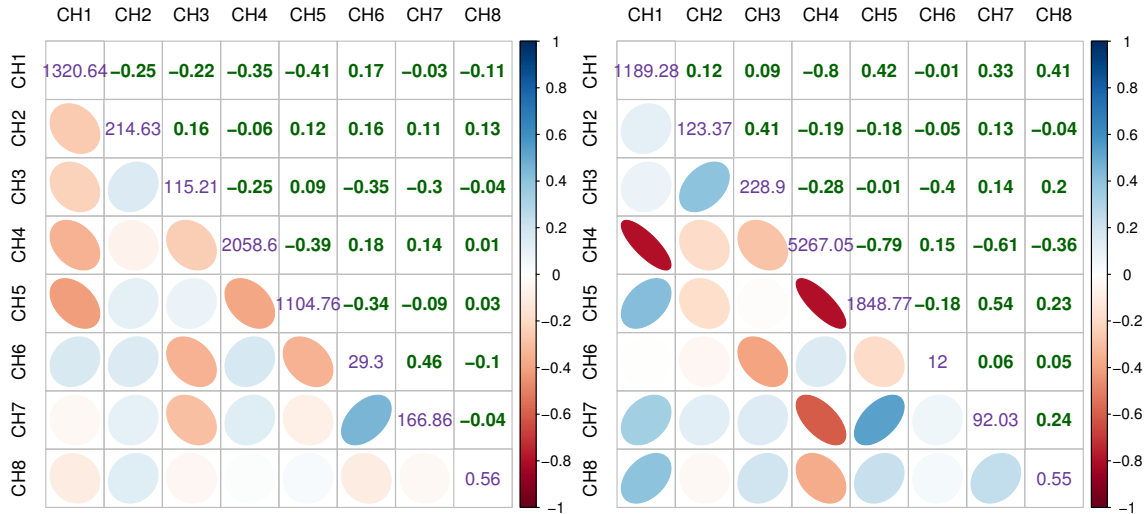


Figure 3: Correlation matrix display for Area 5 and Area 6

According to the plots for Area 6, the correlation between CH4 and CH1, CH5 and CH4, CH4 and CH7 as well as CH5 and CH7 much strong than in Area 5. In addition, the relationship between CH1 and CH5 in Area 6 has a positive sign, however, in Area 5 is a negative. Overall, we can conclude that chemical components in Area 6 highly correlated than in Area 5.

- ii. Compare the marginal standard deviations directly as well as with parallel coordinate plots:

```

1  #ii) Compare marginal standard deviations
2  require(ggplot2)
3  require(GGally)
4  require(RColorBrewer)
5  source("parcoordplot.R")
6
7  SD_5<-supply(olive_R2[olive_R2$Regions == 5, -1], FUN = sd)
8  SD_6<-supply(olive_R2[olive_R2$Regions == 6, -1], FUN = sd)
9  # parallel coordinate plots
10 parcoordplot(xx =olive_R2[, -1] ,cl =
    ↪ as.factor(olive_R2$Regions),FUN=mean,alpha = 0.2)

```

And for Area 5, marginal standard deviations are:

| | CH1 | CH2 | CH3 | CH4 | CH5 | CH6 | CH7 |
|--------|------------|------------|------------|------------|------------|-----------|------------|
| Area 5 | 36.3406228 | 14.6501181 | 10.7336638 | 45.3717550 | 33.2379244 | 5.4126366 | 12.9173966 |
| CH8 | 0.7493587 | | | | | | |

For Area 6:

| | CH1 | CH2 | CH3 | CH4 | CH5 | CH6 | CH7 |
|--------|-----------|-----------|-----------|-----------|-----------|----------|----------|
| Area 6 | 34.485916 | 11.107259 | 15.129554 | 72.574426 | 42.997291 | 3.464375 | 9.593243 |
| CH8 | 0.739830 | | | | | | |

The parallel coordinate plots as in Figure 4.

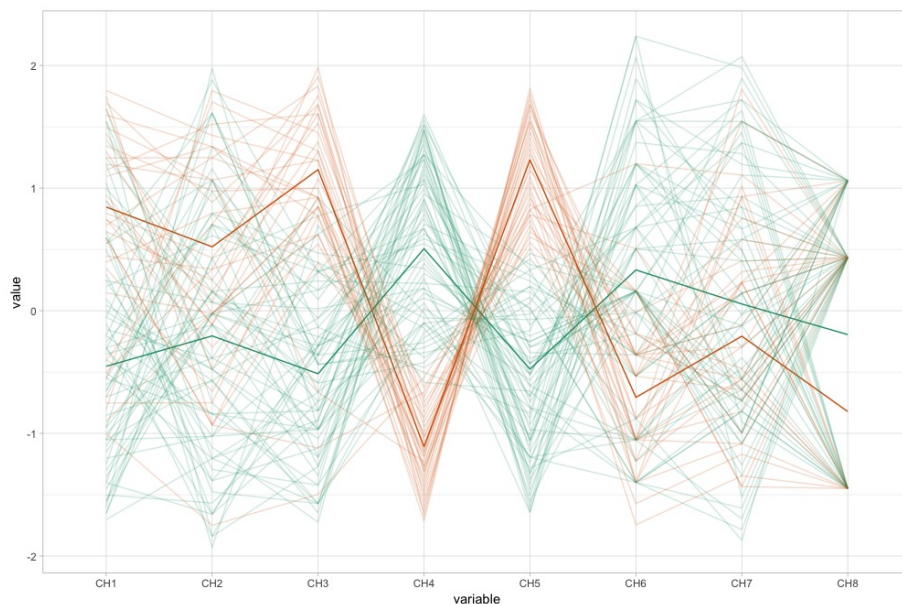


Figure 4: Parallel coordinate plots for Area 5 and Area 6

The standard deviation for Area 5 higher for CH1,CH2, CH7 and CH8 than in Area 6, however other the standard deviations of other chemical components are lower.

iii. Test for difference in dispersions among the two groups

```
1 #iii) Test for difference in dispersions among the two groups
2
3 source("BoxMtest-2.R")
4
5 BoxMTest(X = olive_R2[, -1], cl = as.factor(olive_R2$Regions))
```

The result is

```
1 [1] 2
2 -----
3 MBox Chi-sqr. df P
4 -----
5      109.5204      98.3550      36      0.0000
6 -----
7 Covariance matrices are significantly different.
8 $MBox
9      5
10 109.5204
11
12 $ChiSq
13      5
14 98.35502
15
16 $df
17 [1] 36
18
19 $pValue
20      5
21 1.069438e-07
```

With small p-value we conclude that there is significant evidence that the dispersions are different.

iv. Test for normality

```
1 #iv) Test for normality
2 source("testnormality.R")
3
4 testnormality(X=olive_R2[olive_R2$Regions == 5, -1])
5 testnormality(X=olive_R2[olive_R2$Regions == 6, -1])
```

The p-value for Area 5 is **1.743735e-06** and for Area 6 is **0.3706021**. The test result shows that for the Area 6 we can conclude multivariate normality is reasonable, but for Area 5 not.

v. Hotelling's T^2 test:

```
1 library(ICSNP)
2 T2test <- HotellingsT2(X = olive_R2[olive_R2$Regions == 5,
3   ↪ -1], Y = olive_R2[olive_R2$Regions == 6, -1])
4 T2test
5 df1 <- T2test$parameter['df1']
6 df2 <- T2test$parameter['df2']
```

```

6 T2stat <- T2test$statistic/df2*(df1 + df2 - 1)*df1
7 T2stat

```

The result of test is

```

1      #Hotelling's two sample T2-test
2
3 data:  olive_R2[olive_R2$Regions == 5, -1] and
4       ↪ olive_R2[olive_R2$Regions == 6, -1]
5 T.2 = 112.41, df1 = 8, df2 = 89, p-value < 2.2e-16
6 alternative hypothesis: true location difference is not equal
7 ↪ to c(0,0,0,0,0,0,0,0)

```

and p-value is less than **2.2e-16**, by adjust the result the true statistic

$$T^2 = 969.9727$$

With small p-value we conclude that the two mean vectors are different for Area 5 and Area 6.

- vi. We do 8 individual t-tests for 8 chemicals and adjust the p-value with Bonferroni and FDR.

```

1      #vi) Provide individual t-tests
2
3 tp_value<-function(X, cl){
4   class <- levels(cl)
5   return(t.test(X[cl == class[1]], X[cl == class[2]],
6     ↪ var.equal = T)$p.value)
7 }
8
9 p_vals <- sapply(olive_R2[, -1], tp_value, cl =
10 ↪ as.factor(olive_R2$Regions))
11
12 p.adjust(p_vals, method = "bonferroni")
13 p.adjust(p_vals[order(p_vals)], method = "fdr")

```

The adjusted p-values with Bonferroni:

```

1      CH1      CH2      CH3      CH4      CH5      CH6
2 5.973326e-06 2.176220e-01 9.174890e-16 6.631503e-40 1.023099e-45 3.834440e-05
3      CH7      CH8
4 1.000000e+00 1.000000e+00

```

The adjusted p-values with FDR:

```

1      CH5      CH4      CH3      CH1      CH6      CH2
2 1.023099e-45 3.315752e-40 3.058297e-16 1.493332e-06 7.668880e-06 3.627033e-02
3      CH7      CH8
4 5.459712e-01 5.720031e-01

```

From these two adjusted p-values, we conclude that there is no significant differences in chemical 7 and 8 between Area 5 and 6, but there is differences in other chemical components.

vii. Draw 95% confidence ellipses, the ellipses are shown in Figure 5.

```
1 #vii) Draw 95% Confidence ellipses
2 library(car)
3 dataEllipse(olive_R2$CH5, olive_R2$CH6, groups =
  ↳ as.factor(olive_R2$Regions), levels=0.95, xlab = "CH5",
  ↳ ylab = "CH6", col = c("red", "blue"), ylim = c(10, 45),
  ↳ group.labels = c("A5", "A6"))
```

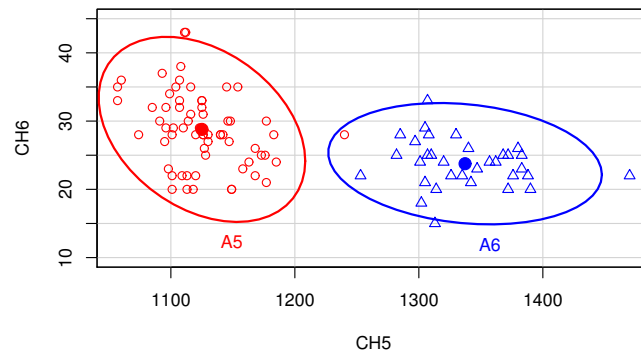


Figure 5: 95% confidence ellipses for Area 5 and Area 6

- (c) i. Display means with Chernoff faces as in Figure 6.

```
1  #c) Three main regions
2  #i) Display the Chernoff faces
3  library(TeachingDemos)
4  mean_R1 <- sapply(olive_R1[, -1], mean)
5  mean_R2 <- sapply(olive_R2[, -1], mean)
6  mean_R3 <- sapply(olive_R3[, -1], mean)
7  mean_Rs <- cbind(rbind(mean_R1, mean_R2, mean_R3))
8
9  faces(mean_Rs, labels = c("R1", "R2", "R3"))
```

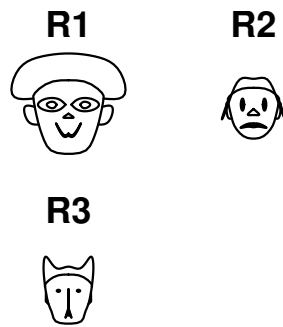


Figure 6: Means for 3 big regions

According to Chernoff faces, we can see that there is difference in the means among the 3 regions.

ii. MANOVA for differences in means among 3 regions:

```

1  #ii) Provide a one-way multivariate analysis of variance.
2  BigRegions <- rep(0, nrow(olive))
3  BigRegions[olive$Regions %in% 1:4] <- 1
4  BigRegions[olive$Regions %in% 5:6] <- 2
5  BigRegions[olive$Regions %in% 7:9] <- 3
6  olive <- data.frame(olive, BigRegions = as.factor(BigRegions))
7  fit.lm <- lm(cbind(CH1, CH2, CH3, CH4, CH5, CH6, CH7, CH8) ~ BigRegions, data =
8    olive)
9  fit.manova <- Manova(fit.lm)
10 summary(fit.manova)

```

The result is

```

1  Type II MANOVA Tests:
2
3  Sum of squares and products for error:
4
5  CH1      CH2      CH3      CH4      CH5      CH6      CH7
6  CH1  8712198.47  2068166.15 -591367.187 -16398164.0  6354230.6 -67379.527  74669.446
7  CH2  2068166.15  951933.35 -239198.820 -5452822.8  3032723.5 -99478.020 -78000.087
8  CH3 -591367.19 -239198.82  769685.235  808789.9 -875296.2  7021.735 -8832.249
9  CH4 -16398163.97 -5452822.78  808789.900  44385022.5 -24868011.8  480314.317  266028.691
10 CH5  6354230.60  3032723.49 -875296.171 -24868011.8  18479382.0 -494033.183 -546173.842
11 CH6 -67379.53 -99478.02  7021.735  480314.3 -494033.2  66053.027  66956.405
12 CH7  74669.45 -78000.09 -8832.249  266028.7 -546173.8  66956.405  183120.455
13 CH8 -143122.66 -59386.98  42218.812  349340.4 -259104.5  9721.942  17177.110
14
15 CH1 -143122.657
16 CH2 -59386.983
17 CH3  42218.812
18 CH4  349340.368
19 CH5 -259104.523
20 CH6  9721.942
21 CH7  17177.110
22 CH8  22808.041
23
24 -----
25 Term: BigRegions
26
27 Sum of squares and products for the hypothesis:
28
29 CH1      CH2      CH3      CH4      CH5      CH6      CH7
30 CH1  7517535.24  2154506.818 -11358.7365 -16313012.3  4413510.5  466041.967  409500.04
31 CH2  2154506.82  621547.557 -5516.9112 -4916126.6  1491309.0  135673.062  134446.80
32 CH3 -11358.74 -5516.911  1273.3995  158440.7 -132434.2 -1874.351 -10109.21
33 CH4 -16313012.29 -4916126.629  158440.7153  49648363.2 -22971632.2 -1135935.429 -1899371.59
34 CH5  4413510.54  1491308.999 -132434.1755 -22971632.2  15181902.6  390760.974  1190534.28
35 CH6  466041.97  135673.062 -1874.3508 -1135935.4  390761.0  29981.812  34226.86
36 CH7  409500.04  134446.801 -10109.2121 -1899371.6  1190534.3  34226.860  94004.06
37 CH8  823641.31  235143.784 -739.1389 -1733475.8  432963.5  50590.072  41048.13
38
39 CH1  823641.3147
40 CH2  235143.7841
41 CH3 -739.1389
42 CH4 -1733475.8370
43 CH5  432963.5194
44 CH6  50590.0723
45 CH7  41048.1276
46 CH8  90443.6429
47
48 Multivariate Tests: BigRegions
49
50 Df test stat approx F num Df den Df Pr(>F)
51 Pillai 2 1.593690 276.0350 16 1126 < 2.22e-16 ***
52 Wilks 2 0.031702 324.3008 16 1124 < 2.22e-16 ***
53 Hotelling-Lawley 2 10.816547 379.2552 16 1122 < 2.22e-16 ***
54 Roy 2 8.494086 597.7713 8 563 < 2.22e-16 ***
55
56 Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

```

From the result we can see the p-value is small, and we conclude that there are differences in means among the 3 main regions.