

Homework 3

```
> smlm = summary.aov(mlm)
```

```
Response GPA :
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
G	2	12.5015	6.2508	173.31	< 2.2e-16
Residuals	82	2.9576	0.0361		

```
Response GMAT :
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
G	2	258471	129236	35.35	8.492e-12
Residuals	82	299784	3656		

```
> SA = summary(MA)
```

```
Multivariate Tests: G
```

	Df	test stat	approx F	num Df	den Df	Pr(>F)
Pillai	2	1.009630	41.79734	4	164	< 2.22e-16
Wilks	2	0.126377	73.42569	4	162	< 2.22e-16
Hotelling-Lawley	2	5.836656	116.73312	4	160	< 2.22e-16
Roy	2	5.646045	231.48783	2	82	< 2.22e-16

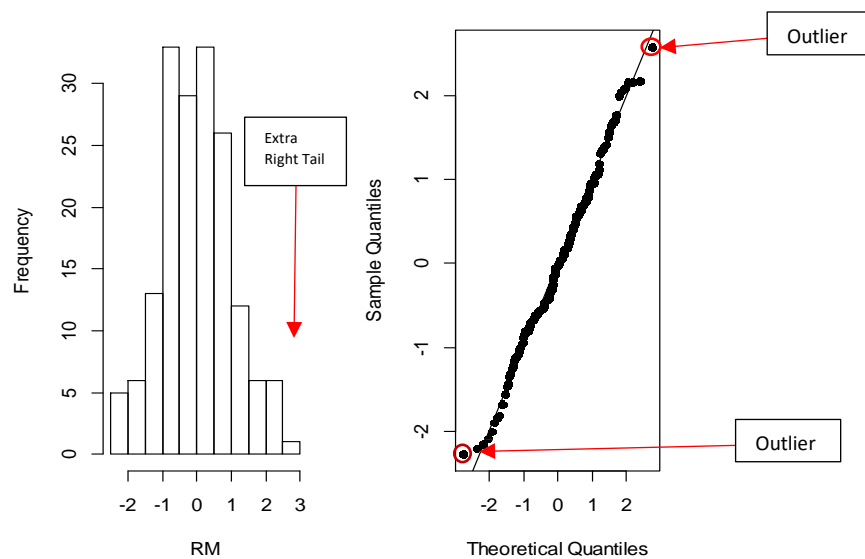
```
> C = c(0,-1,1); linearHypothesis(mlm,C) H0,32 comparison
```

	Df	test stat	approx F	num Df	den Df	Pr(>F)
Pillai	1	0.848797	227.3514	2	81	< 2.22e-16
Wilks	1	0.151203	227.3514	2	81	< 2.22e-16
Hotelling-Lawley	1	5.613616	227.3514	2	81	< 2.22e-16
Roy	1	5.613616	227.3514	2	81	< 2.22e-16

```
> shapiro.test(RM) ← Normality
```

```
Shapiro-Wilk normality test
```

```
data: RM
W = 0.99198, p-value = 0.4645
```



- H.3.1:

(a)

- $H_0 : \mu_1 = \mu_2 = \mu_3$, $H_1 : \mu_1 \neq \mu_2$ or $\mu_1 \neq \mu_3$ or $\mu_2 \neq \mu_3$
- The Wilks test with $F(4,162) = 73.43$ and a p-value < 0.0001 , indicates H_0 should be rejected at the 0.01 level. Thus, at least one of the population means of the 2 variables, GPA and GMAT, are declared to be different across the 3 groups, border, **yes** and **no**.

(b)

- Since the p-value < 0.0001 then $H_{0,32}$ is rejected at the 0.01 level. Thus, there is evidence to claim that the population mean of the 2 scores are not the same between these two groups.

(c)

- The Cholesky residuals all lie very close to the theoretical normal line except for the smallest and largest Cholesky residual value of -2 and 3 which could be outliers.
- Since $w = 0.99198$ and the p-value = 0.4645, fail to reject H_0 at the 0.01 level. Thus, there is not evidence against the assumption that the population distribution of the model error vector is multivariate normal across all observations.

```
> bm.test = boxM(Y,G)
```

Box's M-test for Homogeneity of Covariance Matrices

data: Y

Chi-Sq (approx.) = 16.074, df = 6, p-value = 0.01336

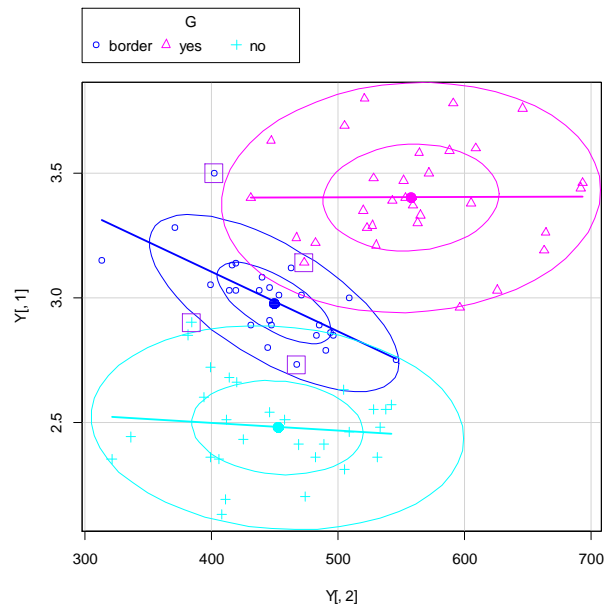
```
> T.class = table(G,G.class)
```

G.class

G	border	no	yes
Border	24	<u>1</u>	<u>1</u>
yes	<u>1</u>	0	30
no	<u>1</u>	27	0
	correct.rate	error.rate	
	0.9529	0.04706	

```
> miss
```

	GPA	GMAT	G	G.class
2	3.14	473	yes	border
59	2.90	384	no	border
66	3.50	402	border	yes
75	2.73	467	border	no



- H.3.2:

(a)

- $H_0: \Sigma_1 = \Sigma_2 = \Sigma_3$, $H_1: \Sigma_1 \neq \Sigma_2$ or $\Sigma_1 \neq \Sigma_3$ or $\Sigma_2 \neq \Sigma_3$
- Since $c(6) = 16.01$ and the p-value < 0.01 , reject H_0 at the 0.01 level. Thus, there is evidence to question the assumption of equal population covariance matrices across the 2 scores.

(b)

- With QDA leave-one-out cross-validation we are nearly perfectly classifying **border**, **yes** and **no** with only 4 misclassifications. **Border** was misclassified twice, once with **yes** and once with **no**. **Yes**, was misclassified one time with **border** and **no** was misclassified once with **border** as well.

(c)

- From the scatterplot above we can determine the following misclassifications:
 - i. A data point in **border** was misclassified with **no** because it has a relatively low GPA score for **border** compared to the other scores in **border** but has a relatively high GMAT score compared to the other scores within **border**. The low GPA caused the data point to be misclassified as **no** instead of **border**.
 - ii. A data point in **yes** was misclassified as **border** because it has a low GPA score and a low GMAT score compared to the other scores within the **yes** group. These low scores caused the misclassification into the **border** group.

**Note: Bold font in answers represents the three groups: "border", "yes" and "no".

R-code

```
> library(car)
> library(MASS)
> library(biotools)

dat = read.csv("C:/Users/Kyle/Desktop/admission.csv")
> Y = as.matrix(dat[,1:2]); n = nrow(Y); p = ncol(Y);
> Gn = dat[,3];
> G = as.factor(Gn);
> levels(G)[3] = "border"
> levels(G)[2] = "no"
> levels(G)[1] = "yes"
> G = relevel(G,ref="border")
> t.G = table(G)
> n1 = t.G[1]; n2 = t.G[2]; n3 = t.G[3]
> ybar = apply(Y,2,mean)
> ybark=by(Y,G,function(x) apply(x,2,mean))
> Sk = by(Y,G,cov)
> mlm = lm(Y~G)
> smlm = summary.aov(mlm)
> MA = Manova(mlm)
> SA = summary(MA)
> E = MA$SSPE
> B = mlm$coefficients
> C = c(0,-1,1);
> bm.test = boxM(Y,G)
> Sp = E/mlm$df.residual
> Uh = mlm$residuals
> Spih = chol(solve(Sp))
> RM = Uh%*%t(Spih)
> par(mfrow=c(1,2))
> hist(RM)
> qqnorm(RM,pch=16,main=NULL);abline(a=0,b=1);
> shapiro.test(RM)
> Tp = ((nk[1]-1)*Sk[[1]]+(nk[2]-1)*Sk[[2]]+(nk[3]-1)*Sk[[3]])
> Sp = Tp/(sum(nk)-3)
> CVS = T
> prior0 = c(1,1,1)/3;
> da2 = qda(G~Y,prior=prior0,CV=CVS)
> if (CVS==F) post.prob = predict(da,as.data.frame(Y))$posterior
> if (CVS==T) post.prob = da$posterior
> if (CVS==F) G.class = predict(da,as.data.frame(Y))$class
> if (CVS==T) G.class = da$class
> t.class = table(G,G.class)
> correct.rate = sum(diag(t.class))/n
> error.rate = 1-sum(diag(t.class))/n
> miss = data.frame(Y,G,G.class)[G!=G.class,]
> scatterplot(Y[,1]~Y[,2]|G,smooth=
> FALSE,ellipse=TRUE,by.groups=TRUE)
> points(miss[,2],miss[,1],pch=22,cex=3,lwd=1.5,col="purple")
> dat = data.frame(Y,G); G.class = NULL
```

```
> for(i in 1:n) { # leave-one-out #
> dat.i = dat[i,]; dat.xi = dat[-i,];
> fit = qda(G~.,data=dat.xi,CV=F)
> G.lab = predict(fit,newdata=dat.i,type="class")[[1]]
> G.class = c(G.class,as.character(G.lab)) }
> ct = table(G,G.class)
```