HW1Notebook

October 1, 2017

- 1 Departamento de Engenharia de Teleinformática
- 2 Inteligência Computacional Aplicada HW1
- 3 Prof^a. Dr^a Michela Mulas
- 4 Aluno: Caio Cid Santiago Barbosa 378596

4.1 Questão 1 e 2

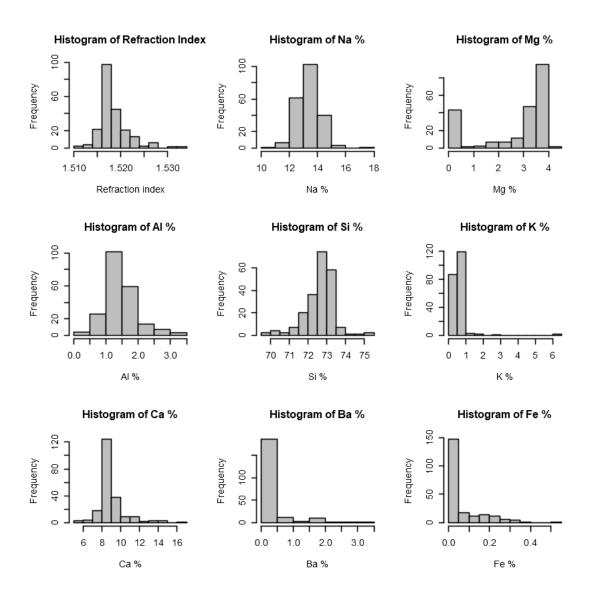
Nas primeiras duas questões, foi pedido que analisassemos os histogramas dos *predictors*, além de suas médias, desvio padrão e *skewness*, sendo na primeira englobando todas as amostras e na segunda dividindo-os por tipo. Começaremos, portanto, primeiro com o histograma por *predictors* de todas as amostras.

```
In [38]: library(mlbench);
         library("AppliedPredictiveModeling");
         library("e1071");
         library(corrplot);
         library(ggplot2);
         library(ggfortify);
         data(Glass);
         #Questao 1
         par(mfrow=c(3,3))
         RI.hist <- hist(Glass$RI, main = "Histogram of Refraction Index",
                         xlab = "Refraction index", col = "Gray")
         Na.hist <- hist(Glass$Na, main = "Histogram of Na %",
                         xlab = "Na %", col = "Gray")
         Mg.hist <- hist(Glass$Mg, main = "Histogram of Mg %",
                         xlab = "Mg %",col = "Gray")
         Al.hist <- hist(Glass$Al, main = "Histogram of Al %",
```

```
xlab = "Al %", col = "Gray")
Si.hist <- hist(Glass$Si, main = "Histogram of Si %",
                xlab = "Si %",col = "Gray")
K.hist <- hist(Glass$K, main = "Histogram of K %",</pre>
               xlab = "K %",col = "Gray")
Ca.hist <- hist(Glass$Ca, main = "Histogram of Ca %",
                xlab = "Ca %",col = "Gray")
Ba.hist <- hist(Glass$Ba, main = "Histogram of Ba ",",
                xlab = "Ba %",col = "Gray")
Fe.hist <- hist(Glass$Fe, main = "Histogram of Fe %",
                xlab = "Fe %", col = "Gray")
meanAll <- c(mean(Glass$RI), mean(Glass$Na), mean(Glass$Mg),</pre>
             mean(Glass$Al), mean(Glass$Si), mean(Glass$K),
             mean(Glass$Ca), mean(Glass$Ba), mean(Glass$Fe))
devAll <- c(sd(Glass$RI), sd(Glass$Na), sd(Glass$Mg),</pre>
            sd(Glass$Al), sd(Glass$Si), sd(Glass$K),
            sd(Glass$Ca), sd(Glass$Ba), sd(Glass$Fe))
skewAll <- c(skewness(Glass$RI), skewness(Glass$Na), skewness(Glass$Mg),
             skewness(Glass$Al), skewness(Glass$Si),
             skewness(Glass$K), skewness(Glass$Ca),
             skewness(Glass$Ba), skewness(Glass$Fe))
dataAll <- data.frame(meanAll, devAll, skewAll)</pre>
rownames(dataAll) <- c("RI", "Na", "Mg", "Al", "Si", "K", "Ca", "Ba", "Fe")
colnames(dataAll) <- c("Mean", "Standard Deviation", "Skewness")</pre>
```

dataAll

	Mean	Standard Deviation	Skewness
RI	1.51836542	0.003036864	1.6027151
Na	13.40785047	0.816603556	0.4478343
Mg	2.68453271	1.442407845	-1.1364523
Αl	1.44490654	0.499269646	0.8946104
Si	72.65093458	0.774545795	-0.7202392
K	0.49705607	0.652191846	6.4600889
Ca	8.95696262	1.423153487	2.0184463
Ba	0.17504673	0.497219261	3.3686800
Fe	0.05700935	0.097438701	1.7298107



Agora, analisaremos os histogramas das amostras por Tipo, indo de 1 a 7 (ressaltamos que não existem amostras do tipo 4).

In [12]: #Questao 2

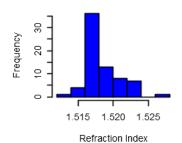
```
Al = numeric(), Si = numeric(), K = numeric(),
                         Ca = numeric(), Ba = numeric(), Fe = numeric())
for (i in 1:3){
  hist(GlassByType[[i]]$RI,
       main = paste(c("Histrogram of Refraction Index - Glass Type",i), collapse = " ")
       xlab = "Refraction Index", col = colors()[26*i])
  hist(GlassByType[[i]]$Na,
       main = paste(c("Histrogram of Na % - Glass Type",i), collapse = " "),
       xlab = "Na %", col = colors()[26*i])
  hist(GlassByType[[i]]$Mg,
       main = paste(c("Histrogram of Mg % - Glass Type",i), collapse = " "),
       xlab = "Mg %", col = colors()[26*i])
  hist(GlassByType[[i]]$Al,
       main = paste(c("Histrogram of Al % - Glass Type",i), collapse = " "),
       xlab = "Al %", col = colors()[26*i])
  hist(GlassByType[[i]]$Si,
       main = paste(c("Histrogram of Si % - Glass Type",i), collapse = " "),
       xlab = "Si %", col = colors()[26*i])
  hist(GlassByType[[i]]$K,
       main = paste(c("Histrogram of K % - Glass Type",i), collapse = " "),
       xlab = "K %", col = colors()[26*i])
  hist(GlassByType[[i]]$Ca,
       main = paste(c("Histrogram of Ca % - Glass Type",i), collapse = " "),
       xlab = "Ca %", col = colors()[26*i])
  hist(GlassByType[[i]]$Ba,
       main = paste(c("Histrogram of Ba % - Glass Type",i), collapse = " "),
       xlab = "Ba %", col = colors()[26*i])
  hist(GlassByType[[i]]$Fe,
       main = paste(c("Histrogram of Fe % - Glass Type",i), collapse = " "),
       xlab = "Fe %", col = colors()[26*i])
meanByType <- rbind(meanByType, c(mean(GlassByType[[i]]$RI), mean(GlassByType[[i]]$Na),</pre>
                                  mean(GlassByType[[i]]$Mg), mean(GlassByType[[i]]$Al),
                                  mean(GlassByType[[i]]$Si), mean(GlassByType[[i]]$K),
                                  mean(GlassByType[[i]]$Ca), mean(GlassByType[[i]]$Ba),
                                  mean(GlassByType[[i]]$Fe)))
devByType <- rbind(devByType, c(sd(GlassByType[[i]]$RI), sd(GlassByType[[i]]$Na),</pre>
```

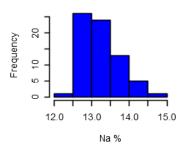
sd(GlassByType[[i]]\$Mg), sd(GlassByType[[i]]\$A1),

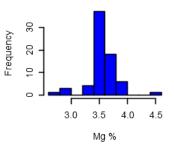
```
sd(GlassByType[[i]]$Si), sd(GlassByType[[i]]$K),
                                 sd(GlassByType[[i]]$Ca), sd(GlassByType[[i]]$Ba),
                                 sd(GlassByType[[i]]$Fe)))
skewByType <- rbind(skewByType, c(skewness(GlassByType[[i]]$RI),</pre>
                                  skewness(GlassByType[[i]]$Na),
                                  skewness(GlassByType[[i]]$Mg),
                                  skewness(GlassByType[[i]]$Al),
                                  skewness(GlassByType[[i]]$Si),
                                  skewness(GlassByType[[i]]$K),
                                  skewness(GlassByType[[i]]$Ca),
                                  skewness(GlassByType[[i]]$Ba),
                                  skewness(GlassByType[[i]]$Fe)))
for (i in 4:6){
  hist(GlassByType[[i]]$RI,
       main = paste(c("Histrogram of Refraction Index - Glass Type",i+1), collapse = "
       xlab = "Refraction Index", col = colors()[120*i])
  hist(GlassByType[[i]]$Na,
       main = paste(c("Histrogram of Na % - Glass Type",i+1), collapse = " "),
       xlab = "Na %", col = colors()[120*i])
  hist(GlassByType[[i]]$Mg,
       main = paste(c("Histrogram of Mg % - Glass Type",i+1), collapse = " "),
       xlab = "Mg %", col = colors()[120*i])
  hist(GlassByType[[i]]$Al,
       main = paste(c("Histrogram of Al % - Glass Type",i+1), collapse = " "),
       xlab = "Al %", col = colors()[120*i])
  hist(GlassByType[[i]]$Si,
       main = paste(c("Histrogram of Si % - Glass Type",i+1), collapse = " "),
       xlab = "Si %", col = colors()[120*i])
  hist(GlassByType[[i]]$K,
       main = paste(c("Histrogram of K % - Glass Type",i+1), collapse = " "),
       xlab = "K %", col = colors()[120*i], xlim = c(0,8))
  hist(GlassByType[[i]]$Ca,
       main = paste(c("Histrogram of Ca % - Glass Type",i+1), collapse = " "),
       xlab = "Ca %", col = colors()[120*i])
  hist(GlassByType[[i]]$Ba,
       main = paste(c("Histrogram of Ba % - Glass Type",i+1), collapse = " "),
       xlab = "Ba %", col = colors()[120*i], xlim = c(0,4))
```

```
hist(GlassByType[[i]]$Fe,
       main = paste(c("Histrogram of Fe % - Glass Type",i+1), collapse = " "),
       xlab = "Fe %", col = colors()[120*i], xlim = c(0,1))
meanByType <- rbind(meanByType, c(mean(GlassByType[[i]]$RI), mean(GlassByType[[i]]$Na),</pre>
                                   mean(GlassByType[[i]]$Mg), mean(GlassByType[[i]]$Al),
                                   mean(GlassByType[[i]]$Ca), mean(GlassByType[[i]]$Ba),
                                   mean(GlassByType[[i]]$Fe)))
devByType <- rbind(devByType, c(sd(GlassByType[[i]]$RI), sd(GlassByType[[i]]$Na),</pre>
                                   sd(GlassByType[[i]]$Mg), sd(GlassByType[[i]]$Al),
                                   sd(GlassByType[[i]]$Si), sd(GlassByType[[i]]$K),
                                   sd(GlassByType[[i]]$Ca), sd(GlassByType[[i]]$Ba),
                                   sd(GlassByType[[i]]$Fe)))
skewByType <- rbind(skewByType, c(skewness(GlassByType[[i]]$RI),</pre>
                                   skewness(GlassByType[[i]]$Na),
                                   skewness(GlassByType[[i]]$Mg),
                                   skewness(GlassByType[[i]]$Al),
                                   skewness(GlassByType[[i]]$Si),
                                   skewness(GlassByType[[i]]$K),
                                   skewness(GlassByType[[i]]$Ca),
                                   skewness(GlassByType[[i]]$Ba),
                                   skewness(GlassByType[[i]]$Fe)))
}
rownames(meanByType) <- c("Tipo 1", "Tipo 2", "Tipo 3", "Tipo 5", "Tipo 6", "Tipo 7")
rownames(devByType) <- c("Tipo 1", "Tipo 2", "Tipo 3", "Tipo 5", "Tipo 6", "Tipo 7")
rownames(skewByType) <- c("Tipo 1", "Tipo 2", "Tipo 3", "Tipo 5", "Tipo 6", "Tipo 7")
colnames(meanByType) <- c("RI", "Na", "Mg", "A1", "Si", "K", "Ca", "Ba", "Fe")
colnames(devByType) <- c("RI","Na","Mg","Al","Si","K","Ca","Ba","Fe")</pre>
colnames(skewByType) <- c("RI","Na","Mg","Al","Si","K","Ca","Ba","Fe")</pre>
```

strogram of Refraction Index - Glass Histrogram of Na % - Glass Type Histrogram of Mg % - Glass Type



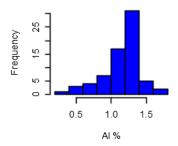


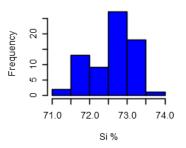


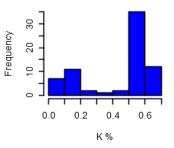
Histrogram of Al % - Glass Type 1

Histrogram of Si % - Glass Type 1

Histrogram of K % - Glass Type 1



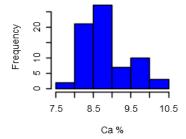


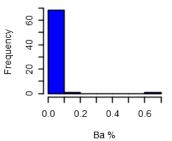


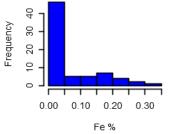
Histrogram of Ca % - Glass Type *

Histrogram of Ba % - Glass Type *

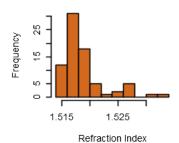
Histrogram of Fe % - Glass Type '

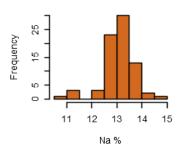


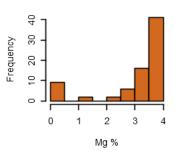




strogram of Refraction Index - Glass Histrogram of Na % - Glass Type : Histrogram of Mg % - Glass Type :



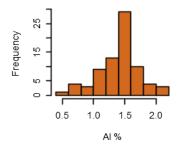


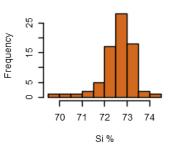


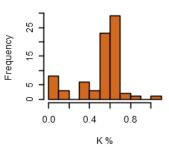
Histrogram of Al % - Glass Type 2

Histrogram of Si % - Glass Type 2

Histrogram of K % - Glass Type 2



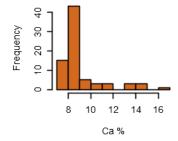


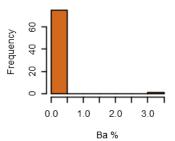


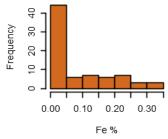
Histrogram of Ca % - Glass Type 2

Histrogram of Ba % - Glass Type 2

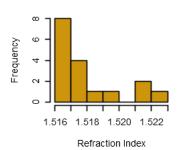
Histrogram of Fe % - Glass Type 2

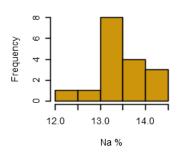


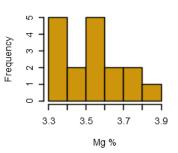




strogram of Refraction Index - Glass . Histrogram of Na % - Glass Type : Histrogram of Mg % - Glass Type



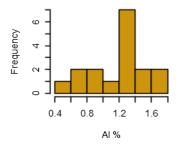


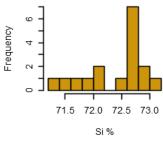


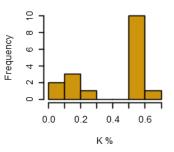
Histrogram of Al % - Glass Type 3

Histrogram of Si % - Glass Type 3

Histrogram of K % - Glass Type 3



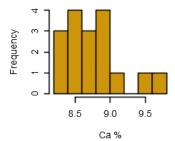


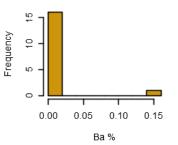


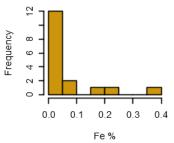
Histrogram of Ca % - Glass Type (

Histrogram of Ba % - Glass Type :

Histrogram of Fe % - Glass Type 3

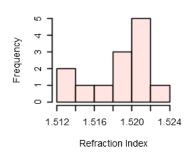


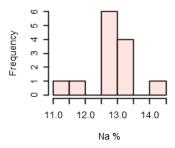


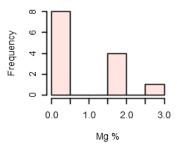


strogram of Refraction Index - Glass . Histrogram of Na % - Glass Type {

Histrogram of Mg % - Glass Type



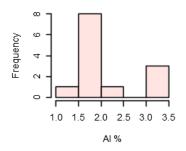


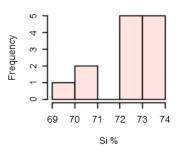


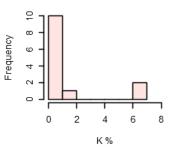
Histrogram of Al % - Glass Type 5

Histrogram of Si % - Glass Type 5

Histrogram of K % - Glass Type 5



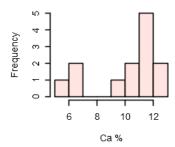


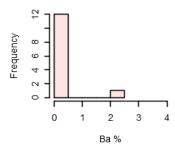


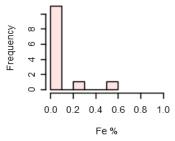
Histrogram of Ca % - Glass Type {

Histrogram of Ba % - Glass Type {

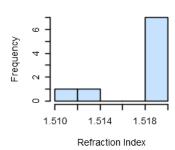
Histrogram of Fe % - Glass Type !

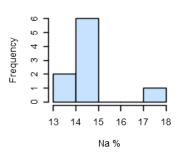


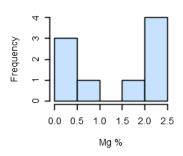




strogram of Refraction Index - Glass Type Histrogram of Na % - Glass Type Histrogram of Mg % - Glass Type



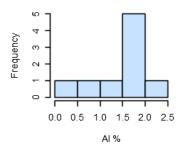


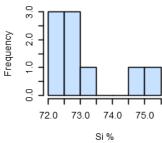


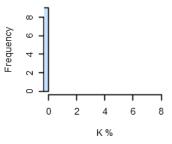
Histrogram of Al % - Glass Type 6

Histrogram of Si % - Glass Type 6

Histrogram of K % - Glass Type 6



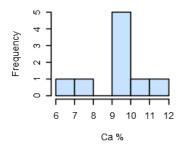


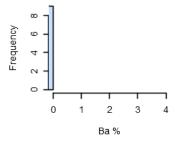


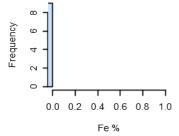
Histrogram of Ca % - Glass Type (

Histrogram of Ba % - Glass Type (

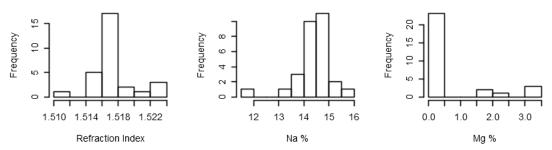
Histrogram of Fe % - Glass Type (







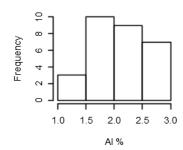


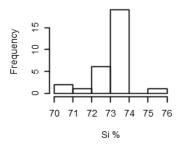


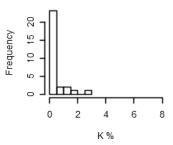
Histrogram of Al % - Glass Type 7

Histrogram of Si % - Glass Type 7

Histrogram of K % - Glass Type 7



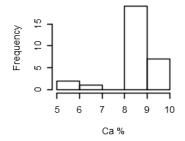


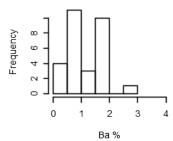


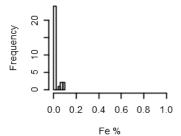
Histrogram of Ca % - Glass Type 7

Histrogram of Ba % - Glass Type 7

Histrogram of Fe % - Glass Type 7







4.1.1 Mean by type

In [6]: meanByType

		Na				K		Ba	Fe
Tipo 1	1.518718	13.24229	3.5524286	1.163857	72.61914	0.4474286	8.797286	0.012714286	0.05700000
Tipo 2	1.518619	13.11171	3.0021053	1.408158	72.59803	0.5210526	9.073684	0.050263158	0.07973684
Tipo 3	1.517964	13.43706	3.5435294	1.201176	72.40471	0.4064706	8.782941	0.008823529	0.05705882
								0.187692308	
								0.000000000	
Tipo 7	1.517116	14.44207	0.5382759	2.122759	72.96586	0.3251724	8.491379	1.040000000	0.01344828

4.1.2 Standard Deviation by type

In [13]: devByType

	RI	Na		Al			Ca	Ba	Fe
Tipo 1	0.002268097	0.4993015	0.2470430	0.2731581	0.5694842	0.2148790	0.5748066	0.08383769	0.08907496
Tipo 2	0.003802126	0.6641594	1.2156615	0.3183403	0.7245726	0.2137262	1.9216353	0.36234044	0.10643275
Tipo 3	0.001916360	0.5068871	0.1627859	0.3474889	0.5122758	0.2298897	0.3801112	0.03638034	0.10786361
Tipo 5	0.003345355	0.7770366	0.9991458	0.6939205	1.2823191	2.1386951	2.1837908	0.60825096	0.15558821
Tipo 6	0.003115783	1.0840203	1.0971339	0.5718610	1.0794675	0.0000000	1.4499483	0.00000000	0.00000000
	0.002545069								

4.1.3 Skewness by type

In [14]: skewByType

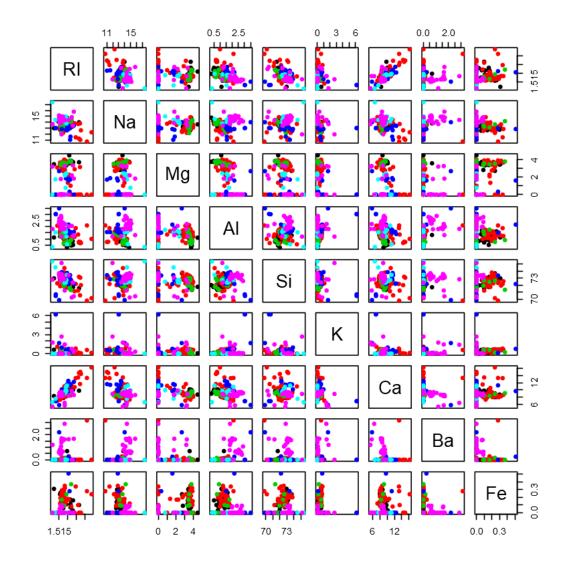
	RI	Na	Mg		Si		Ca	Ba	Fe
Tipo 1	0.7437286	0.7538231	-0.6767263	-1.0800373	-0.5542691	-0.8997727	0.6863776	7.5619933	1.3041178
Tipo 2	2.0576334	-1.0495492	-1.7735903	-0.3715251	-1.3759015	-0.9699909	2.0816494	8.2385374	0.9489729
Tipo 3	0.9707950	-0.4619438	0.6021565	-0.3325460	-0.6913984	-0.6377215	0.7853627	3.4240324	1.6919393
Tipo 5	-0.5692461	-0.9348808	0.5860668	0.9982672	-0.6439219	1.5919612	-0.7898330	2.7606112	2.0163265
Tipo 6	-1.1310170	1.6786808	-0.2194845	-0.6702752	0.9974867	NaN	-0.5485900	NaN	NaN
Tipo 7	0.9765233	-1.4473029	1.6320747	-0.2928373	-1.2115324	2.1395094	-1.9355386	0.4505834	1.7805965

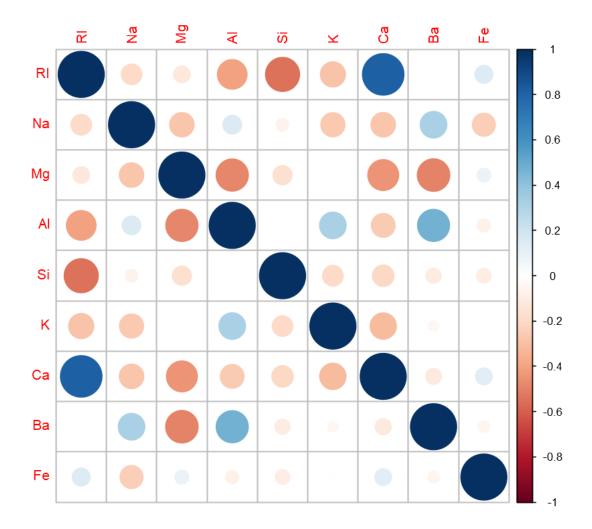
Analisando os histogramas, percebemos que não existe nenhum *predictor* com poder discriminativo. Ou seja, nenhum *predictor* sozinho consegue distinguir os tipos. Percebemos isso pois não há nenhuma relação distintiva dos histogramas. Nenhum deles aumentar linearmente, por exemplo.

4.2 Questão 3

Nessa questão, foi pedido um *scatter plot* dos *predictors*, além de uma analise deles e da matriz de correlação. Começamos mostrando o *scatter plot*.

```
In [17]: #Questao 3
    pairs(Glass[1:9], col = Glass$Type, pch=20)
    par(mfrow=c(1,1))
    correlation <- cor(Glass[1:9])
    corrplot(correlation)</pre>
```





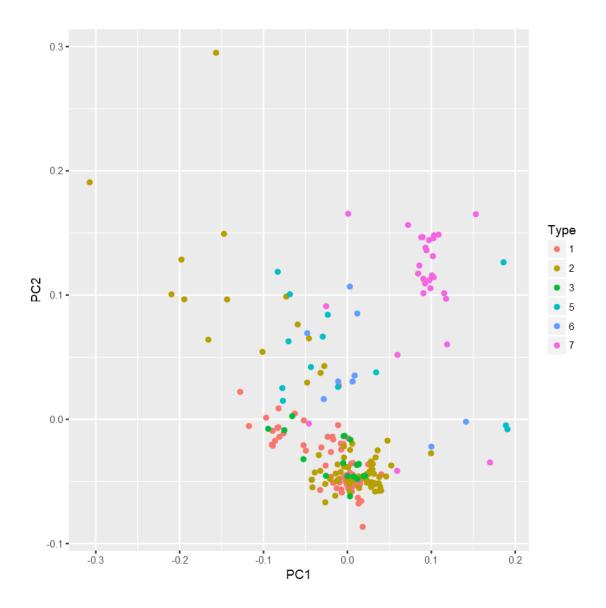
Analisando o *scatter plot*, conseguimos identificar alguns graficos com aparentes relações lineares, como o do RI x Ca e o do RI x Si. Com a matriz de correlação, confirmamos nossas suspeitas ao visualisarmos que os dois elementos com maiores modulo são o do RI x Ca e do RI x Si. Isso indica que existe uma relação linear entre esses *predictors*, sendo a do RI x Ca proporcinal e a do RI x Si inversamente proporcional.

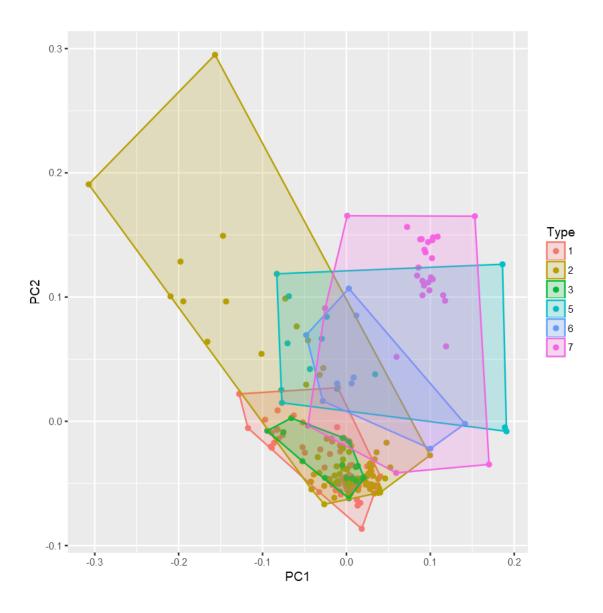
4.3 Questao 4

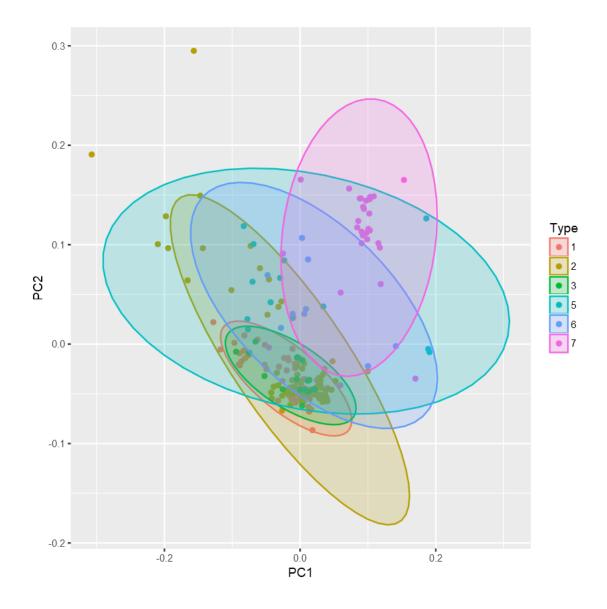
Por último, foi pedido que façamos uma PCA dos *predictors*. Pelos dados passadas, analisando a matriz de correlação, podemos adiantar que os dois principais componentes provavelmente serão o do RI e do Ca. Dessa forma, os dados serão ortogonalizados nesses dois *predictors* Agora, iremos para o codigo. Primeiro, vamos verificar que a função **prcomp** fornece valores coerentes. Para isso, compararemos os valores de PCs fornecidos por ela, com os autovalores e autovetores fornecidos pela matriz de correlação.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
RI	-0.5451766	0.2856831	8 -0.086910829	93 -0.14738099	0.073542700	-0.11528772	-0.08186724	-0.75221590	-0.02573194
Na	0.2581256	0.2703500	7 0.384919619	7 -0.49124204	-0.153683304	4 0.55811757	-0.14858006	-0.12769315	0.31193718
Mg	-0.1108810	-0.5935582	26 -0.008417959	90 -0.37878577	-0.123509124	4 -0.30818598	0.20604537	-0.07689061	0.57727335
Al	0.4287086	0.2952115	4 -0.329237118	83 0.13750592	-0.014108879	9 0.01885731	0.69923557	-0.27444105	0.19222686
Si	0.2288364	-0.1550989	91 0.458708838	2 0.65253771	-0.008500117	7 -0.08609797	-0.21606658	-0.37992298	0.29807321
K	0.2193440	-0.153970	13 -0.662574119	97 0.03853544	0.307039842	0.24363237	-0.50412141	-0.10981168	0.26050863
Ca	-0.4923061	0.3453798	0.000984732	1 0.27644322	0.188187742	0.14866937	0.09913463	0.39870468	0.57932321
Ba	0.2503751	0.4847021	8 -0.074054730	09 -0.13317545	-0.251334261	1 -0.65721884	-0.35178255	0.14493235	0.19822820
Fe	-0.1858415	-0.062038	79 -0.28445055	24 0.23049202	-0.873264047	7 0.24304431	-0.07372136	-0.01627141	0.01466944
0.545	51766 -0.	28568318	-0.0869108293	0.14738099	0.073542700	-0.11528772	0.08186724	0.75221590	0.02573194
-0.25	581256 -0.	27035007	0.3849196197	0.49124204 -	-0.153683304	0.55811757	0.14858006	0.12769315	-0.31193718
0.110	08810 0.5	9355826	-0.0084179590	0.37878577 -	0.123509124	-0.30818598	-0.20604537	0.07689061	-0.57727335
-0.42	287086 -0.	29521154	-0.3292371183	-0.13750592 -	-0.014108879	0.01885731	-0.69923557	0.27444105	-0.19222686
-0.22	288364 0.1	5509891	0.4587088382	-0.65253771 -	-0.008500117	-0.08609797	0.21606658	0.37992298	-0.29807321
-0.21	193440 0.1	5397013	-0.6625741197	-0.03853544	0.307039842	0.24363237	0.50412141	0.10981168	-0.26050863
0.492	23061 -0.	34537980	0.0009847321	-0.27644322	0.188187742	0.14866937	-0.09913463	-0.39870468	-0.57932321
-0.25	503751 -0.	48470218	-0.0740547309	0.13317545 -	-0.251334261	-0.65721884	0.35178255	-0.14493235	-0.19822820
0.18	58415 0.0	6203879	-0.2844505524	-0.23049202 -	-0.873264047	0.24304431	0.07372136	0.01627141	-0.01466944

Com isso, verificamos que os autovetores estão iguais, comprovando a eficacia do **prcomp** e de seus parâmetros. Agora, iremos plotar os dados ortogonalizados em PC1 e PC2. Nos plots abaixos, utilizamos a biblioteca **ggfortify** e **ggplot2** para melhor visualização e distribuição dos dados.







Observando o PCA, vemos que os dados do tipo 7 foram os que ficaram mais clusterizados(clustered), desse modo, ficando razoavelmente simples sua identificação. Contudo, ao agruparmos os dados por frames, para melhor visualização, vemos que ainda existe muita sobreposição por todos os tipos. No primeiro gráfico agrupado, vemos um sistema que considera os pontos mais longíquos e envolve todos os pontos desse tipo, o que não é uma aproximação desejada, tendo em vista que pega todos os outliers. É fácil perceber isso quando vemos o agrupamento do tipo 2, que envolve quase todos. O segunda agrupamento, por elipses, é mais coerente, pois desconsidera alguns outliers, porém, ainda também não é o ideal, pois tipos com poucos dados, como o tipo 2, acabam envolvendo uma área muito grande, enquanto não deveria ser tanto.

Percebemos pelos gráficos que as fronteiras das classes projetadas nos PCAs não são lineares, e que são de difícil separação apenas observando o gráfico. Além disso, identificamos também que os tipos 1,2,3 são os mais sobrepostos, sendo os de mais dificil separação.