

## 12 - PCA Additional Example

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SIUE, F2017, Stat 589

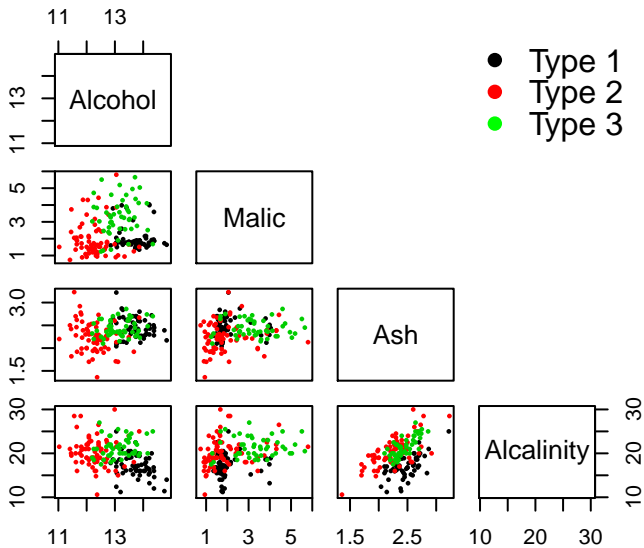
October 02, 2017

## Wine Data

The wine data is the result of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivars. The analysis determined the quantities of 13 constituents found in each of the three types of wines.

```
data(wine, package = 'rattle.data')  
names(wine)
```

```
# [1] "Type"           "Alcohol"         "Malic"  
# [4] "Ash"            "Alcalinity"      "Magnesium"  
# [7] "Phenols"        "Flavanoids"      "Nonflavanoids"  
# [10] "Proanthocyanins" "Color"           "Hue"  
# [13] "Dilution"       "Proline"
```



## PCA Wine Data using prcomp

```
# need to center and scale the data
```

```
wine.pca1 <- prcomp(wine[, -1], scale. = T, center = T)  
names(wine.pca1)
```

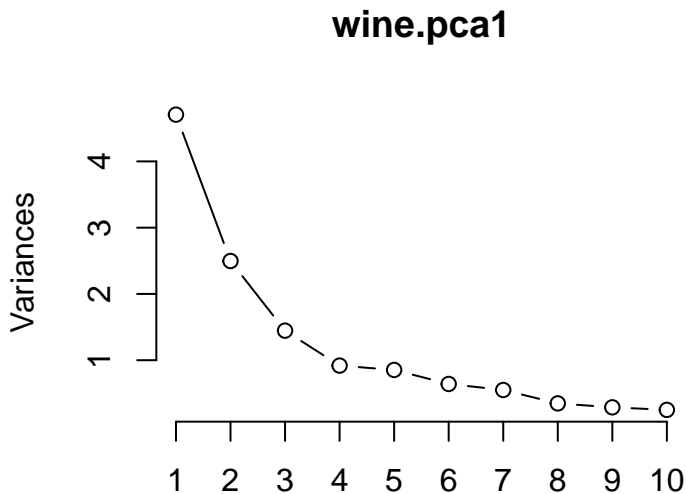
```
# [1] "sdev"      "rotation" "center"    "scale"     "x"
```

```
# Variances/Eigenvalues of PCA
```

```
(wine.pca1$sdev)^2
```

```
# [1] 4.71 2.50 1.45 0.92 0.85 0.64 0.55 0.35 0.29 0.25 0
```

```
screepplot(wine.pca1, type="lines")
```



## Summary of PCA

```
summary(wine.pca1)
```

```
# Importance of components%s:
```

#	PC1	PC2	PC3	PC4	PC5
# Standard deviation	2.169	1.580	1.203	0.9586	0.9237
# Proportion of Variance	0.362	0.192	0.111	0.0707	0.0656
# Cumulative Proportion	0.362	0.554	0.665	0.7360	0.8016

#	PC8	PC9	PC10	PC11	PC12
# Standard deviation	0.5903	0.5375	0.5009	0.4752	0.411
# Proportion of Variance	0.0268	0.0222	0.0193	0.0174	0.013
# Cumulative Proportion	0.9202	0.9424	0.9617	0.9791	0.992

## First Four Eigenvectors (or Loadings) using prcomp

```
wine.pca1$rotation[,1:4]
```

#	PC1	PC2	PC3	PC4
# Alcohol	-0.1443	0.4837	-0.207	0.018
# Malic	0.2452	0.2249	0.089	-0.537
# Ash	0.0021	0.3161	0.626	0.214
# Alkalinity	0.2393	-0.0106	0.612	-0.061
# Magnesium	-0.1420	0.2996	0.131	0.352
# Phenols	-0.3947	0.0650	0.146	-0.198
# Flavanoids	-0.4229	-0.0034	0.151	-0.152
# Nonflavanoids	0.2985	0.0288	0.170	0.203
# Proanthocyanins	-0.3134	0.0393	0.149	-0.399
# Color	0.0886	0.5300	-0.137	-0.066
# Hue	-0.2967	-0.2792	0.085	0.428
# Dilution	-0.3762	-0.1645	0.166	-0.184
# Proline	-0.2868	0.3649	-0.127	0.232

## First Four Principal Components (or Scores) using prcomp

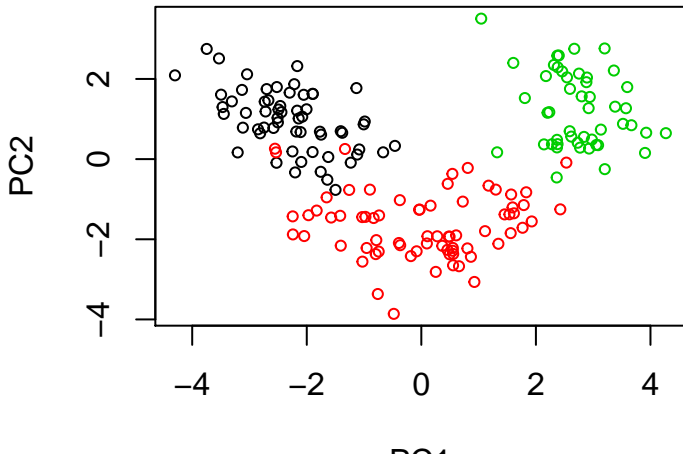
```
head(wine.pca1$x[,1:4], 10)
```

#		PC1	PC2	PC3	PC4
#	[1,]	-3.3	1.44	-0.17	0.215
#	[2,]	-2.2	-0.33	-2.02	0.291
#	[3,]	-2.5	1.03	0.98	-0.723
#	[4,]	-3.7	2.75	-0.18	-0.566
#	[5,]	-1.0	0.87	2.02	0.409
#	[6,]	-3.0	2.12	-0.63	0.514
#	[7,]	-2.4	1.17	-0.97	0.066
#	[8,]	-2.1	1.60	0.15	1.189
#	[9,]	-2.5	0.92	-1.77	-0.056
#	[10,]	-2.7	0.79	-0.98	-0.348



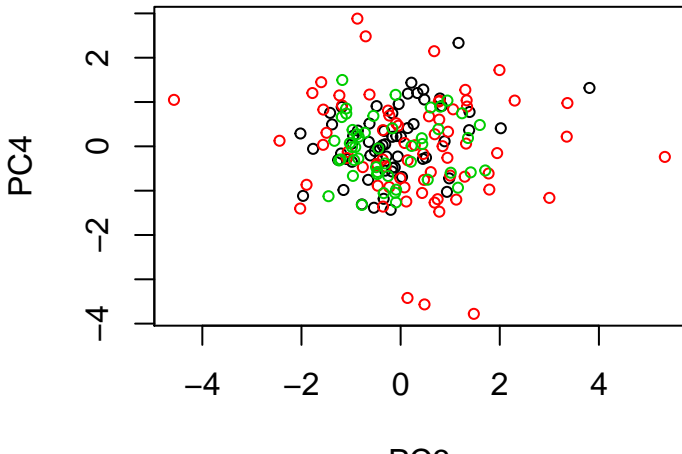
```
plot(wine.pca1$x[,1:2], col = wine$type, cex = 0.7, main =
```

## 1st and 2nd PC's



```
plot(wine.pca1$x[,3:4], col = wine$Type, cex = 0.7, main =
```

### 3rd and 4th PC's



## PCA Wine Data using princomp

```
# set cor = TRUE to use scaled data  
wine.pca2 <- princomp(wine[, -1], cor = TRUE)  
names(wine.pca2)
```

```
# [1] "sdev"      "loadings" "center"    "scale"     "n.obs"  
# [7] "call"
```

```
# Variances/Eigenvalues of PCA  
(wine.pca2$sdev)^2
```

```
# Comp.1  Comp.2  Comp.3  Comp.4  Comp.5  Comp.6  Comp.7  
#   4.71   2.50   1.45   0.92   0.85   0.64   0.55  
# Comp.10 Comp.11 Comp.12 Comp.13  
#   0.25   0.23   0.17   0.10
```

## First Four Eigenvectors (or Loadings) using princomp

```
wine.pca2$loadings[,1:4]
```

#	Comp.1	Comp.2	Comp.3	Comp.4
# Alcohol	-0.1443	-0.4837	-0.207	-0.018
# Malic	0.2452	-0.2249	0.089	0.537
# Ash	0.0021	-0.3161	0.626	-0.214
# Alcalinity	0.2393	0.0106	0.612	0.061
# Magnesium	-0.1420	-0.2996	0.131	-0.352
# Phenols	-0.3947	-0.0650	0.146	0.198
# Flavanoids	-0.4229	0.0034	0.151	0.152
# Nonflavanoids	0.2985	-0.0288	0.170	-0.203
# Proanthocyanins	-0.3134	-0.0393	0.149	0.399
# Color	0.0886	-0.5300	-0.137	0.066
# Hue	-0.2967	0.2792	0.085	-0.428
# Dilution	-0.3762	0.1645	0.166	0.184
# Proline	-0.2868	-0.3649	-0.127	-0.232

## First Four Principal Components (or Scores) using princomp

```
head(wine.pca2$scores[,1:4], 10)
```

#		Comp.1	Comp.2	Comp.3	Comp.4
#	[1,]	-3.3	-1.44	-0.17	-0.216
#	[2,]	-2.2	0.33	-2.03	-0.291
#	[3,]	-2.5	-1.03	0.98	0.725
#	[4,]	-3.8	-2.76	-0.18	0.568
#	[5,]	-1.0	-0.87	2.03	-0.410
#	[6,]	-3.1	-2.12	-0.63	-0.516
#	[7,]	-2.4	-1.17	-0.98	-0.066
#	[8,]	-2.1	-1.61	0.15	-1.193
#	[9,]	-2.5	-0.92	-1.77	0.056
#	[10,]	-2.8	-0.79	-0.98	0.349