Machine Learning Hw6

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```
library(ISLR)
library(factoextra)
library(gridExtra)
library(corrplot)
library(RColorBrewer)
library(gplots)
library(igraph)
library(jpeg)
library(imager)
```

Data

```
data("USArrests")
seed = 1
usarrests = scale(USArrests)
```

Cluster Analysis

We perform hierarchical clustering on the states using the USArrests data in the ISLR package. For each of the 50 states in the United States, the dataset contains the number of arrests per 100,000 residents for each of three crimes: Assault, Murder, and Rape. The dataset also contains the percent of the population in each state living in urban areas, UrbanPop. The four variables will be used as features for clustering.

Question a) Using hierarchical clustering with complete linkage and Euclidean distance, cluster the states.

```
set.seed(seed)
hc_noscale = hclust(dist(USArrests, method = 'euclidean'), method = 'complete')
```

Question b) Cut the dendrogram at a height that results in three distinct clusters. Which states belong to which clusters?

```
hc_3_noscale = cutree(hc_noscale, 3)
```

States in the first cluster

```
USArrests[hc_3_noscale == 1,]
```

```
##                Murder Assault UrbanPop Rape
## Alabama          13.2     236       58 21.2
## Alaska           10.0     263       48 44.5
## Arizona           8.1     294       80 31.0
## California        9.0     276       91 40.6
## Delaware          5.9     238       72 15.8
## Florida          15.4     335       80 31.9
## Illinois         10.4     249       83 24.0
## Louisiana        15.4     249       66 22.2
## Maryland         11.3     300       67 27.8
## Michigan         12.1     255       74 35.1
## Mississippi      16.1     259       44 17.1
## Nevada           12.2     252       81 46.0
## New Mexico       11.4     285       70 32.1
## New York         11.1     254       86 26.1
## North Carolina   13.0     337       45 16.1
## South Carolina   14.4     279       48 22.5
```

States in the 2nd Cluster

```
USArrests[hc_3_noscale == 2,]
```

```
##               Murder Assault UrbanPop Rape
## Arkansas         8.8     190       50 19.5
## Colorado         7.9     204       78 38.7
## Georgia         17.4     211       60 25.8
## Massachusetts    4.4     149       85 16.3
## Missouri         9.0     178       70 28.2
## New Jersey       7.4     159       89 18.8
## Oklahoma         6.6     151       68 20.0
## Oregon           4.9     159       67 29.3
## Rhode Island     3.4     174       87  8.3
## Tennessee       13.2     188       59 26.9
## Texas           12.7     201       80 25.5
## Virginia         8.5     156       63 20.7
## Washington       4.0     145       73 26.2
## Wyoming          6.8     161       60 15.6
```

States in the 3rd Cluster

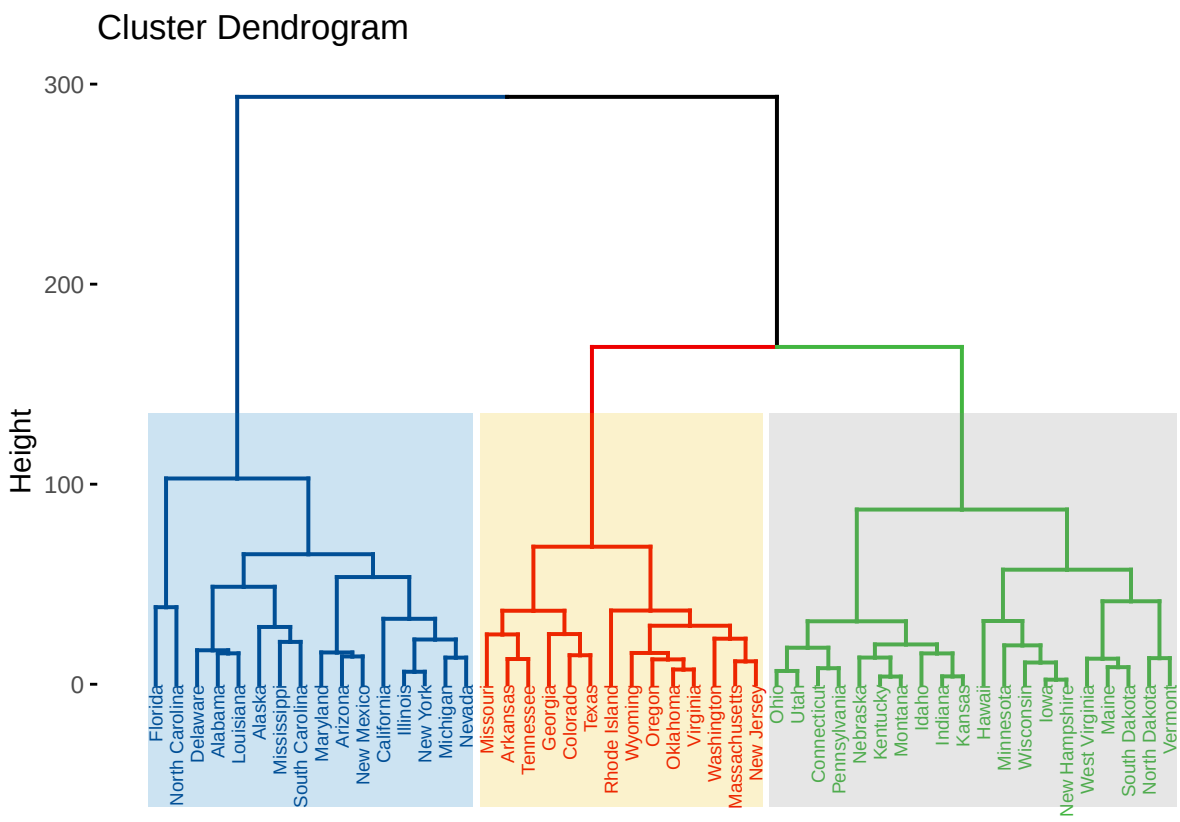
```
USArrests[hc_3_noscale == 3,]
```

```
##               Murder Assault UrbanPop Rape
## Connecticut      3.3     110       77 11.1
## Hawaii           5.3      46       83 20.2
## Idaho            2.6     120       54 14.2
```

```
## Indiana          7.2     113       65 21.0
## Iowa             2.2      56       57 11.3
## Kansas           6.0     115       66 18.0
## Kentucky         9.7     109       52 16.3
## Maine            2.1      83       51  7.8
## Minnesota        2.7      72       66 14.9
## Montana          6.0     109       53 16.4
## Nebraska         4.3     102       62 16.5
## New Hampshire    2.1      57       56  9.5
## North Dakota     0.8      45       44  7.3
## Ohio             7.3     120       75 21.4
## Pennsylvania     6.3     106       72 14.9
## South Dakota     3.8      86       45 12.8
## Utah             3.2     120       80 22.9
## Vermont          2.2      48       32 11.2
## West Virginia    5.7      81       39  9.3
## Wisconsin        2.6      53       66 10.8
```

Visualization of the dendrogram and showing graphically which states belong to which clusters

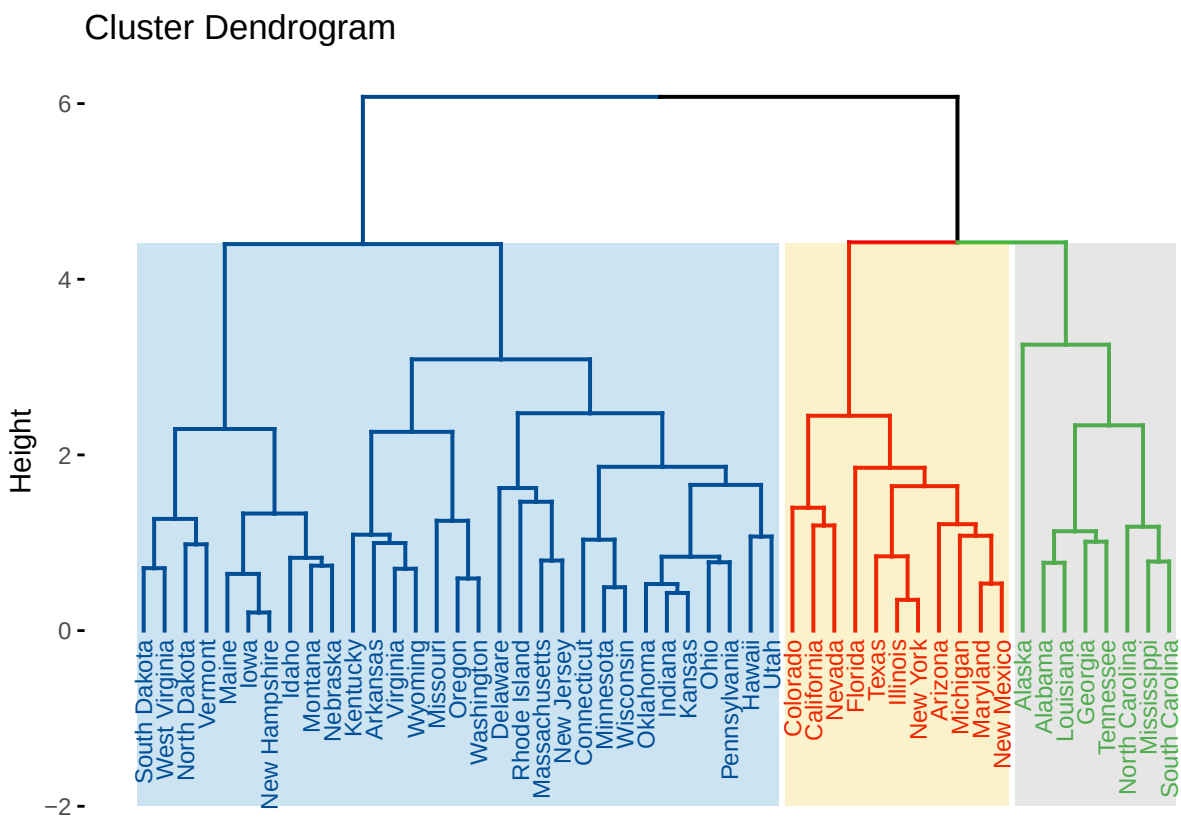
```
fviz_dend(hc_noscale, k = 3,
          cex = 0.5,
          palette = "lancet",
          color_labels_by_k = TRUE,
          rect = TRUE,
          rect_fill = TRUE,
          rect_border = "jco",
          type = 'rectangle',
          labels_track_height = 60.5
          )
```



Question c) Hierarchically cluster the states using complete linkage and Euclidean distance, after scaling the variables to have standard deviation one.

```
set.seed(seed)
hc_scaled = hclust(dist(usarrests, method = 'euclidean'), method = 'complete')
```

```
fviz_dend(hc_scaled, k = 3,
          cex = 0.6,
          palette = "lancet",
          color_labels_by_k = TRUE,
          rect = TRUE,
          rect_fill = TRUE,
          rect_border = "jco",
          type = 'rectangle',
          labels_track_height = 1.5
          )
```



Question d) What effect does scaling the variables have on the hierarchical clustering obtained? In your opinion, should the variables be scaled before the inter-observation dissimilarities are computed?

```
# number of states in each cluster when scaling
table(cutree(hc_scaled, 3))
```

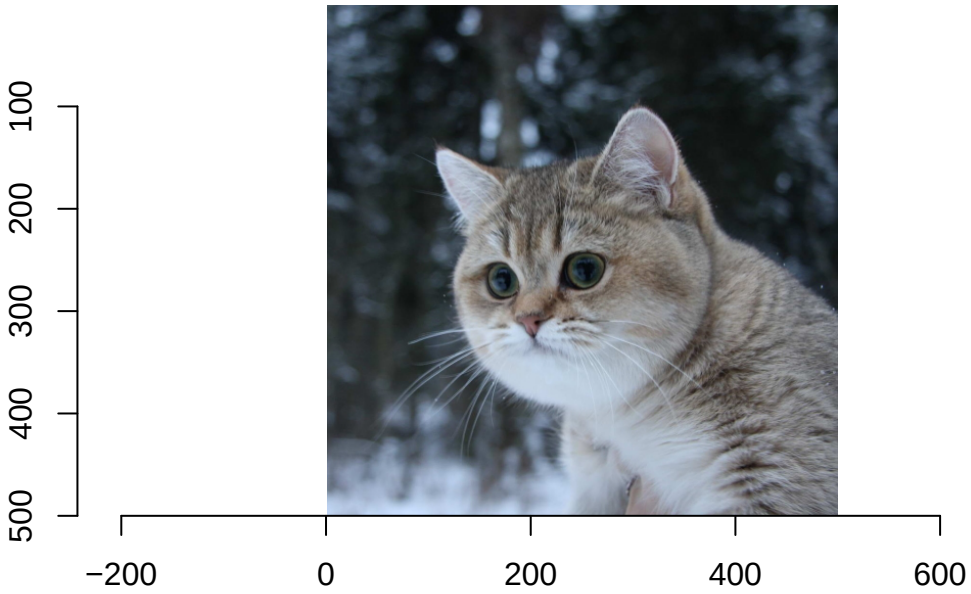
```
##
##  1  2  3
##  8 11 31
```

```
# number of states in each cluster when not scaling
table(cutree(hc_noscale, 3))
```

```
##
##  1  2  3
## 16 14 20
```

PCA

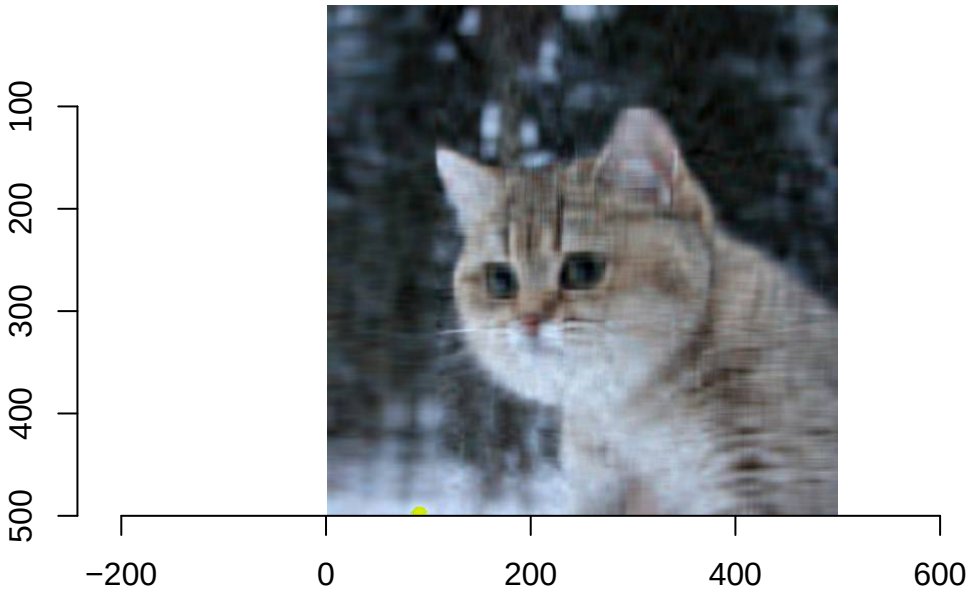
```
img <- readJPEG('cat.jpg')
plot(load.image('cat.jpg'))
```




```
dim(img)
```

```
## [1] 500 500   3
```

```
r <- img[,,1]
g <- img[,,2]
b <- img[,,3]
img.r.pca <- prcomp(r, center = FALSE)
img.g.pca <- prcomp(g, center = FALSE)
img.b.pca <- prcomp(b, center = FALSE)
rgb.pca <- list(img.r.pca, img.g.pca, img.b.pca)
# Approximate X with XV_kV_k^T
compress <- function(pr, k)
{
  compressed.img <- pr$x[,1:k] %*% t(pr$rotation[,1:k])
  compressed.img
}
# Using first 20 PCs
pca20 <- sapply(rgb.pca, compress, k = 20, simplify = "array")
writeJPEG(pca20, "pca20.jpg")
# Try to increase the number of PCs!
plot(load.image('pca20.jpg'))
```



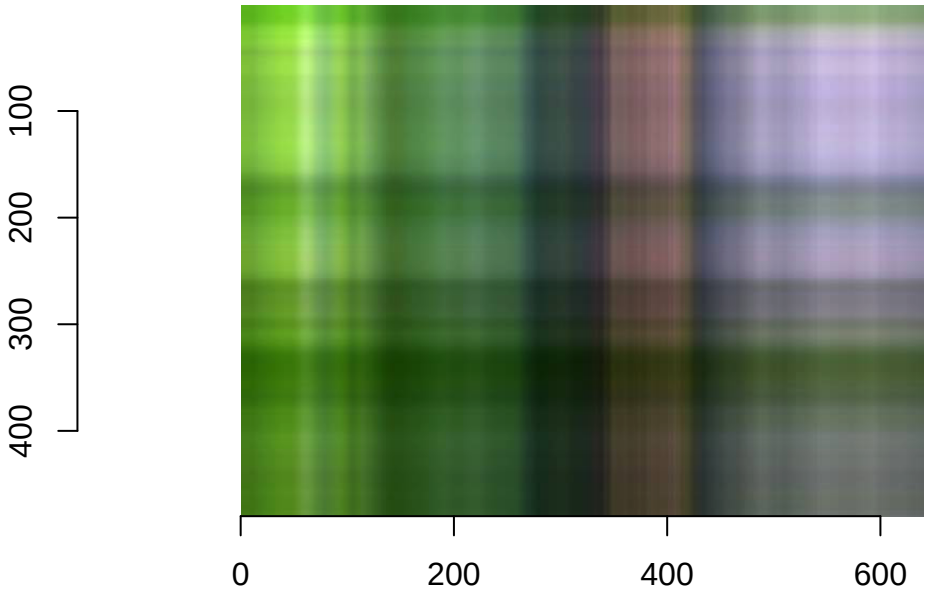

```
plot(load.image('Panda.jpg'))
```


```
img <- readJPEG('Panda.jpg')
dim(img)
```

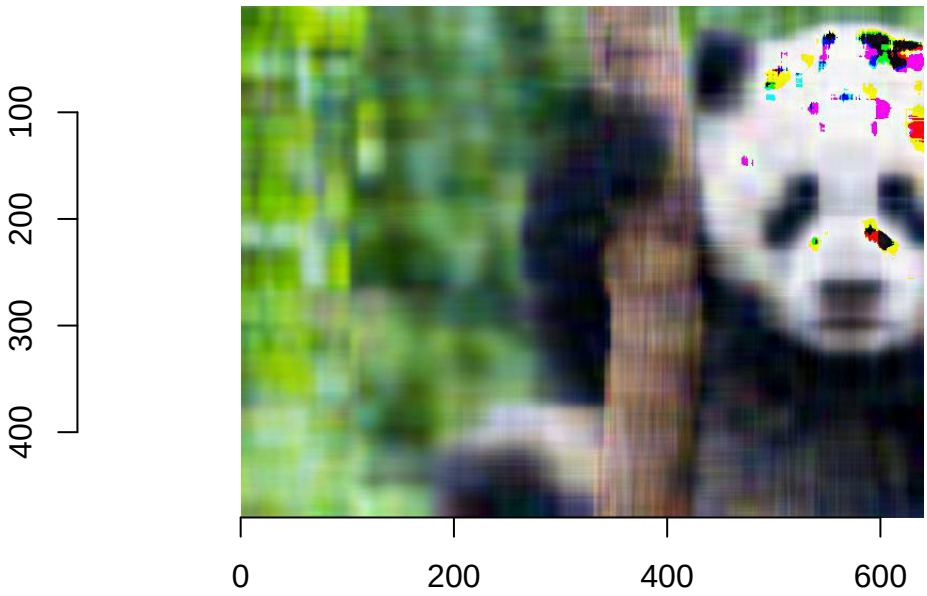
```
## [1] 480 640   3
```

```
r <- img[,,1]
g <- img[,,2]
b <- img[,,3]
img.r.pca <- prcomp(r, center = FALSE)
img.g.pca <- prcomp(g, center = FALSE)
img.b.pca <- prcomp(b, center = FALSE)
rgb.pca <- list(img.r.pca, img.g.pca, img.b.pca)
```

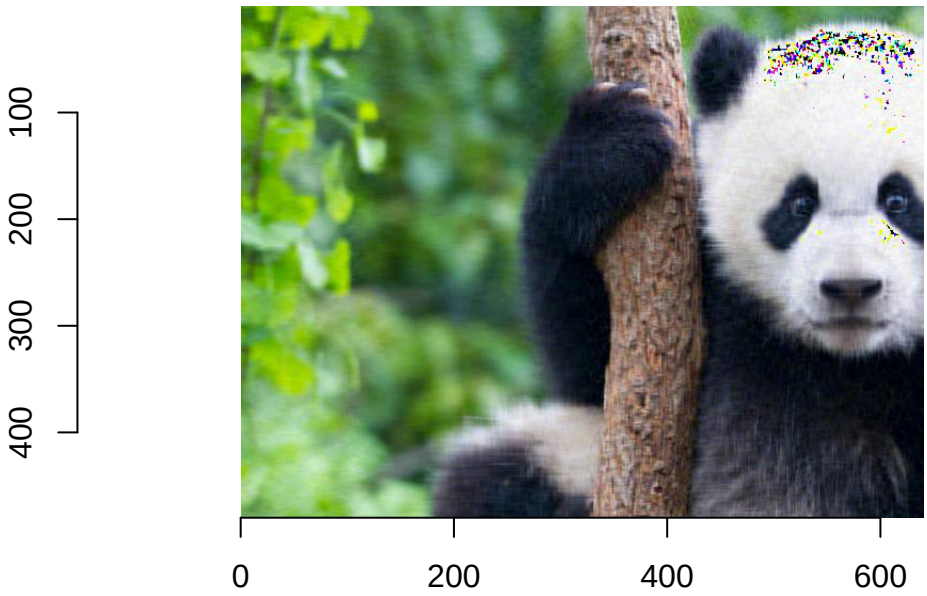
```r
# Approximate X with XV_kV_k^T
compress <- function(pr, k)
{
  compressed.img <- pr$x[,1:k] %*% t(pr$rotation[,1:k])
  compressed.img
}
# Using first PC
p1 <- sapply(rgb.pca, compress, k = 1, simplify = "array")
writeJPEG(p1, "parrot1.jpg")
plot(load.image('parrot1.jpg'))
```




```r
# Using first 10 PCs
p10 <- sapply(rgb.pca, compress, k = 10, simplify = "array")
writeJPEG(p10, "parrot10.jpg")
plot(load.image('parrot10.jpg'))
```



```r
# Using first 50 PCs
p50 <- sapply(rgb.pca, compress, k = 50, simplify = "array")
writeJPEG(p50, "parrot50.jpg")
plot(load.image('parrot50.jpg'))
```




```r
# Using first 100 PCs
p100 <- sapply(rgb.pca, compress, k = 100, simplify = "array")
writeJPEG(p100, "parrot100.jpg")
plot(load.image('parrot100.jpg'))
```


```r
# Using first 200 PCs
p200 <- sapply(rgb.pca, compress, k = 200, simplify = "array")
writeJPEG(p200, "parrot200.jpg")
plot(load.image('parrot200.jpg'))
```


100
200
300
400
0
200
400
600