

Cluster Analysis(CA) and PCA(Principal Component Analysis)

```
library(caret)

## Loading required package: ggplot2
## Loading required package: lattice
library(neuralnet)
library(randomForest)

## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##     margin
library(rpart)
library(rattle)

## Loading required package: tibble
## Loading required package: bitops
## Rattle: A free graphical interface for data science with R.
## Version 5.5.1 Copyright (c) 2006-2021 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
##
## Attaching package: 'rattle'
## The following object is masked from 'package:randomForest':
##
##     importance
library(MASS)
library(tidyverse)

## Warning: package 'tidyr' was built under R version 4.2.3
## Warning: package 'readr' was built under R version 4.2.3
## Warning: package 'dplyr' was built under R version 4.2.3
## Warning: package 'stringr' was built under R version 4.2.3
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr    1.5.1
## v lubridate  1.9.3      v tidyr      1.3.1
## v purrr      1.0.2
```

```
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::combine()      masks randomForest::combine()
## x dplyr::compute()      masks neuralnet::compute()
## x dplyr::filter()       masks stats::filter()
## x dplyr::lag()          masks stats::lag()
## x purrr::lift()         masks caret::lift()
## x randomForest::margin() masks ggplot2::margin()
## x dplyr::select()       masks MASS::select()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
library(glmnet)
```

```
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
##
## The following objects are masked from 'package:tidyr':
##
##   expand, pack, unpack
##
## The following object is masked from 'package:bitops':
##
##   %&%
##
## Loaded glmnet 4.1-8
```

```
library(leaps)
library(ggplot2)
```

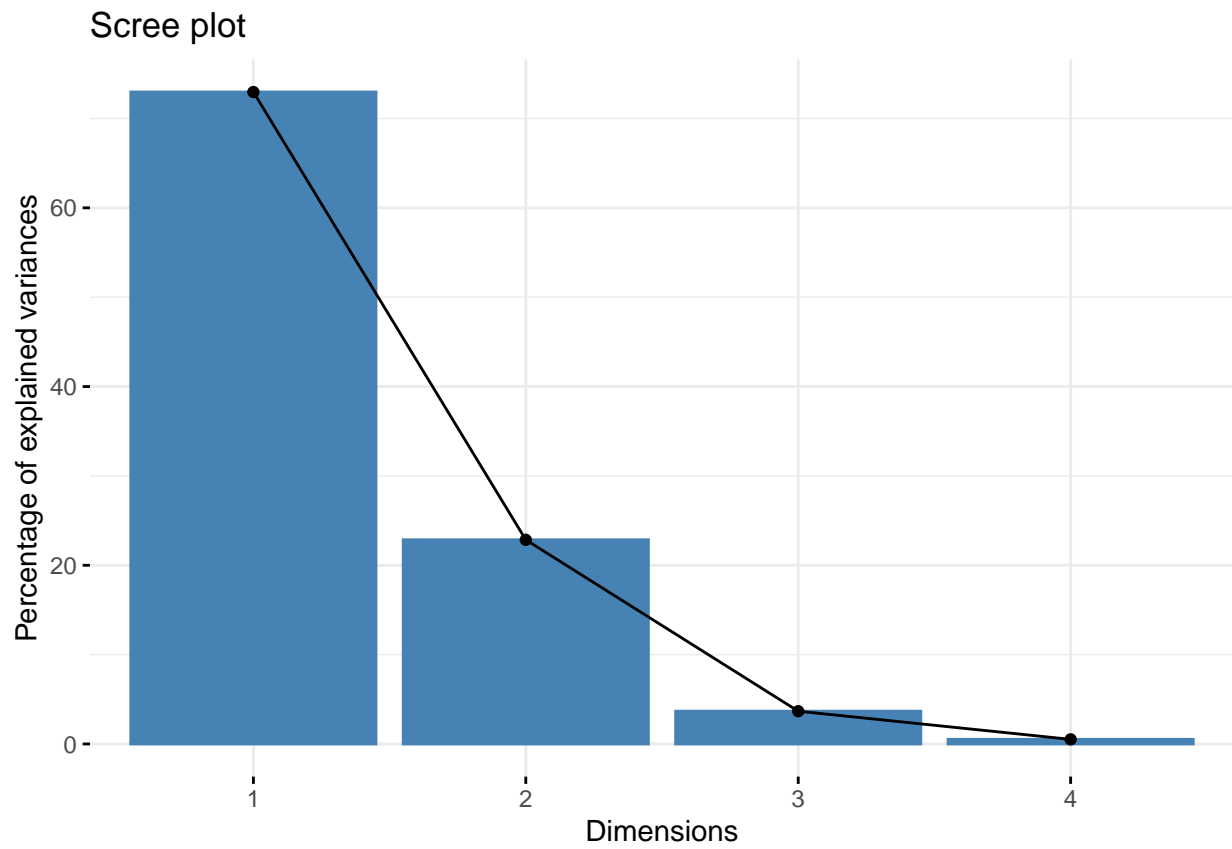
1.

```
str(iris)
```

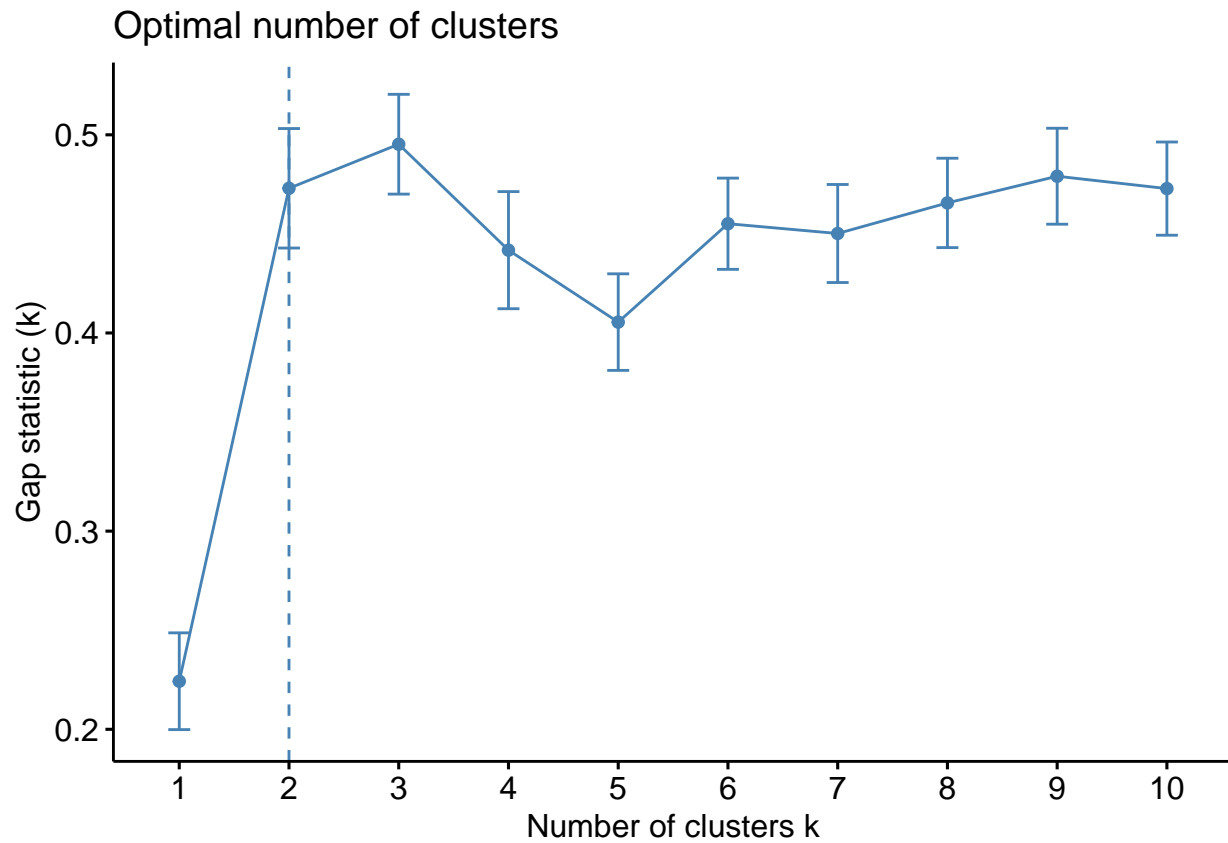
```
## 'data.frame':   150 obs. of  5 variables:
## $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
## $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
## $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
## $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
## $ Species      : Factor w/ 3 levels "setosa","versicolor",...: 1 1 1 1 1 1 1 1 1 1 ...
```

```
data <- na.omit(iris)
data <- scale(data[, -5])
pc <- princomp(data, cor=TRUE)
# princomp performs a principal components analysis on the given numeric data matrix and returns the results
# Scree-plot
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
fviz_eig(pc)
```



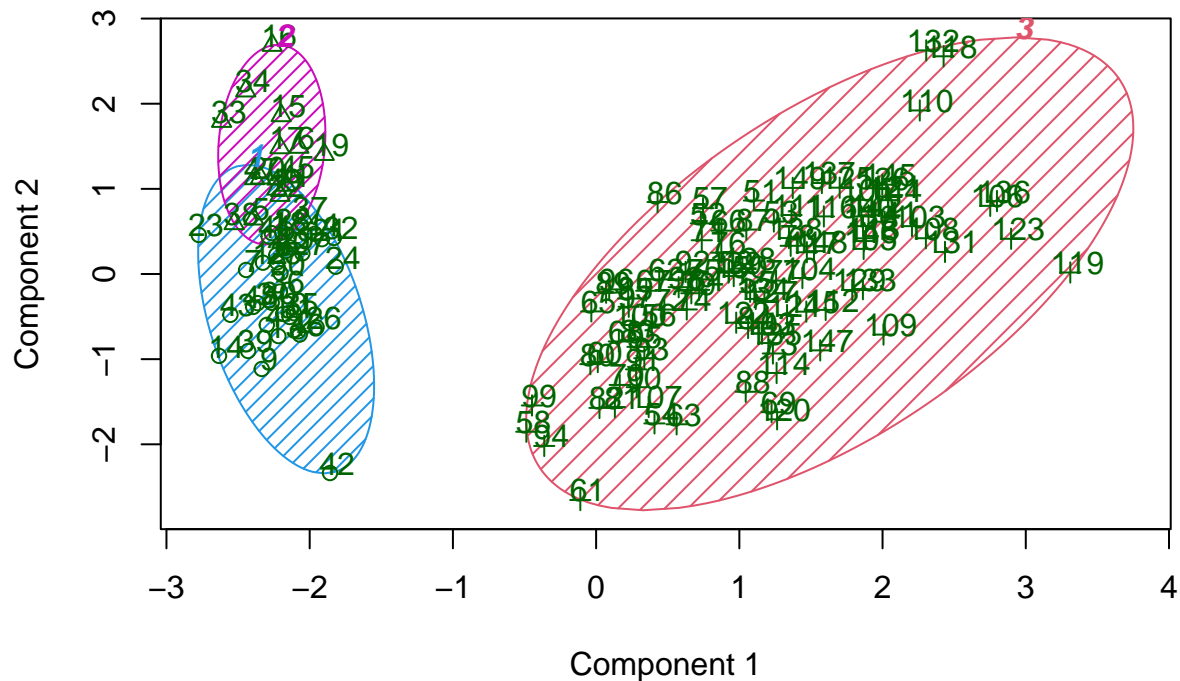
```
fviz_nbclust(data,kmeans,method="gap_stat")
```



K means

```
k.means.fit <- kmeans(data,3)
library(cluster)
clusplot(data,k.means.fit$cluster,main="2D representation of the Cluster solution",color=TRUE,shade=TRUE)
```

2D representation of the Cluster solution



These two components explain 95.81 % of the point variability.

```
table(k.means.fit$cluster,iris$Species)
```

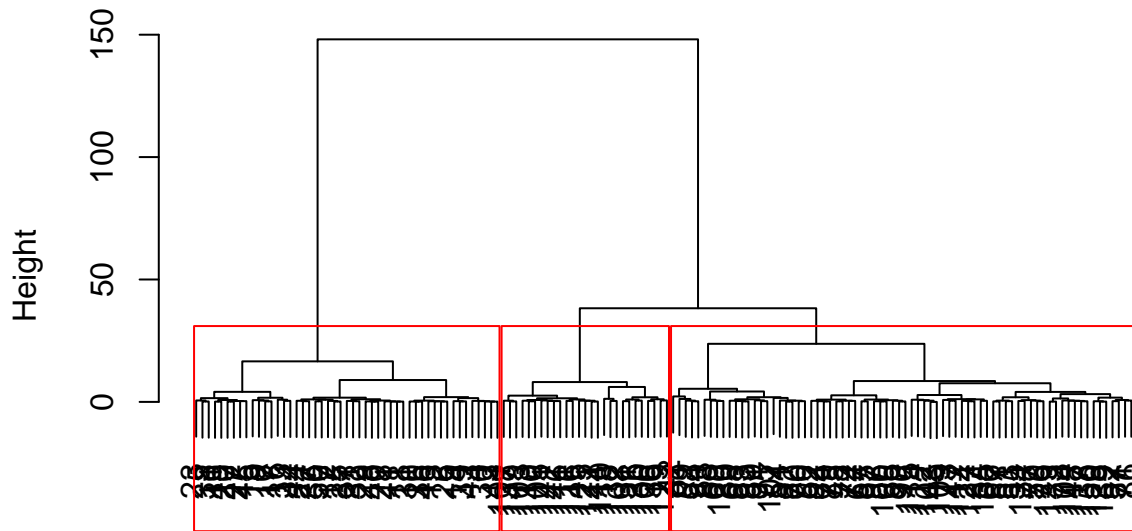
```
##
##      setosa versicolor virginica
## 1      34           0           0
## 2      16           0           0
## 3       0          50          50
```

```
# accuracy = (50+39+36)/150 = 125/150
```

H.ward

```
d <- dist(data, method="euclidean")
H.fit <- hclust(d,method="ward.D")
plot(H.fit)
rect.hclust(H.fit,k=3,border="red")
```

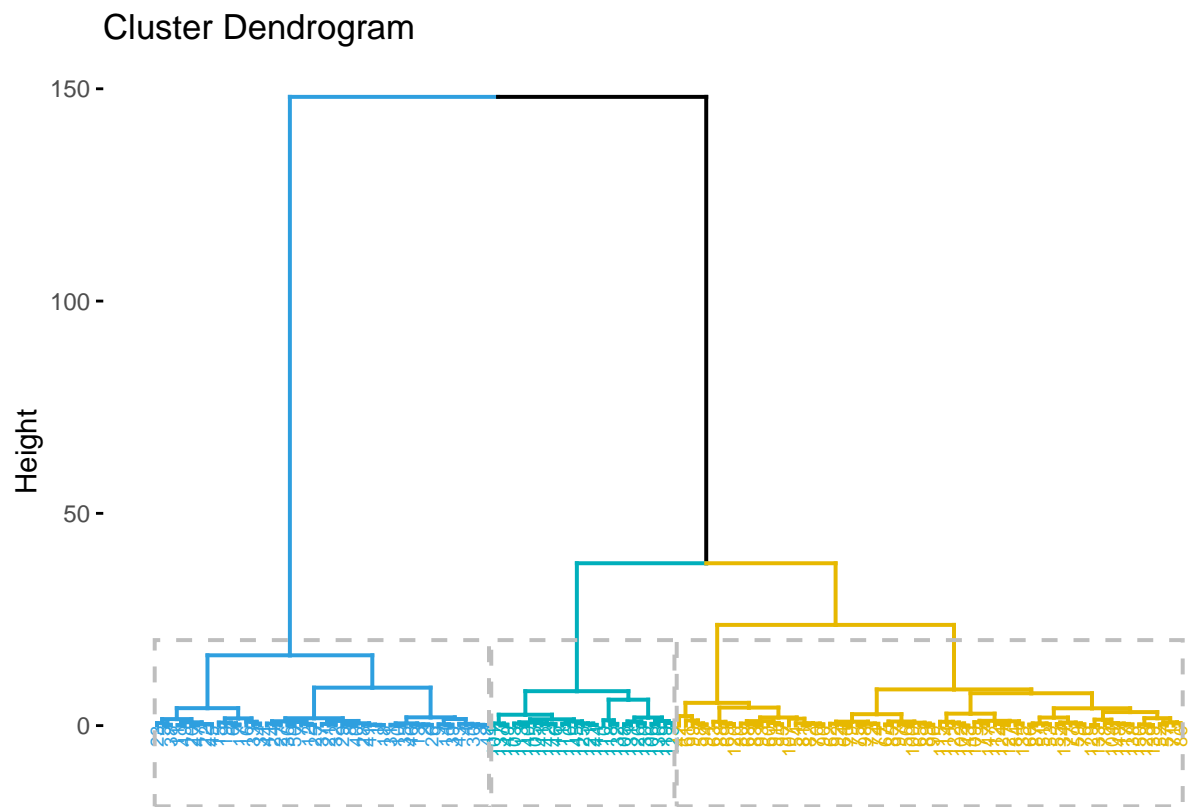
Cluster Dendrogram



d
hclust (*, "ward.D")

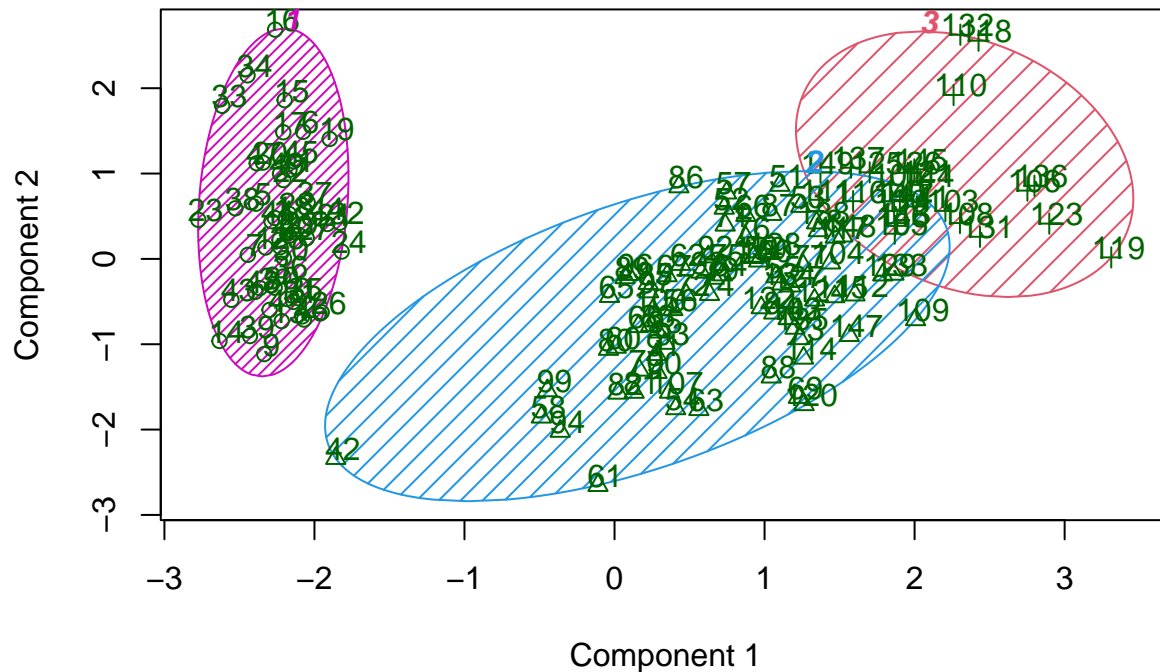
```
fviz_dend(H.fit,k=3,cex=0.5,k_colors=c("#2E9FDF", "#00AFBB", "#E7B800"),color_labels_by_k = TRUE,rect = T
```

```
## Warning: The `<scale>` argument of `guides()` cannot be `FALSE`. Use "none" instead as
## of ggplot2 3.3.4.
## i The deprecated feature was likely used in the factoextra package.
## Please report the issue at <https://github.com/kassambara/factoextra/issues>.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```



```
groups <- cutree(H.fit,k=3)
clusters <- factor(groups, levels=1:3,labels=c("setosa","versicolor","virginica"))
clusplot(data,groups,main="2D representation of the Cluster solution", color=TRUE, shade=TRUE, labels=2
```

2D representation of the Cluster solution



These two components explain 95.81 % of the point variability.

```
table(iris[,5],clusters)
```

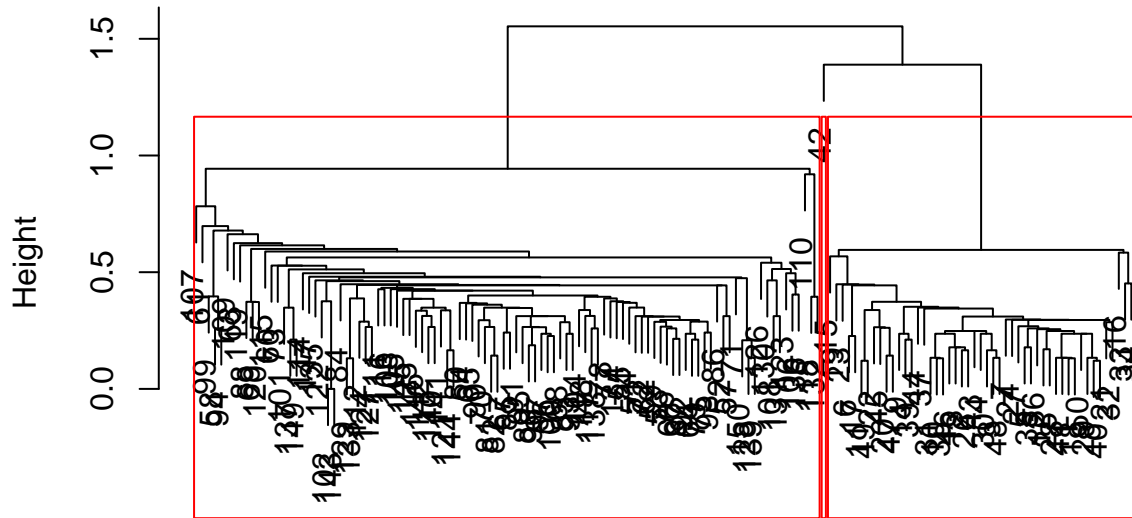
```
##           clusters
##           setosa versicolor virginica
## setosa         49          1          0
## versicolor      0          50          0
## virginica       0          23         27
```

```
# accuracy = (49+50+27)/150
```

H.single

```
H.fit <- hclust(d,method="single")
plot(H.fit)
rect.hclust(H.fit,k=3,border="red")
```

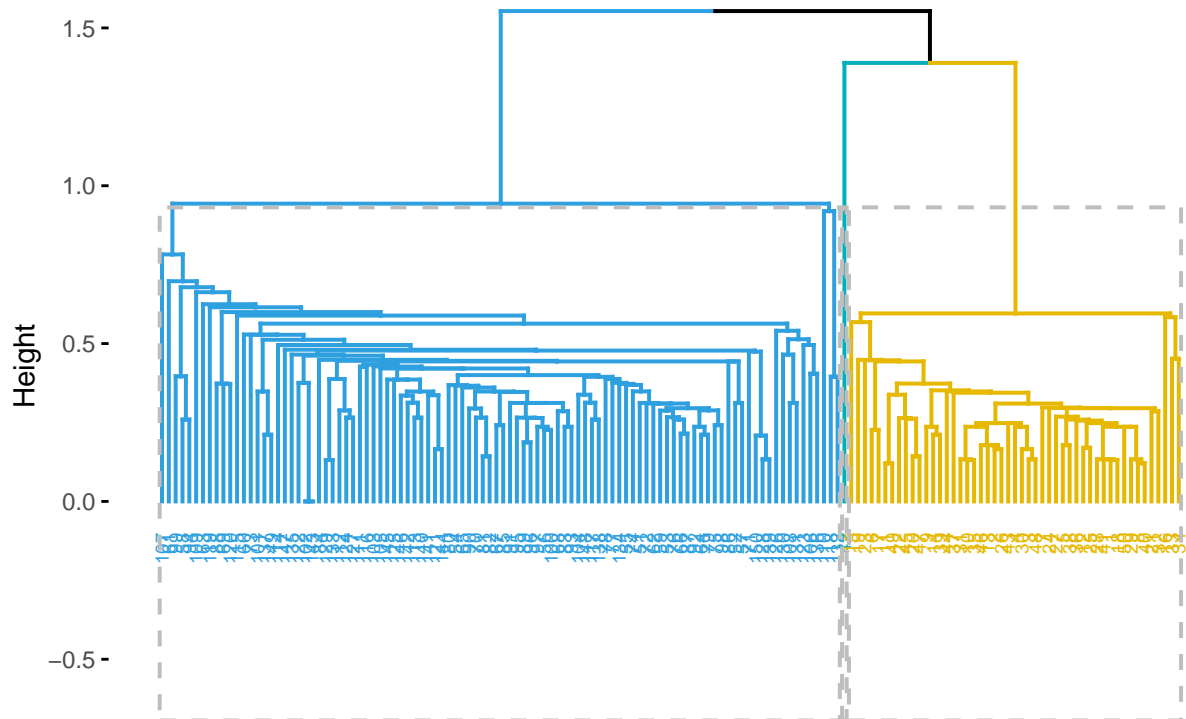

Cluster Dendrogram



d
hclust (*, "single")

```
fviz_dend(H.fit,k=3,cex=0.5,k_colors=c("#2E9FDF", "#00AFBB", "#E7B800"),color_labels_by_k = TRUE,rect = T
```

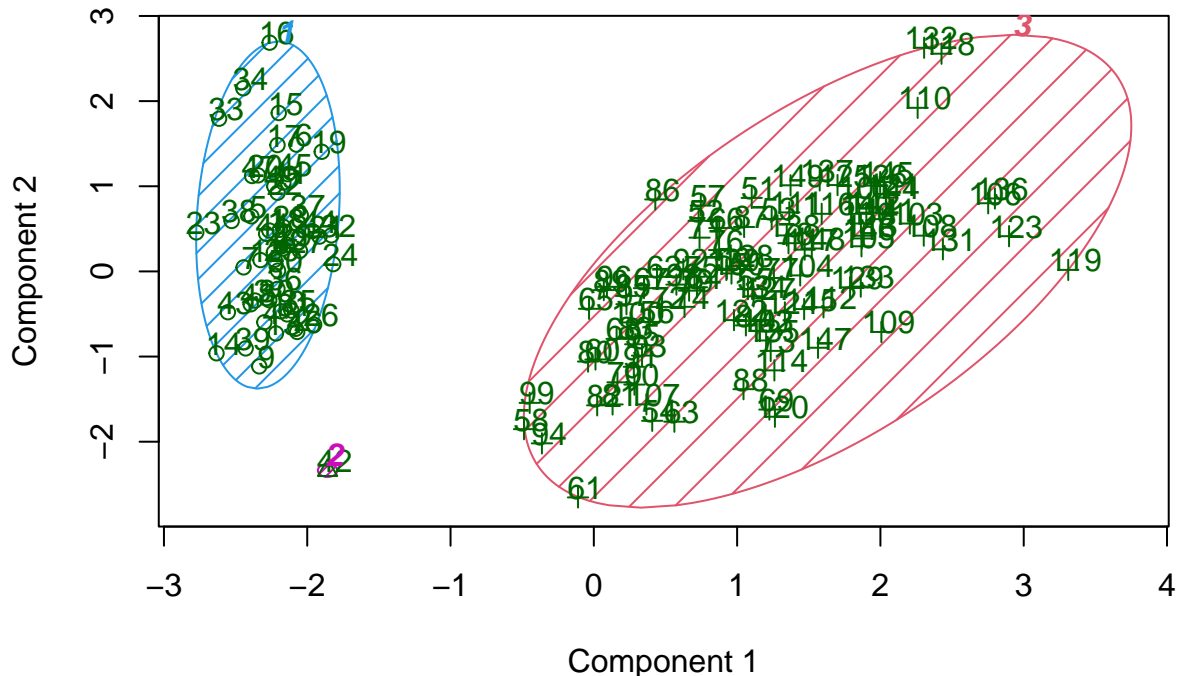
Cluster Dendrogram



```
groups <- cutree(H.fit,k=3)
```

```
clusplot(data,groups,main="2D representation of the Cluster solution",color=TRUE, shade=TRUE, labels = TRUE)
```

2D representation of the Cluster solution



These two components explain 95.81 % of the point variability.

```
clusters <- factor(groups,levels=1:3,labels=c("setosa","versicolor","virginica"))
table(iris[,5],clusters)
```

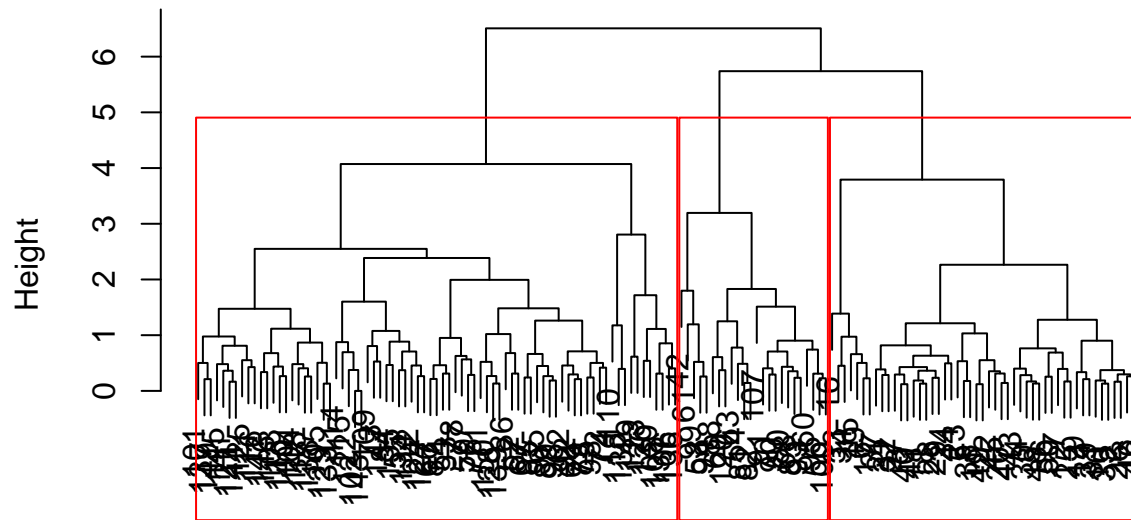
```
##          clusters
##          setosa versicolor virginica
## setosa          49             1             0
## versicolor       0             0            50
## virginica         0             0            50
```

```
# accuracy = (49+50)/150
```

H.complete

```
H.fit <- hclust(d, method="complete")
plot(H.fit)
rect.hclust(H.fit,k=3,border="red")
```

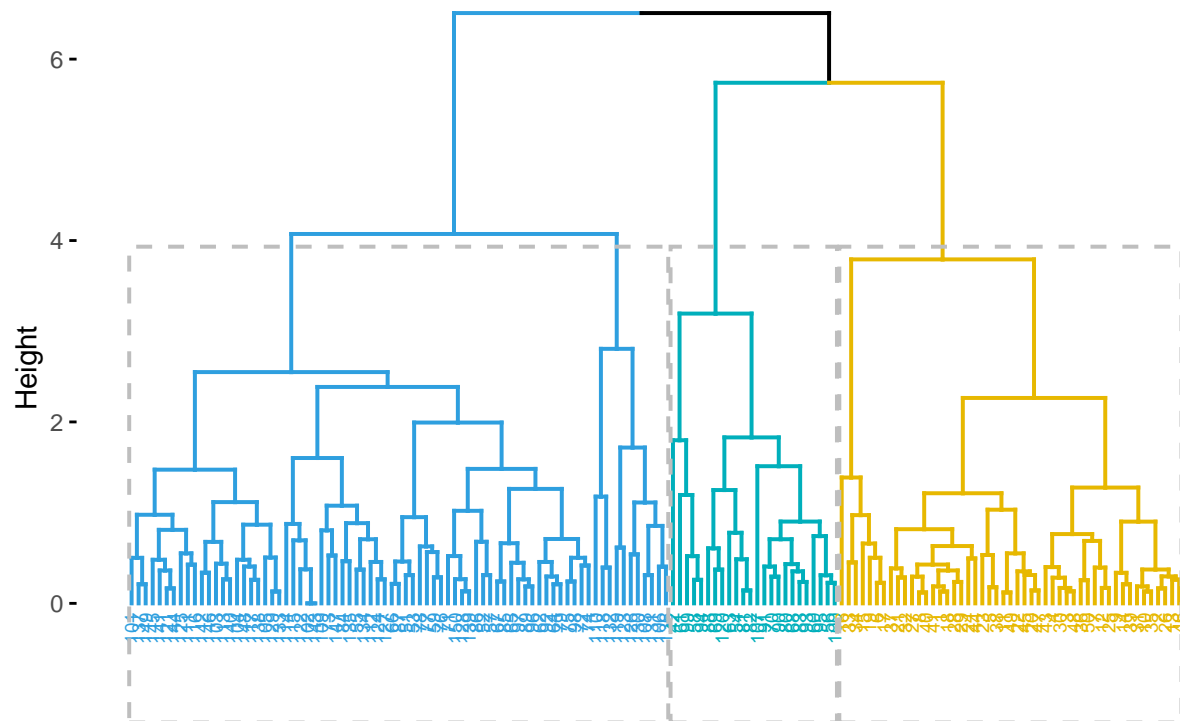
Cluster Dendrogram



d
hclust (*, "complete")

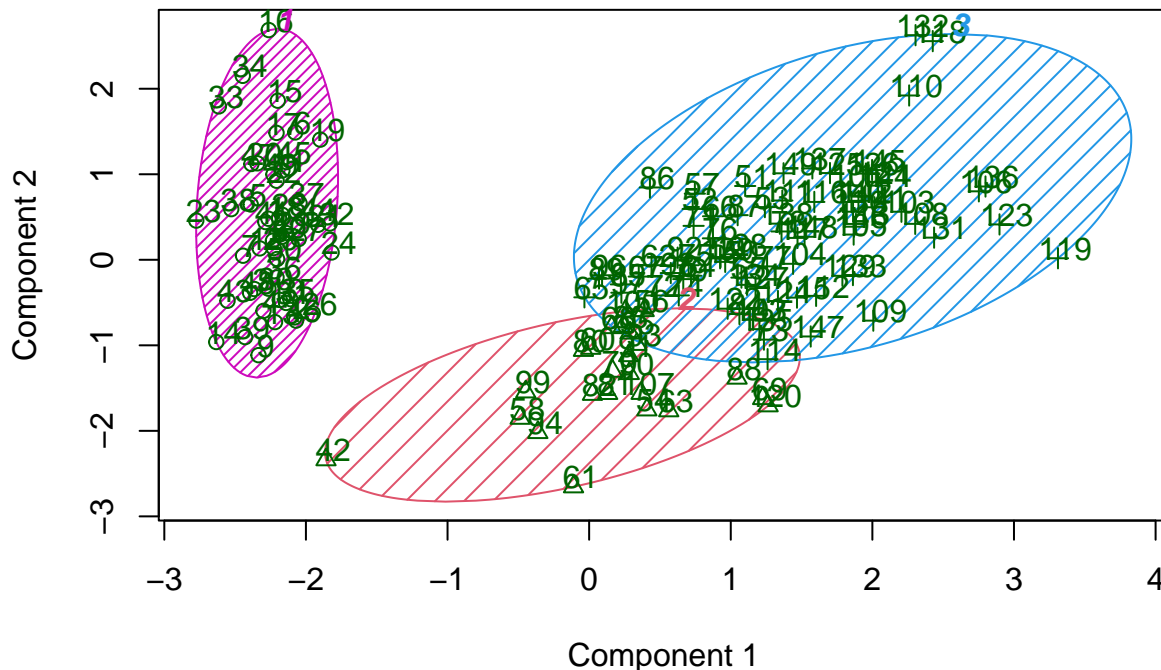
```
fviz_dend(H.fit,k=3,cex=0.5,k_colors=c("#2E9FDF", "#00AFBB", "#E7B800"),color_labels_by_k = TRUE,rect = T
```

Cluster Dendrogram



```
groups <- cutree(H.fit,k=3)
clusplot(data,groups,main="2D representation of the Cluster solution",color=TRUE,shade=TRUE,labels=2,li
```

2D representation of the Cluster solution



These two components explain 95.81 % of the point variability.

```
clusters <- factor(groups,levels=1:3,labels=c("setosa","versicolor","virginica"))
table(iris[,5],clusters)
```

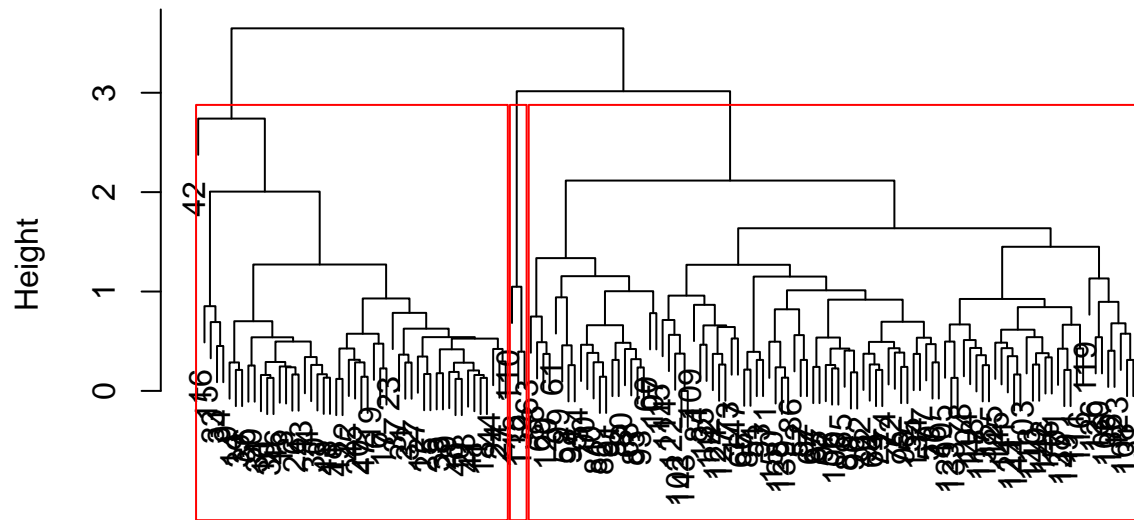
```
##           clusters
##           setosa versicolor virginica
## setosa         49           1         0
## versicolor      0          21        29
## virginica       0           2        48
```

```
# accuracy = (49+21+48)/150
```

H.Average

```
H.fit <- hclust(d,method="average")
plot(H.fit)
rect.hclust(H.fit,k=3,border="red")
```

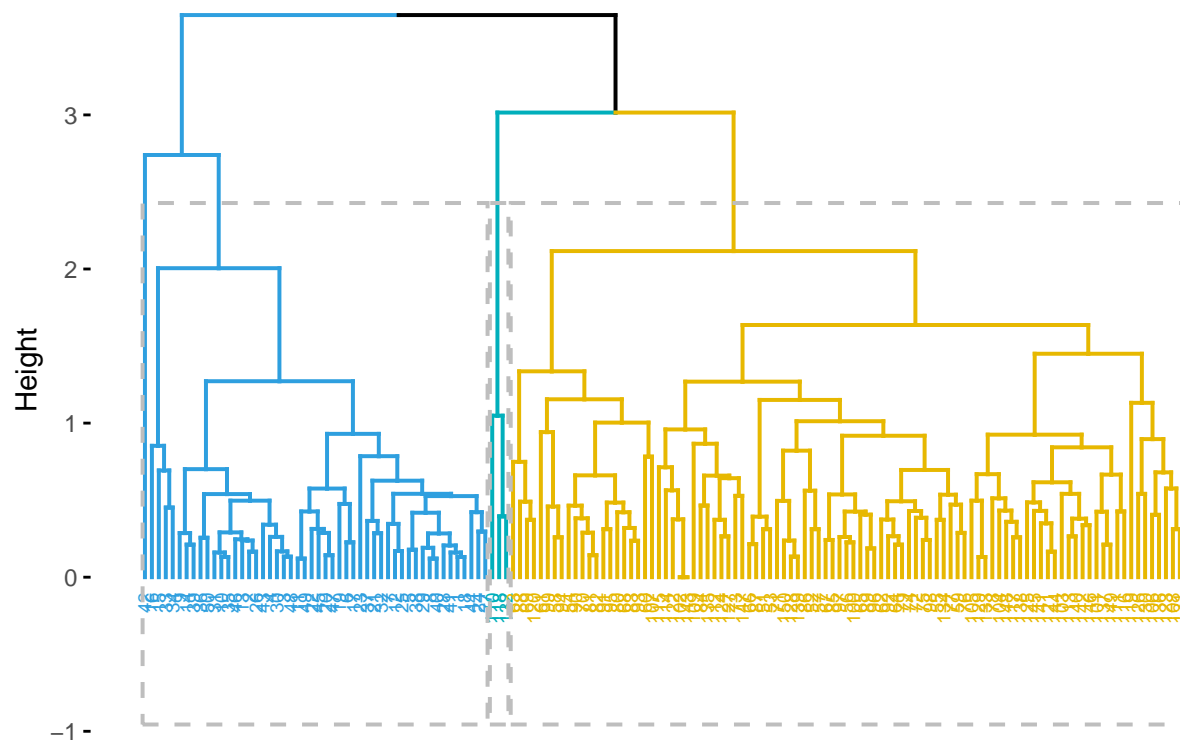
Cluster Dendrogram



d
hclust (*, "average")

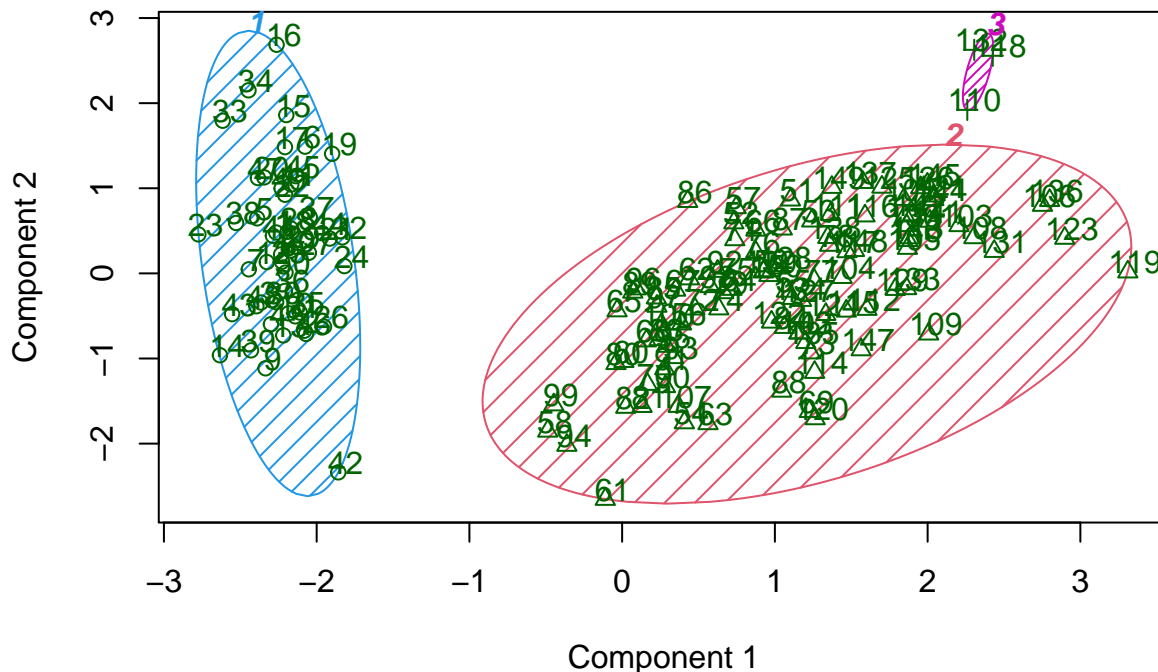
```
fviz_dend(H.fit,k=3,cex=0.5,k_colors=c("#2E9FDF", "#00AFBB", "#E7B800"),color_labels_by_k = TRUE,rect = T
```

Cluster Dendrogram



```
groups <- cutree(H.fit,k=3)
clusplot(data,groups,main="2D representation of the Cluster solution",color=TRUE,shade=TRUE,labels = 2,
```

2D representation of the Cluster solution



These two components explain 95.81 % of the point variability.

```
clusters <- factor(groups,levels=1:3,labels=c("setosa","versicolor","virginica"))
table(iris[,5],clusters)
```

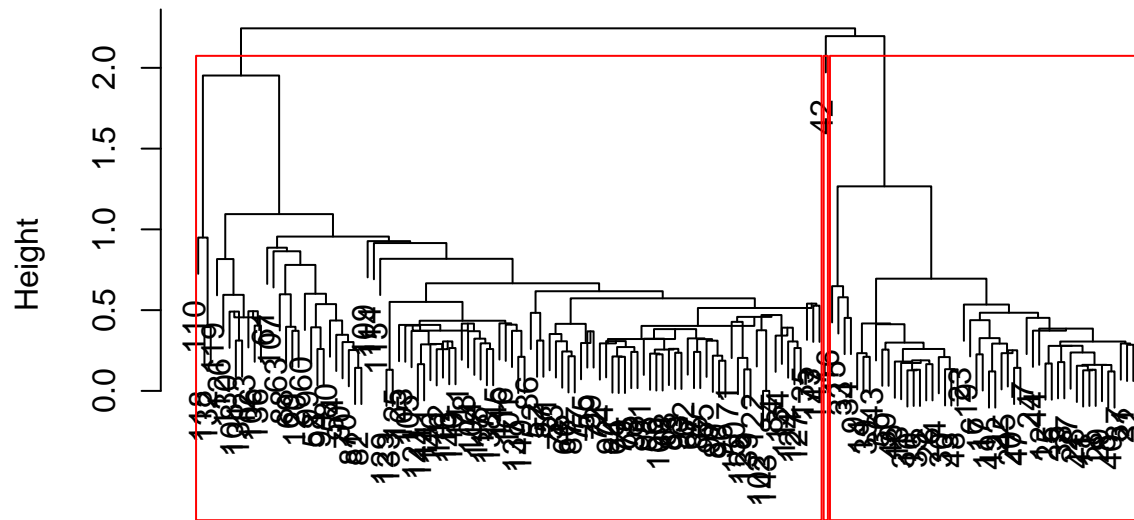
```
##          clusters
##          setosa versicolor virginica
##   setosa         50          0          0
## versicolor         0          50          0
##  virginica         0          47          3
```

```
# accuracy = (50+50+3)/150
```

H.centroid

```
H.fit <- hclust(d,method="centroid")
plot(H.fit)
rect.hclust(H.fit,k=3,border="red")
```

Cluster Dendrogram

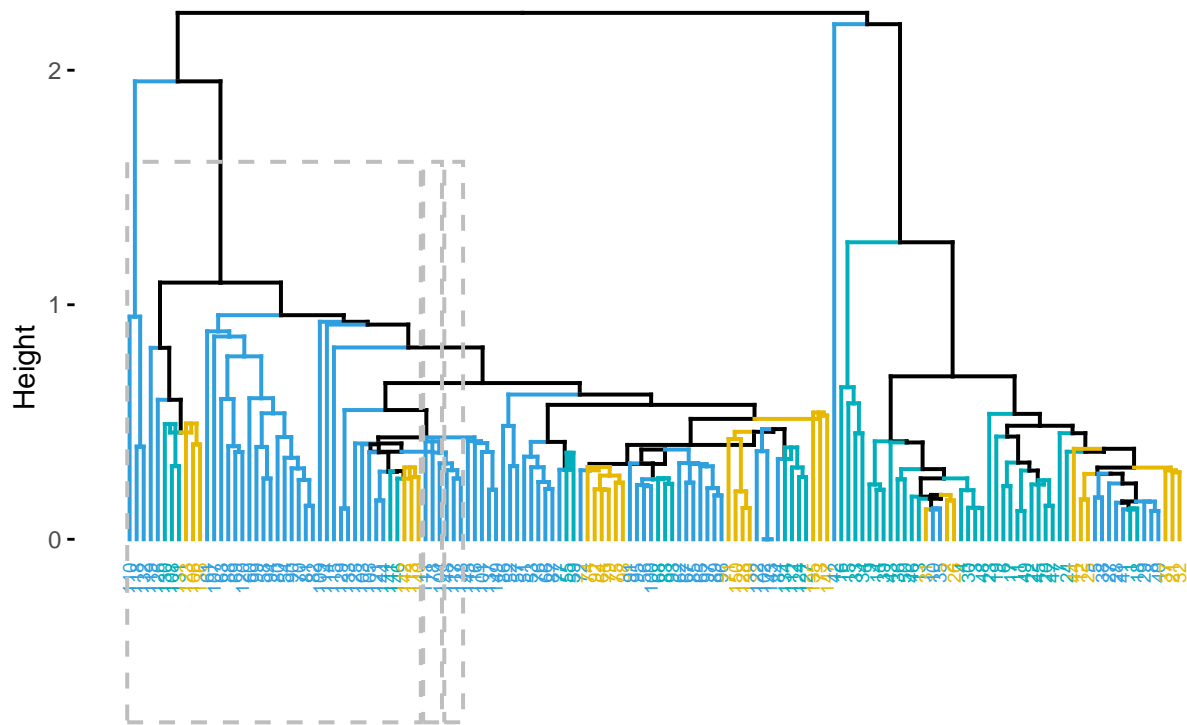


d
hclust (*, "centroid")

```
fviz_dend(H.fit,k=3,cex=0.5,k_colors=c("#2E9FDF","#00AFBB","#E7B800"),color_labels_by_k = TRUE,rect = T
```

```
## Warning in get_col(col, k): Length of color vector was shorter than the number  
## of clusters - color vector was recycled
```

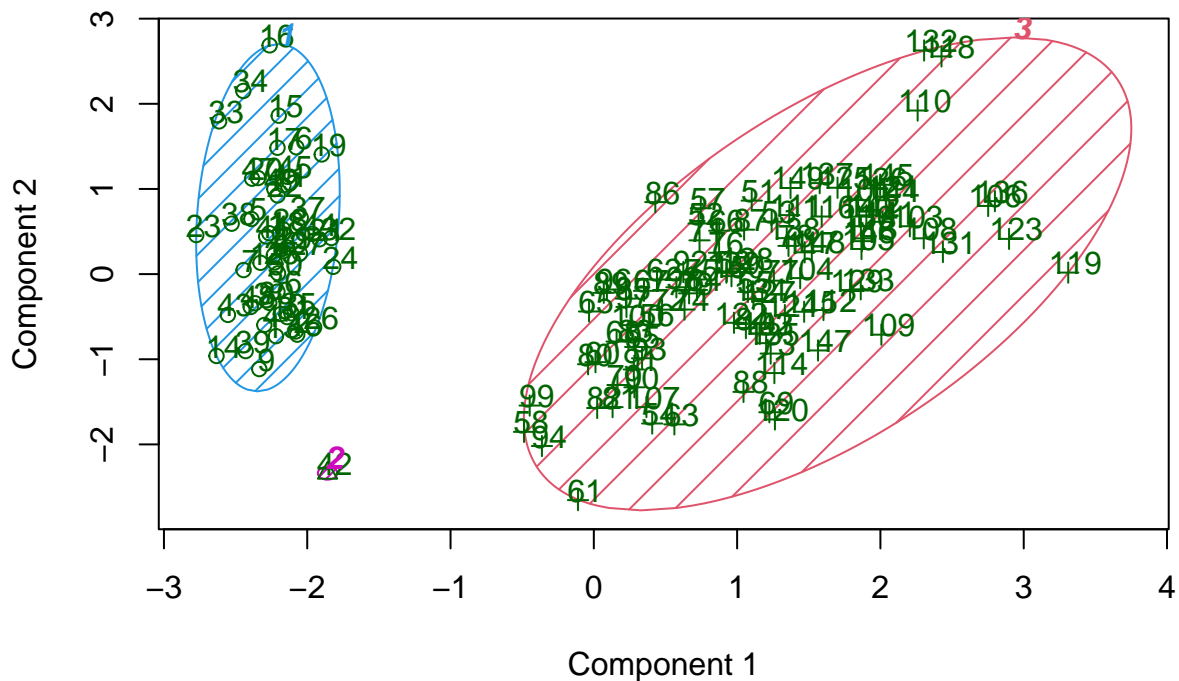
Cluster Dendrogram



```
groups <- cutree(H.fit,k=3)
```

```
clusplot(data,groups,main="2D representation of the Cluster solution",color=TRUE,shade = TRUE, labels =
```

2D representation of the Cluster solution



These two components explain 95.81 % of the point variability.


```
clusters <- factor(groups,levels=1:3,labels=c("setosa","versicolor","virginica"))
table(iris[,5],clusters)
```

```
##           clusters
##           setosa versicolor virginica
## setosa         49          1          0
## versicolor      0          0         50
## virginica       0          0         50
```

```
# accuracy = (49+50)/150
```

Comparison Ward > K-means > Complete > Average > Single = Centroid **I would recommend the cluster analysis as a good way to deal with the IRIS dataset. K-means and complete methods are usually great, but here Ward method is the best one from the confusion matrix.**

2.

```
library(devtools)
```

```
## Loading required package: usethis
```

```
## Warning: package 'usethis' was built under R version 4.2.3
```

```
library(ggbiplot)
```

```
## Warning: package 'ggbiplot' was built under R version 4.2.3
```

```
##
```

```
## Attaching package: 'ggbiplot'
```

```
## The following object is masked from 'package:rattle':
```

```
##
```

```
## wine
```

(a)

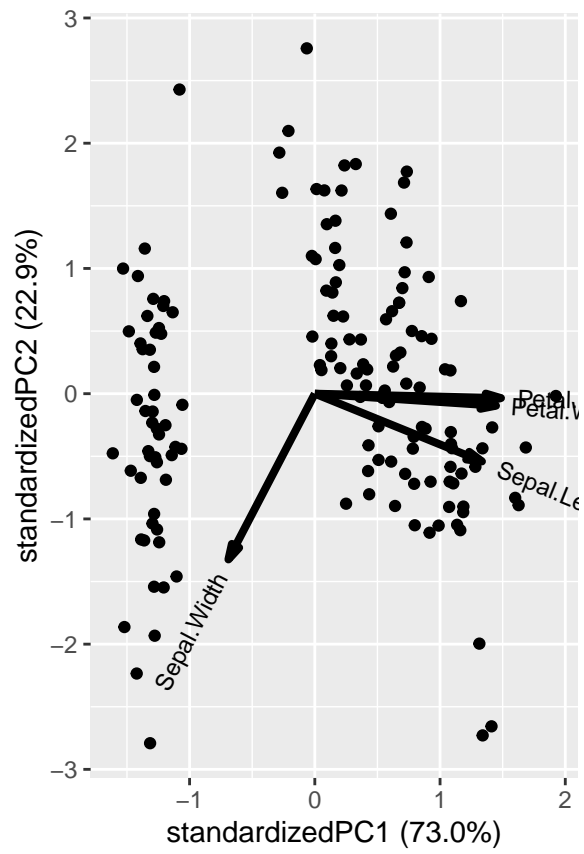
```
iris.pca <- prcomp(data,center=TRUE,scale. = TRUE)
summary(iris.pca)
```

```
## Importance of components:
```

```
##           PC1      PC2      PC3      PC4
## Standard deviation  1.7084 0.9560 0.38309 0.14393
## Proportion of Variance 0.7296 0.2285 0.03669 0.00518
## Cumulative Proportion 0.7296 0.9581 0.99482 1.00000
```

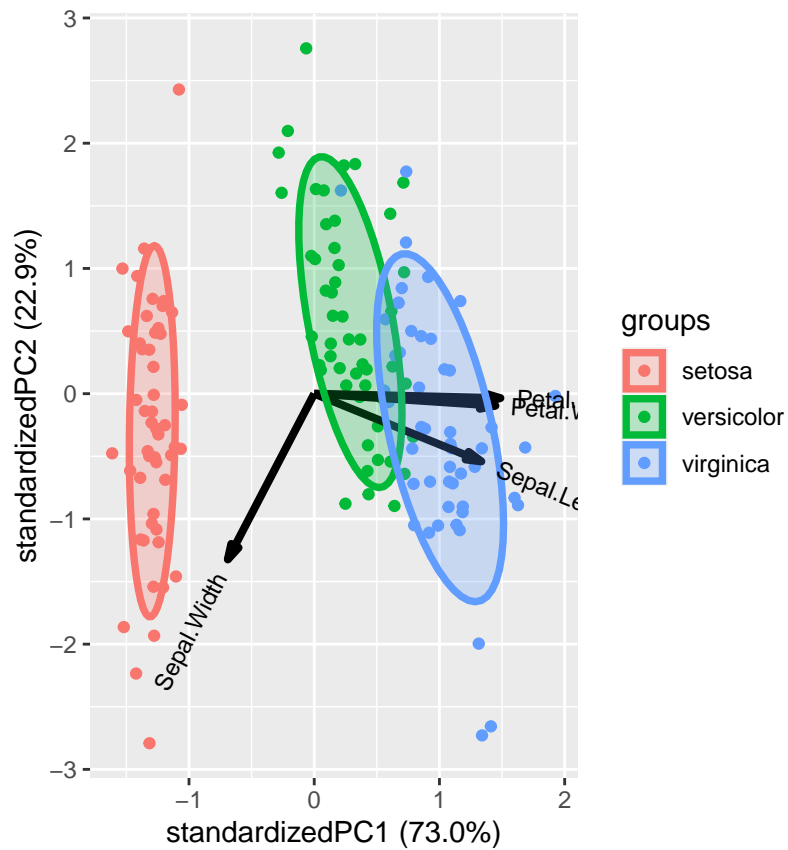
(b)

```
ggbiplot(iris.pca)
```



(c)

```
ggbiplot(iris.pca, ellipse = TRUE, groups = iris$Species)
```



(d)

```
iris.pca$rotation[,1] #PC1
```

```
## Sepal.Length Sepal.Width Petal.Length Petal.Width
## 0.5210659 -0.2693474 0.5804131 0.5648565
```

I recommend the PCA method as an efficient way here. It can reduce the dimension of the data, and the first two PC have a cumulative proportion of variance over 95%, which means this two PCs contains most of the information of the original variables. Additionally, the bi-plot created in part (c) would allows the biologists to see the groupings of species clearly.