Project 3 notebook

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Dataset – Wholesale customers data

http://archive.ics.uci.edu/ml/datasets/Wholesale+customers

This is an R Markdown Notebook. When you execute code within the notebook, the results appear beneath the code.

Try executing this chunk by clicking the *Run* button within the chunk or by placing your cursor inside it and pressing *Cmd+Shift+Enter*.

```
#Meenakshi Nagarajan
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library("dplyr")
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
#Load the data into 'mydata'
mydata=read.csv(file="/Users/meenakshinagarajan/Desktop/Datamining/Project3/W
holesale customers data.csv")
head(mydata)
```

```
##   Channel Region Fresh Milk Grocery Frozen Detergents_Paper Delicassen
## 1       2      3 12669 9656    7561    214             2674       1338
## 2       2      3  7057 9810    9568   1762             3293       1776
## 3       2      3  6353 8808    7684   2405             3516       7844
## 4       1      3 13265 1196    4221   6404              507       1788
## 5       2      3 22615 5410    7198   3915             1777       5185
## 6       2      3  9413 8259    5126    666             1795       1451
```

Background of data

The dataset used in this study is obtained from the UCI Machine learning repository. (http://archive.ics.uci.edu/ml/datasets/Wholesale+customers). It consists of clients of a wholesale distributor. It includes annual spending on products in monetary units (m.u.).

Dataset Characteristics: Multivariate

Attribute characteristics: integer

Date Donated: 2014/ 03/31

Number of instances: 440

Number of Attributes: 8

Missing values: None

Attributes

FRESH: annual spending (m.u.) on fresh products (Continuous)

MILK: annual spending (m.u.) on milk products (Continuous)

GROCERY: annual spending (m.u.)on grocery products (Continuous)

FROZEN: annual spending (m.u.)on frozen products (Continuous)

DETERGENTS_PAPER: annual spending (m.u.) on detergents and paper products (Continuous)

DELICATESSEN: annual spending (m.u.)on and delicatessen products (Continuous)

CHANNEL: customersâ€™ Channel - Horeca (Hotel/Restaurant/CafÃ©) or Retail channel (Nominal)

REGION: customersâ€™ Region â€“ Lisnon, Oporto or Other (Nominal)

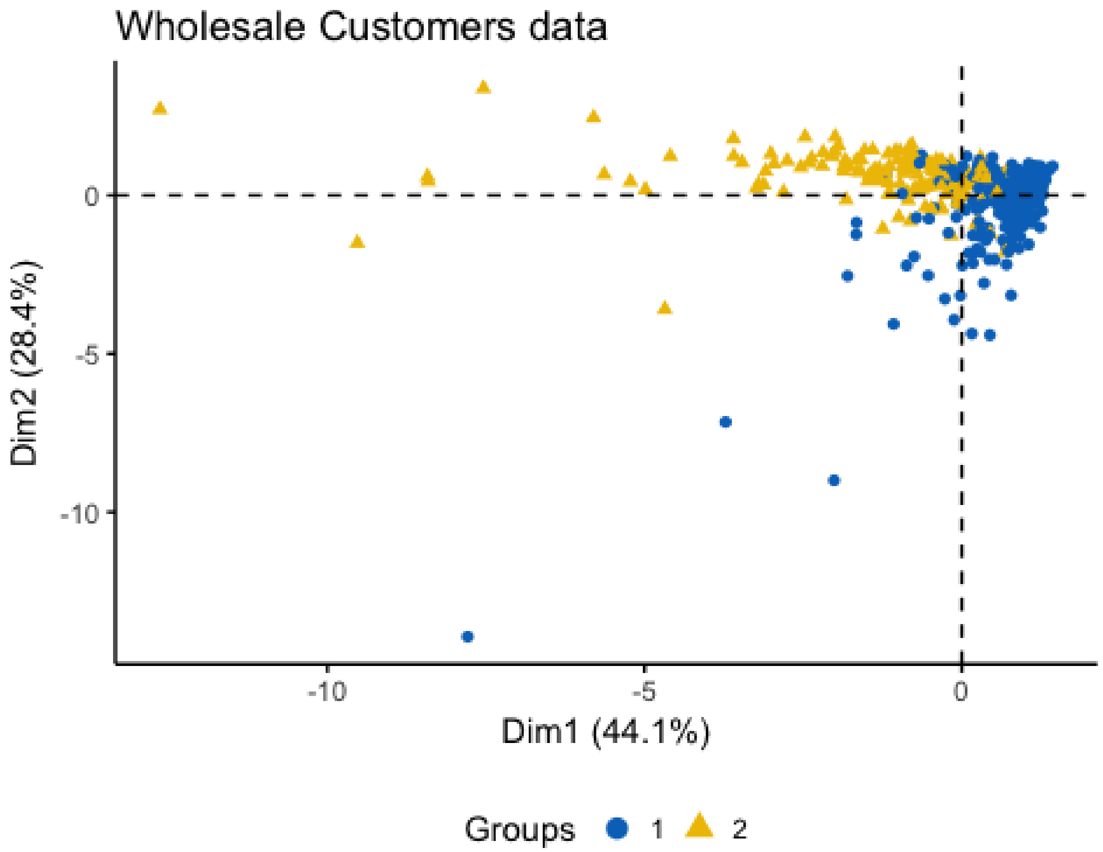
Assessing cluster tendency

```
#removing channel and region from data
df <- mydata[,-1]
df <- df[,-1]
df <- mydata.scaled <- scale(df)
library("factoextra")
```

```
## Loading required package: ggplot2
```

```
## Welcome! Related Books: `Practical Guide To Cluster Analysis in R` at
https://goo.gl/13EFCZ
```

```
fviz_pca_ind(prcomp(df), title = "Wholesale Customers data",
             habillage = mydata$Channel,  palette = "jco",
             geom = "point", ggtheme = theme_classic(),
             legend = "bottom")
```



It can be seen that this dataset contains 2 clusters.

Evaluating cluster tendency with Hopkins statistic

```
library(clustertend)
set.seed(123)
hopkins(df, n = nrow(df)-1)

## $H
## [1] 0.06370234
```

Here, H is 0.06 which is < 0.5 threshold. Therefore, we can reject the null hypothesis and conclude that dataset has a significantly clusterable data.

Choosing the best clustering algorithm and number of clusters

```
library(clValid)
```

```
## Loading required package: cluster
```

```r
# Compute clValid
clmethods <- c("hierarchical","kmeans","pam")
intern <- clValid(df, nClust = 2:6,
              clMethods = clmethods, validation = "stability")
```

```
## Warning in clValid(df, nClust = 2:6, clMethods = clmethods, validation =
## "stability"): rownames for data not specified, using 1:nrow(data)
```

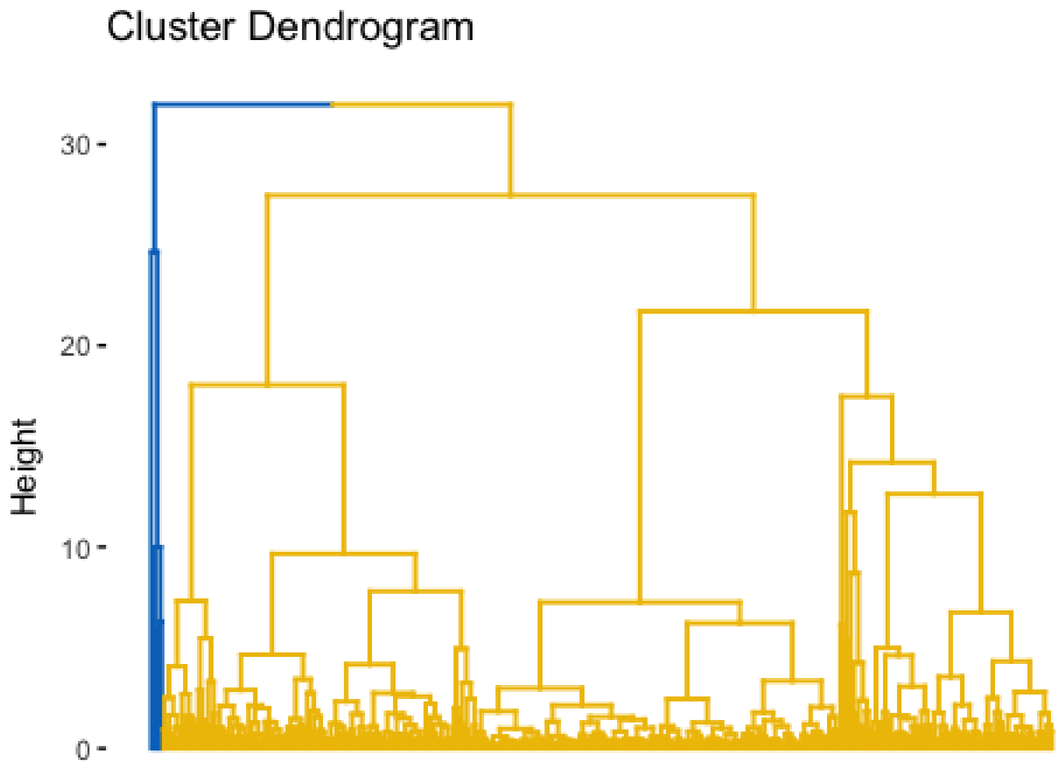
```r
# Summary
summary(intern)
```

```
##
## Clustering Methods:
##  hierarchical kmeans pam
##
## Cluster sizes:
##  2 3 4 5 6
##
## Validation Measures:
##                         2      3      4      5      6
##
## hierarchical APN  0.0037 0.0075 0.0083 0.0123 0.0128
##              AD   2.5094 2.4526 2.3596 2.2847 2.2680
##              ADM  0.0431 0.1990 0.1506 0.1130 0.1180
##              FOM  0.9854 0.9609 0.9475 0.8906 0.8781
## kmeans       APN  0.0272 0.0482 0.1040 0.1904 0.1833
##              AD   2.4706 2.2158 2.0491 2.0257 1.8412
##              ADM  0.5173 0.2968 0.4547 0.6367 0.5546
##              FOM  0.9307 0.8682 0.8500 0.8383 0.7909
## pam          APN  0.0620 0.1886 0.3117 0.3577 0.2571
##              AD   2.1928 2.0341 1.9962 1.9089 1.7420
##              ADM  0.1832 0.4669 0.8206 0.8465 0.6112
##              FOM  0.8895 0.8760 0.8730 0.8339 0.8167
##
## Optimal Scores:
##
##     Score  Method       Clusters
## APN 0.0037 hierarchical 2
## AD  1.7420 pam          6
## ADM 0.0431 hierarchical 2
## FOM 0.7909 kmeans       6
```

It can be seen that, for APN and ADM, hierarchical clustering with 2 clusters performs the best

Performing hierarchical clustering of data

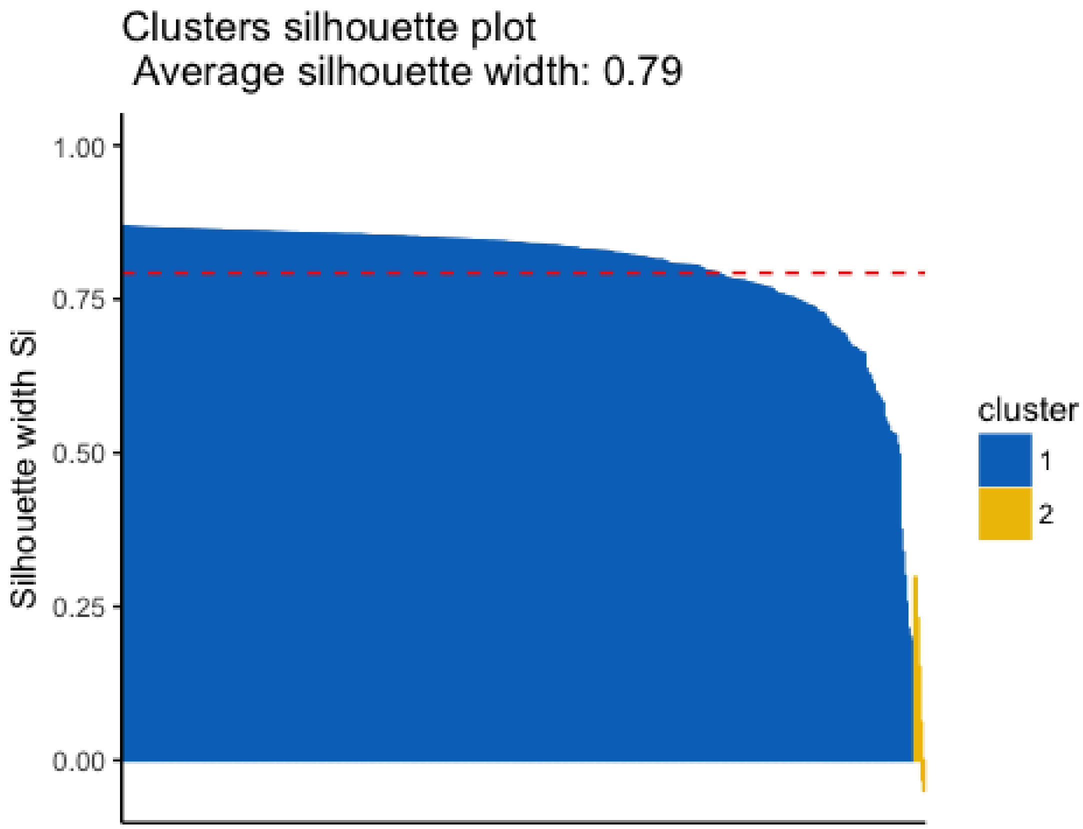
```
library(factoextra)
# Hierarchical clustering using eclust() [enhanced clustering]
hc <- eclust(df, "hclust", k = 2, hc_metric = "euclidean",
                 hc_method = "ward.D2", graph = FALSE)
# Visualize dendrograms
fviz_dend(hc, show_labels = FALSE,
         palette = "jco", as.ggplot = TRUE)
```



Cluster validation

```
fviz_silhouette(hc, palette = "jco",
                ggtheme = theme_classic())

##   cluster size ave.sil.width
## 1       1  434          0.80
## 2       2    6          0.11
```



It can be seen that objects of cluster 1 are well clustered compared to cluster 2.

Determining the closer clusters

```
dsil <- hc$silinfo$widths[, 1:3]
neg_sil <- which(dsil[, 'sil_width'] < 0)
dsil[neg_sil, , drop = FALSE]

##     cluster neighbor   sil_width
## 184       2        1 -0.03159430
## 334       2        1 -0.04926217
```

The closer cluster to two of cluster 2 members are cluster 1.

Agreement between channel and hierarchical clusters

```
library("fpc")
# Compute cluster stats
channel <- as.numeric(mydata$Channel)
d_clust_stats <- cluster.stats(d = dist(df),
                             channel, hc$cluster)
# Corrected Rand index
d_clust_stats$corrected.rand
```

```
## [1] 0.02256532
```

Agreement between Channel type and cluster solution is 0.022 which is very low.

extracting sample data

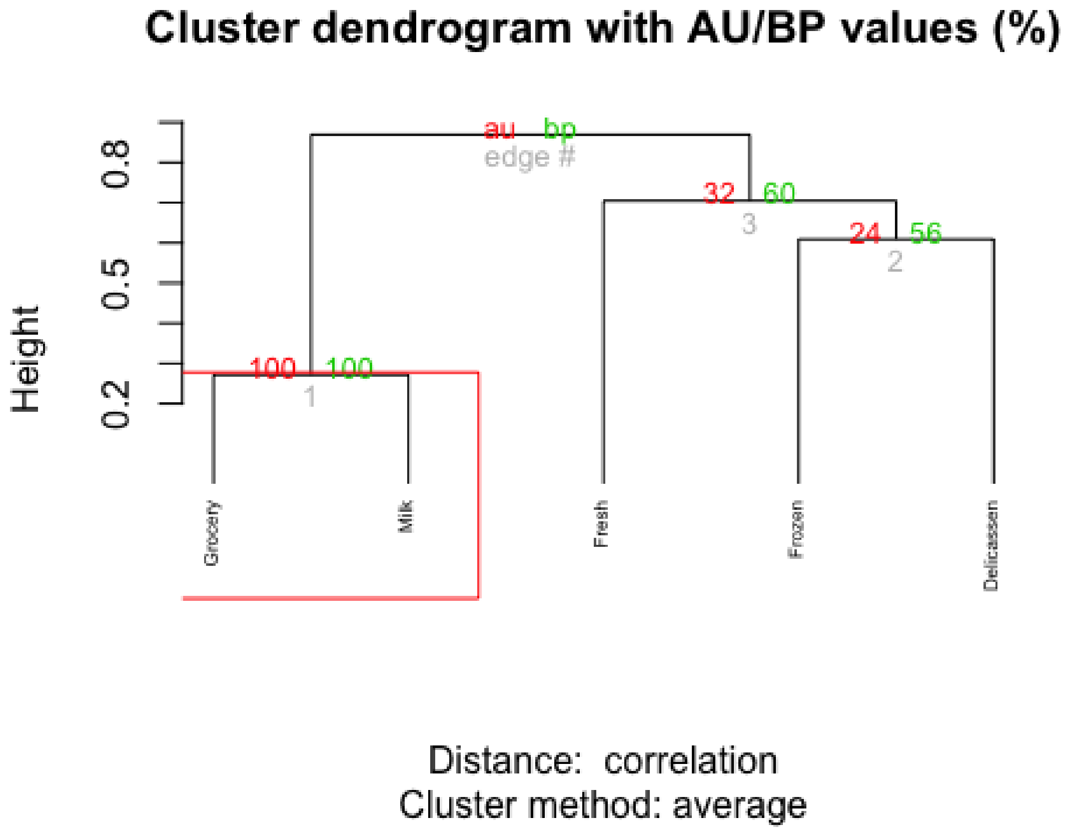
```
set.seed(123)
ss <- sample(1:8, 5)
df <- mydata[, ss]
```

computing p value and extracting significant clusters

```
library(pvclust)
set.seed(123)
pv <- pvclust(df, method.dist="cor",
                  method.hclust="average", nboot = 10)

## Bootstrap (r = 0.5)... Done.
## Bootstrap (r = 0.6)... Done.
## Bootstrap (r = 0.7)... Done.
## Bootstrap (r = 0.8)... Done.
## Bootstrap (r = 0.9)... Done.
## Bootstrap (r = 1.0)... Done.
## Bootstrap (r = 1.1)... Done.
## Bootstrap (r = 1.2)... Done.
## Bootstrap (r = 1.3)... Done.
## Bootstrap (r = 1.4)... Done.

# Default plot
plot(pv, hang = -1, cex = 0.5)
pvrect(pv)
```



```
#extract objects from significant clusters
clusters <- pvpick(pv)
clusters
```

```
## $clusters
## $clusters[[1]]
## [1] "Grocery" "Milk"
##
##
## $edges
## [1] 1
```

Milk and grocery are the two significant cluster objects in determining the channel type.