# **Segmentation: Clustering**

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### Please Read Me

• This presentation is based on (Chapman and Feit 2019, chap. 11)

### **Purpose**

• Find groups of customers that differ in different dimensions to engage in more effective promotion

- age: age of the consumer in years
- gender: if the consumer is male of female
- income: yearly disposable income of the consumer
- **kids**: number of children of the consumer
- ownHome: if the consumer owns a home
- subscribe: if the consumer is subscribed or not

#### Import data

```
segmentation <- read_csv(file = "http://goo.gl/qw303p") |>
select(-Segment) # Remove Segment column to understand how it was build
segmentation |> head(n = 5)

# A tibble: 5 x 6
age gender income kids ownHome subscribe
(db) (db) (db) (db) (db) (db) (db)
```

#### Inspect data

segmentation |> glimpse()

#### Transform data

```
segmentation <- segmentation |>
mutate(gender = factor(gender, ordered = FALSE),
    kids = as.integer(kids),
    ownHome = factor(ownHome, ordered = FALSE),
    subscribe = factor(subscribe, ordered = FALSE))

segmentation |> head(n = 5)

# A tibble: 5 x 6
    age gender income kids ownHome subscribe
    <dbl> <fct> <dbl> <int> <fct> <fct> <fct> <
1 47.3 Male 49483. 2 ownNo subNo
2 31.4 Male 35546. 1 ownYes subNo
3 43.2 Male 44169. 0 ownYes subNo
3 43.2 Male 44169. 0 ownYes subNo</pre>
```

subNo

37.3 Female 81042. 1 ownNo

5 41.0 Female 79353. 3 ownYes subNo

#### Summarize data

 Ups the table is really big!!! Try it in your console to see the complete table

segmentation |> skim()

**Table 1:** Data summary

| Name<br>Number of rows<br>Number of columns | segmentation<br>300<br>6 |
|---|--------------------------|
| Column type frequency:<br>factor<br>numeric | 3<br>3                   |
| Group variables                             | _<br>None                |

#### Variable type: factor

| skim_variable        | n_missing      | complete_rate | ordered    | n_unique | top_counts         | ,    |
|----------------------|----------------|---------------|------------|----------|--------------------|------|
| gender               | 0              | 1             | FALSE      | 2        | Fem: 157, Mal: 143 |      |
| ownHome              | 0              | 1             | FALSE      | 2        | own: 159, own: 141 |      |
| subscribe            | 0              | 1             | FALSE      | 2        | sub: 260. sub: 40  |      |
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#### Segmentation

- Classification (We will not cover this topic)
  - Supervised learning
    - Dependent variable is known and the goal is to predict the dependent variable from the independent variables
    - Naive bayes, Random Forest
- Classification (This topic will be covered)
  - Unsupervised learning
    - Dependent variable is unknown and the goal is to discover it from the independent variables
    - Model-based clustering, (We will not cover these methods)
    - Hierarchical clustering, k-means (These methods will be covered)

#### Clustering

- Grouping a set of observations in such a way that observations in the same group (cluster) are more similar to each other than to those in other groups (clusters).
- A notation of how "close" 2 observations is necessary to group objects where this is formalized using the concept of distance (know as metric<sup>1</sup> in mathematics)
  - There are many notations of distance (Deza and Deza 2016) where in this chapter the Euclidean and the Gower distance will be used

Euclidean distance: it can only be used for numerical data

• 
$$x = (x_1, x_2, \dots, x_n)$$

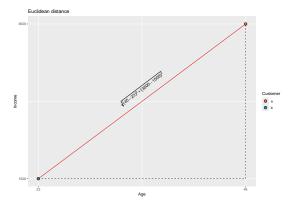
• 
$$y = (y_1, y_2, \dots, y_n)$$

$$\begin{split} d(x,y) &= \sqrt{(x_1-y_1)^2 + (x_2-y_2)^2 + \ldots + (x_n-y_n)^2} \\ &= \sqrt{\sum_{k=1}^n (x_k-y_k)^2} \end{split}$$

- An example:
  - 2 customers characteristic by age and income
    - a = (45, 3500)
    - b = (23, 1500)

#### Manual calculation

• 
$$d(a,b) = \sqrt{(45-23)^2 + (3500-1500)^2} = 2000.121$$



### Using R

```
customers <- tibble(Customer = c("a", "b"),
                   Age = c(45, 23),
                  Income = c(3500, 1500)
customers
# A tibble: 2 x 3
 Customer Age Income
 <chr> <dbl> <dbl>
1 a
          45 3500
2 b
    23 1500
library(cluster)
customers |>
 select(-Customer) |>
 daisy(metric = "euclidean")
Dissimilarities :
```

```
2 2000 121
Metric : euclidean
Number of objects: 2
```

- Gower distance: it can be used for categorical, numerical data and missing values
  - $x = (x_1, x_2, \dots, x_n)$
  - $\bullet \ y=(y_1,y_2,\ldots,y_n)$

$$\begin{split} d(x,y) &= \left[\frac{w_1 \delta_{x_1 y_1}^k}{\sum_{k=1}^n w_k \delta_{x_i y_i}^k}\right] d_{x_1 y_1}^1 + \left[\frac{w_2 \delta_{x_2 y_2}^k}{\sum_{k=1}^n w_k \delta_{x_i y_i}^k}\right] d_{x_2 y_2}^2 + \ldots + \left[\frac{w_n \delta_{x_n y_n}^k}{\sum_{k=1}^n w_k \delta_{x_i y_i}^k}\right] d_{x_n y_n}^n \\ &= \frac{\sum_{k=1}^n w_k \delta_{x_i y_i}^k d_{x_i y_i}^k}{\sum_{k=1}^n w_k \delta_{x_i y_i}^k} \end{split}$$

Where:

$$w_k \in \mathbb{R}$$
 for  $k = 1, 2, \dots, n$ 

$$\sum_{k=1}^n w_k \delta_{x_i y_i}^k = w_1 \delta_{x_1 y_1}^1 + w_2 \delta_{x_2 y_2}^2 + \ldots + w_n \delta_{x_n y_n}^n$$

- Gower distance: it can be used for categorical, numerical data and missing values
  - $x = (x_1, x_2, \dots, x_n)$
  - $y = (y_1, y_2, \dots, y_n)$

$$d(x,y) = \frac{\sum_{k=1}^n w_k \delta_{x_k y_k}^k d_{x_k y_k}^k}{\sum_{k=1}^n w_k \delta_{x_k y_k}^k}$$

Where<sup>2</sup>:

$$\delta_{x_ky_k}^k = \begin{cases} 0 & \text{if } x_k \text{ or } y_k \text{ is a missing value} \\ 0 & \text{if } x_k, y_k \text{ represent an asymmetric binary variable and } x_k = y_k = 0 \\ 1 & \text{otherwise} \end{cases}$$

<sup>&</sup>lt;sup>2</sup>See (Kaufman and Rousseeuw 1990, 25–27) for a definition of asymmetric binary variable

 Gower distance: it can be used for categorical, numerical data and missing values

$$\bullet \ x=(x_1,x_2,\dots,x_n)$$

$$\bullet \ y=(y_1,y_2,\dots,y_n)$$

$$d(x,y) = \frac{\sum_{k=1}^{n} w_k \delta_{x_k y_k}^k d_{x_k y_k}^k}{\sum_{k=1}^{n} w_k \delta_{x_k y_k}^k}$$

Where:

$$d_{x_ky_k}^k = \begin{cases} 0\\1\\\frac{|x_k-y_k|}{max(x_k,y_k)-min(x_k,y_k)} \end{cases}$$

 $d^k_{x_ky_k} = \begin{cases} 0 & \text{if } x_k, y_k \text{ represent a nominal or binary variable and } x_k = y_k \\ 1 & \text{if } x_k, y_k \text{ represent a nominal or binary variable and } x_k \neq y_k \end{cases}$  otherwise

If  $x_k, y_k$  represent an ordinal variable they are replaced by their integer codes. For example if  $x_k \lesssim y_k$  then 1 is assigned to  $x_k$  and 2 is assigned to  $y_k$ 

#### An example:

- 2 customers characteristic by sex (nominal), income (numerical), satisfaction (ordinal with levels  $Low \preceq Medium \preceq High$ ) and age (with a missing value (NA))
  - $\bullet \ \ a = (Female, 3500, Medium, 45)$
  - $\bullet \ b = (Male, 1500, High, NA)$

#### Manual calculation:

- $\bullet$  In R  $w_k=1$  for every k as a default value where in this example k=1,2,3,4
- $\sum_{k=1}^{4} w_k \delta_{x_k y_k}^k = 1 * 1 + 1 * 1 + 1 * 1 + 1 * 1 + 1 * 0 = 1 + 1 + 1 + 0 = 3$
- $\bullet \ \sum_{k=1}^4 w_k \delta^k_{x_k y_k} d^k_{x_k y_k} = 1*1+1*\frac{|3500-1500|}{3500-1500} + 1*\frac{|2-3|}{3-2} + 0 = 3$
- $d(x,y) = \frac{\sum_{k=1}^{4} w_k \delta_{x_k y_k}^k d_{x_k y_k}^k}{\sum_{k=1}^{4} w_k \delta_{x_k y_k}^k} = \frac{3}{3} = 1$

#### • Gower distance range:

- $d(x,y) \in [0,1]$ • If  $d(x,y) \longrightarrow 0$  is more similar • If  $d(x,y) \longrightarrow 1$  is more dissimilar
- Using R

### Using R

```
customers2 |>
  select(-Customer) |>
  daisy(metric = "gower")

Dissimilarities:
  1
2 1
```

• In this case:

Number of objects: 2

Metric: mixed; Types = N, I, O, I

- Metric: mixed because it includes categorical and numerical data
- For Types = N, I, O, I check out
  ?cluster::dissimilarity.object3
  - N: Nominal (factor)
  - I: Interval scaled (numeric)
  - 0: Ordinal (ordered factor)

<sup>&</sup>lt;sup>3</sup>See (Stevens 1946) and Level of measurement

### Using R

```
customers2 |>
  select(-Customer) |>
  daisy(metric = "gower")

Dissimilarities :
  1
  2 1
```

In this case:

Number of objects: 2

Metric : mixed ; Types = N, I, O, I

- Number of objects : 2
  - There are 2 observations that correspond to customers  ${\bf a}$  and  ${\bf b}$ : a=(Female,3500,Medium,45) and b=(Male,1500,High,NA)

- ullet The original dissimilarity matrix is of dimension 300 imes 300
  - ullet Showing only the relation between the first 5 observations
  - $\bullet$  The position (i,j) means the dissimilarity between the observations i and j
    - For example (4,3), which is equal to 0.425, is the dissimilarity between the observations 4 and 3

```
segmentation_dist <- segmentation |>
daisy(metric = "gower")

segmentation_dist |>
as.matrix() |>
as_tibble() |>
select('1':'5') |>
slice(1:5)
```

#### # A tibble: 5 x 5 Customer Sex Income Satisfaction <chr> <fct> <dhl> <ord> <dh1> 1 a Female 3500 Medium 45 2 b Male 1500 High NA Female 200 Low 3 с 34 Female 450 Low 4 d 23

Male 5000 Medium

5 e

55

#### Hierarchical clustering

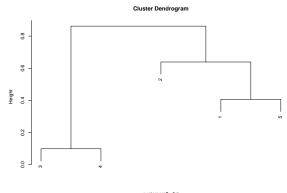
• Method: Complete Linkage Clustering

```
customers3_dist <- daisy(x = select(customers3, -Customer),</pre>
                        metric = "gower")
customers3_dist
Dissimilarities :
2 0.63888889
3 0 38281250 0 75694444
4 0 45572917 0 73958333 0 09895833
5 0.40625000 0.40972222 0.78906250 0.86197917
Metric: mixed; Types = N, I, O, I
Number of objects: 5
customers3 hc <- hclust(d = customers3 dist.
                        method = "complete")
customers3 hc
```

```
Call:
hclust(d = customers3_dist, method = "complete")
Cluster method : complete
```

- Hierarchical clustering
  - Method: Complete Linkage Clustering

plot(customers3\_hc)



customers3\_dist hclust (\*, "complete")

• Compare each observation and find the pair that is more similar

|   | 1         | 2         | 3          | 4         | 5         |
|---|-----------|-----------|------------|-----------|-----------|
| 1 | 0.0000000 | 0.6388889 | 0.3828125  | 0.4557292 | 0.4062500 |
| 2 | 0.6388889 | 0.0000000 | 0.75694444 | 0.7395833 | 0.4097222 |
| 3 | 0.3828125 | 0.7569444 | 0          | 0.0989583 | 0.7890625 |
| 4 | 0.4557292 | 0.7395833 | 0.09895833 | 0.0000000 | 0.8619792 |
| 5 | 0.4062500 | 0.4097222 | 0.7890625  | 0.8619792 | 0.0000000 |

- $\bullet$  Now we have the first cluster that includes the observations 3 and 4 : C(3,4)
- $\bullet$  Then we need to create clusters with observations  $1,\,2$  and 5 and the cluster C(3,4)
  - How we compare a cluster with an observation
    - Complete Linkage Clustering: Use the maximum distance between an observation and an observation that belongs to the cluster

- Compare each observation, including the clusters build, and find the pair that is more similar
  - In our case 1, 2, 5 and C(3,4)
    - ullet The distance between 1 and C(3,4) is 0.45572917
    - ullet The distance between 2 and C(3,4) is 0.7569444
    - ullet The distance between 5 and C(3,4) is 0.8619792

|   | 1          | 2         | 3          | 4         | 5         |
|---|------------|-----------|------------|-----------|-----------|
| 1 | 0          | 0.6388889 | 0.3828125  | 0.4557292 | 0.4062500 |
| 2 | 0.63888889 | 0.0000000 | 0.75694444 | 0.7395833 | 0.4097222 |
| 3 | 0.3828125  | 0.7569444 | 0          | 0.0989583 | 0.7890625 |
| 4 | 0.45572917 | 0.7395833 | 0.09895833 | 0.0000000 | 0.8619792 |
| 5 | 0.40625    | 0.4097222 | 0.7890625  | 0.8619792 | 0.0000000 |

- $\bullet$  Now we have the second cluster that includes the observations 1 and  $5\colon\thinspace C(1,5)$
- Then we need to create clusters with observation 2 and clusters C(3,4) and C(1,5)
  - How we compare a cluster with another cluster
    - Complete Linkage Clustering: Use the maximum distance between an observation that belongs to the first cluster and an observation that belongs to the second cluster

- Compare each observation, including the clusters build, and find the pair that is more similar
  - In our case 2, C(3,4) and C(1,5)
    - The distance between 2 and C(3,4) is 0.7569444
    - ullet The distance between 2 and C(1,5) is 0.6388889

|   | 1          | 2         | 3          | 4         | 5         |
|---|------------|-----------|------------|-----------|-----------|
| 1 | 0          | 0.6388889 | 0.3828125  | 0.4557292 | 0.4062500 |
| 2 | 0.63888889 | 0.0000000 | 0.75694444 | 0.7395833 | 0.4097222 |
| 3 | 0.3828125  | 0.7569444 | 0          | 0.0989583 | 0.7890625 |
| 4 | 0.45572917 | 0.7395833 | 0.09895833 | 0.0000000 | 0.8619792 |
| 5 | 0.40625    | 0.4097222 | 0.7890625  | 0.8619792 | 0.0000000 |

- Now we have the third cluster that includes the observation 2 and the cluster  $C(1,5)\colon C(2,C(1,5))$
- $\bullet$  Then we need to create clusters with cluster C(2,C(1,5)) and cluster C(3,4)
  - This is the cluster that includes all the observations

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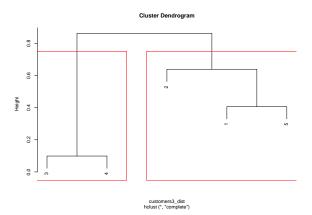
- Compare each observation, including the clusters build, and find the pair that is more similar
  - In our case C(3,4) and C(2,C(1,5))
    - ullet The distance between C(3,4) and C(2,C(1,5)) is 0.86197917

|   | 1          | 2         | 3          | 4          | 5         |
|---|------------|-----------|------------|------------|-----------|
| 1 | 0          | 0.6388889 | 0.3828125  | 0.45572917 | 0.4062500 |
| 2 | 0.63888889 | 0.0000000 | 0.75694444 | 0.73958333 | 0.4097222 |
| 3 | 0.3828125  | 0.7569444 | 0          | 0.09895833 | 0.7890625 |
| 4 | 0.45572917 | 0.7395833 | 0.09895833 | 0          | 0.8619792 |
| 5 | 0.40625    | 0.4097222 | 0.7890625  | 0.86197917 | 0.0000000 |

 $\bullet$  The heights of the **Cluster Dendrogram** are: 0.09895833, 0.40625, 0.63888889 and 0.86197917

• Select a number of clusters, for example: 2 clusters

```
plot(customers3_hc)
rect.hclust(customers3_hc, k = 2, border = "red")
```



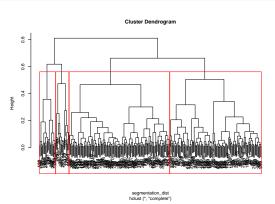
#### Extract clusters and assign them to observations

```
customers3_hc_clusters <- cutree(customers3_hc, k = 2)
customers3 |>
mutate(cluster = customers3_hc_clusters)
```

```
# A tibble: 5 x 6
 Customer Sex
              Income Satisfaction
                                 Age cluster
 <chr>>
        <fct> <dbl> <ord>
                               <dbl>
                                      <int>
        Female 3500 Medium
    Male 1500 High
3 c
    Female 200 Low
                                34
    Female 450 Low
                                 23
       Male
                5000 Medium
                                 55
```

• Select a number of clusters, using segmentation, for example: 4 clusters

```
segmentation_hc <- hclust(d = segmentation_dist,</pre>
                           method = "complete")
plot(segmentation_hc)
rect.hclust(segmentation_hc, k = 4, border = "red")
```



Segmentation: Clustering

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 Extract clusters and assign them to observations, using segmentation

```
segmentation_hc_clusters <- cutree(segmentation_hc, k = 4)
segmentation |>
 mutate(cluster = segmentation_hc_clusters)
# A tibble: 300 x 7
     age gender income kids ownHome subscribe cluster
   <dbl> <fct> <dbl> <int> <fct>
                                     <fct>
                                                  <int>
 1 47.3 Male 49483.
                           2 ownNo
                                     subNo
  31.4 Male 35546.
                           1 own Yes subNo
3 43.2 Male 44169. 0 ownYes
4 37.3 Female 81042. 1 ownNo
5 41.0 Female 79353. 3 ownYes
                           O ownYes subNo
                                     subNo
                           3 own Yes subNo
6 43.0 Male 58143. 4 ownYes subNo
7 37.6 Male 19282.
                                    subNo
                           3 ownNo
8 28 5 Male 47245 0 own No
                                    subNo
  44.2 Female 48333.
                       1 ownNo
                                     subNo
  35.2 Female 52568.
                           O ownYes subNo
# i 290 more rows
```

### References

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