Marketing Analytics

Cluster Analysis

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Objectives

Learn

1. The basic concept of cluster analysis
2. Popular clustering algorithms
   - Core idea
   - Determining the number of clusters
   - Visualization

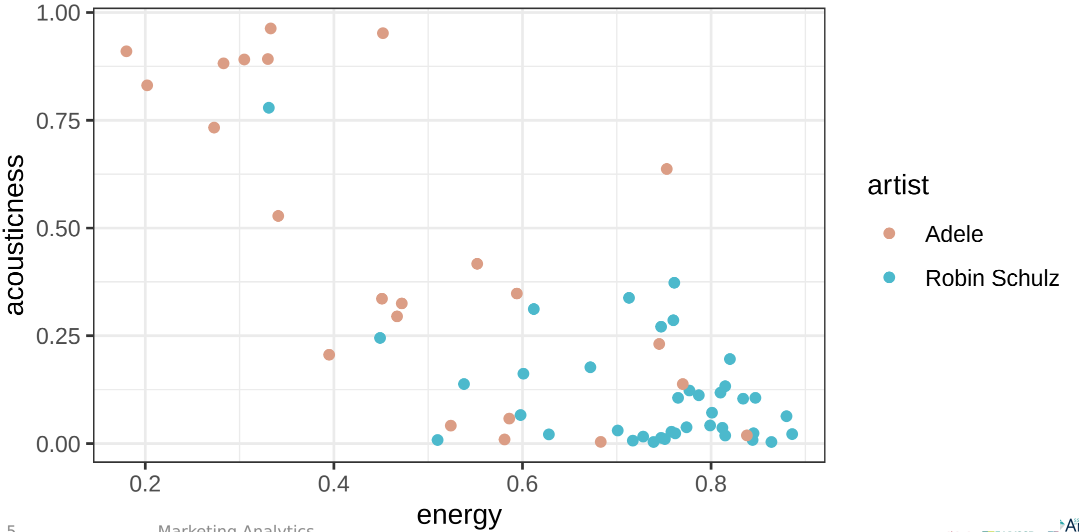
Basic concept of cluster analysis

- Goal: Group observations into **clusters** such that those in the same cluster are more “similar” than those of other clusters.
- Reduction in number of *rows*
- No distinction between dependent and independent variables.
- What exactly constitutes a cluster is not clear and many different concepts exist.
- We are going to discuss two popular concepts:
  - Centroid based: K-Means
  - Connectivity based: Hierarchical clustering

K-Means

- Assigns each observation to one of K clusters.
- Iterative procedure repeated until cluster assignments no longer change:
  1. Assign each observation to the cluster with the closest mean
  2. Re-calculate the cluster means taking into account the changed assignments
- The number of clusters K is a priori unclear (more later)

A first example



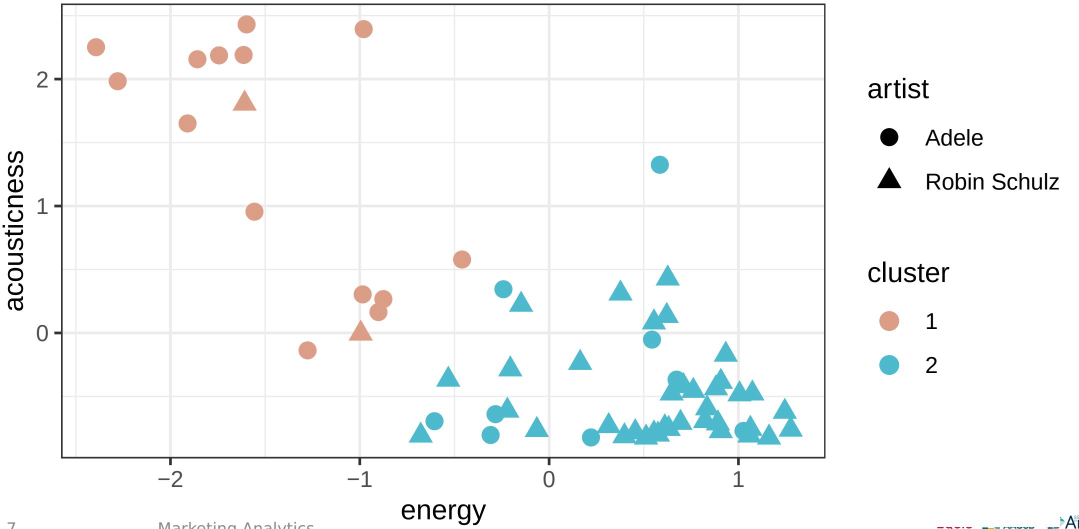
A first example

- Example: two artists and two variables, $K = 2$.
- Important: scale all variables before clustering to ensure equal contribution to distance

```
tracks_scale <- data.frame(
  artist = example_tracks$artist,
  energy = scale(example_tracks$energy),
  acousticness = scale(example_tracks$acousticness))
kmeans_clusters <- kmeans(tracks_scale[-1], 2)
kmeans_clusters$centers
```

```
     energy acousticness
1 -1.439466    1.3234653
2  0.500684   -0.4603358
```

A first example



Choosing the number of clusters

- If we extend the sample to the more interesting case of multiple artists the optimal K is unclear
- We can calculate varying indices for the optimal K and use the one that is optimal for the most indices
- In this case 3 is the best number of clusters according to the majority rule, chosen by 13 indices

```
library(NbClust)
opt_K <- NbClust(famous_tracks_scale,
                 method = "kmeans", max.nc = 10)
```

```
table(opt_K$Best.nc["Number_clusters", ])
```

```
 0  2  3  4  8 10
 2  5 13  1  1  4
```

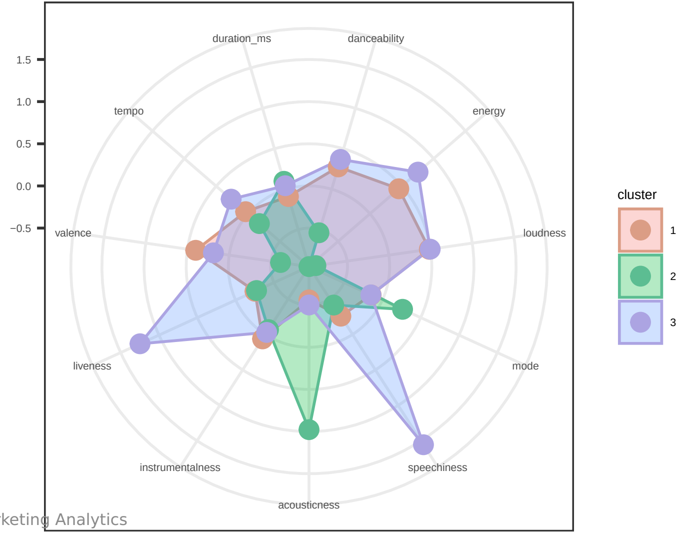
Extended example

```
kmeans_tracks <- kmeans(famous_tracks_scale, 3)
kmeans_tracks$centers
```

```
  danceability     energy   loudness       mode speechiness
1    0.2758301  0.4526214  0.4853302 -0.1461378  -0.2576401
2   -0.5385548 -0.9566495 -0.8742383  0.2632910  -0.4147683
3    0.3678342  0.7543900  0.4954862 -0.1492974   1.5546155
  acousticness instrumentalness   liveness    valence
1   -0.5618965       0.06266324 -0.2524251  0.4012080
2    0.9772843      -0.06816719 -0.2728148 -0.6158085
3   -0.5015270      -0.02849344  1.2469257  0.1885188
        tempo duration_ms
1  0.03789976 -0.09047459
2 -0.17761023  0.09754255
3  0.26482862  0.04295692
```

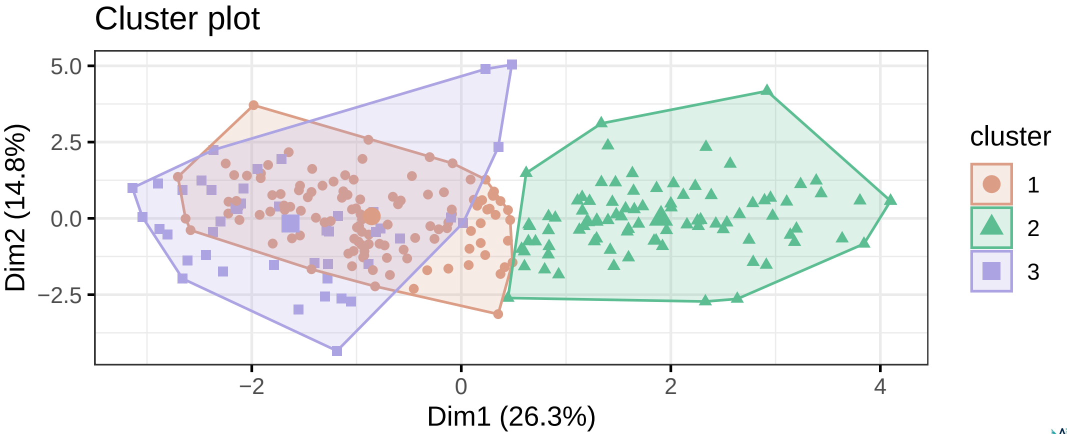
Extended example

- Characterize clusters



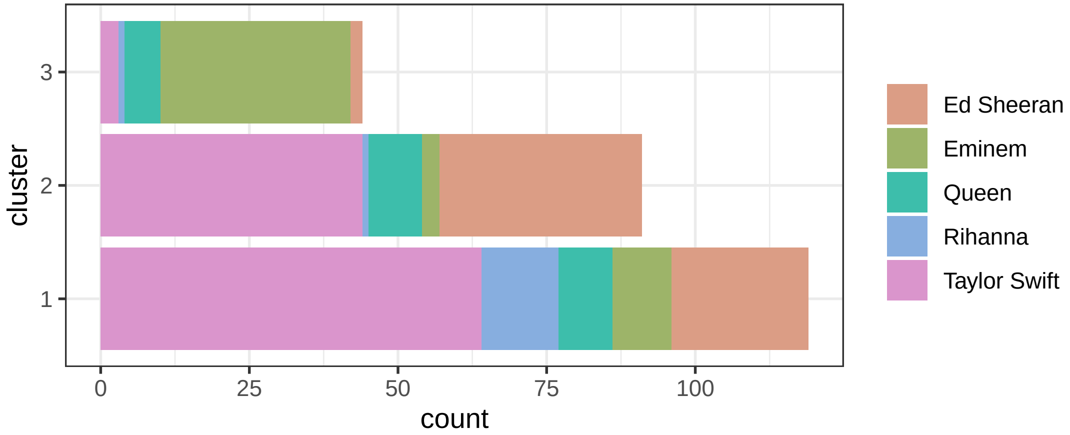
2D-Visualization

- Reduce dimensions with PCA and plot 2 components
- Gives a *partial* picture



Extended example

- Characterize artists



Making a recommendation

- Given a liked song, recommend songs in the same cluster

```
famous_tracks[famous_tracks$trackName=="The Archer","cluster"]
```

```
[1] 2
Levels: 1 2 3
```

trackName	artistName	cluster
Bohemian Rhapsody - Remastered 2011	Queen	2
Photograph	Ed Sheeran	2
The A Team	Ed Sheeran	2
I See Fire - From “The Hobbit - The Desolation Of Smaug”	Ed Sheeran	2
Give Me Love	Ed Sheeran	2
Tenerife Sea	Ed Sheeran	2

Hierarchical clustering

- Idea: similar observations can be “merged” to one cluster
- Starts out merging pairs of the most similar or closest observations
- Iteratively merges the most similar clusters until there is only one cluster left
- Does not require a priori setting of the number of clusters
- Number of clusters is determined post-hoc by “cutting-off” at some iteration

Visualization

Example

- Calculate distances between observations (default: Euclidean) using `dist`
- Use distances in `hclust` to perform a hierarchical cluster analysis

```
hclust_tracks <- hclust(dist(pf_ri_scale))
hclust_tracks
```

```
Call:
hclust(d = dist(pf_ri_scale))

Cluster method   : complete
Distance         : euclidean
Number of objects: 34
```

Characterize clusters

- Decide on cut-off based on dendrogram. Specify the desired number of clusters using `cutree`.
- Calculate summary statistics for cluster

```
hclusters <- cutree(hclust_tracks,4)
pf_ri_hier <- data.frame(pf_ri_scale)
pf_ri_hier$cluster <- as.factor(hclusters)
aggregate(. ~ cluster, pf_ri_hier, mean)[,1:5]
```

```
  cluster danceability     energy   loudness       mode
1       1    0.6301558 -0.8423205  0.4931387 -1.1087884
2       2    0.6793570  0.7636001  0.6540518 -0.2407238
3       3   -0.6149044 -0.7835601 -0.7125465  0.4785297
4       4   -1.1381509  0.1890603 -0.1348845 -1.1087884
```