# Lab 4

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### Part 1 - Taste clustering and influence

In the first part of this lab, we will consider a (simulated) data set which contains information about a sample of (fictive) individuals' music tastes as well as a measure of their influence on others.

#### Task 1

Begin by importing the file "taste\_influence.csv". Report the number of rows and columns of the data set, and the genres contained in it. Create a scatter-plot of two combinations of genres of your choice. Based on this, do you get any indication that the data is clustered along musical tastes?

```
library(data.table)

library(scatterplot3d)

library(tibble)

library(kableExtra)

setwd("~/Github/ML-Labs/4")

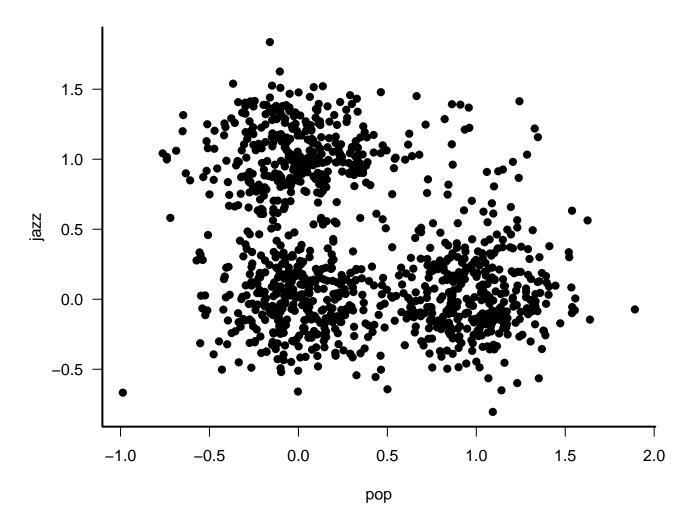
d <- fread("taste_influence.csv")

tribble(
   ~Name,   ~Value,
   "Rows",   nrow(d) |> as.character(),
```

```
"Columns", ncol(d) |> as.character(),
"Genre 1", names(d)[1],
"Genre 2", names(d)[2],
"Genre 3", names(d)[3]
) |> kable()
```

Name	Value
Rows	1075
Columns	4
Genre 1	jazz
Genre 2	pop
Genre 3	hiphop

# **Scatterplot**



There are defined clusters visible in the plot. The main observation is that individuals that like pop a lot do not seem to like jazz and the other way around.

### Task 2

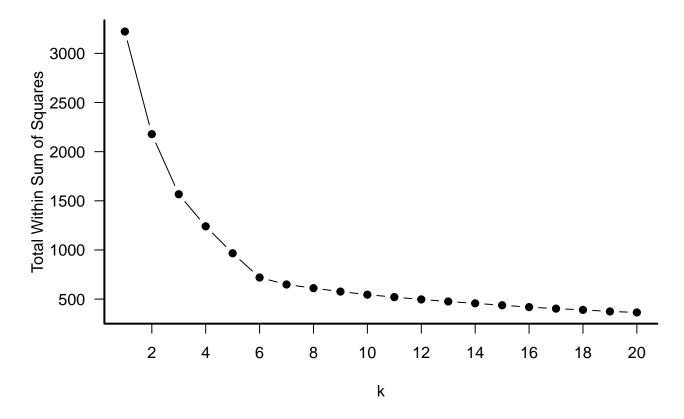
Now you shall do some clustering. To prepare the data, do the following: (i) store/copy the data to a new R object, and subset it so that it only contains the three "taste columns"—these are the columns you will cluster based upon, (ii) standardize this data table (hint: you can e.g., use scale() for this purpose), (iii) transform it into a matrix (hint: e.g., by using as.matrix()).

```
dc <- d[,-"influence"] |>
  scale() |>
  as.matrix()
```

#### Task 3

Having formatted the data according to #2, you shall now use the kmeans algorithm to cluster your data. Recall that a requisite for running kmeans is that the parameter k has been specified. In practice—and as is the case here—we often do not know the appropriate number of clusters a priori. Therefore, you shall implement a loop that, at every iteration, runs kmeans with a different number of clusters, and extracts the total within cluster sum of squares (hint 1: which can be extracted using \$tot.withinss | hint 2: set the argument nstart=100 to ensure robustness of the local optima you find). Consider no. clusters ranging from 1 to 20, with an interval of 1. Plot k against tot.withinss. Which number of clusters do you find appropriate? Motivate.

# Total "Within Sum of Squares" per k



At k=6 the plot seems to have an elbow, indicating decreasing gain in the total within sum of squares.

#### Task 4

For the specification (of k) that you decided on in #3, extract the centroids and interpret each cluster in terms of what distinguishes it from the rest. Do the clusters seem meaningfully distinct?

# **Center of K-Means Cluster**

