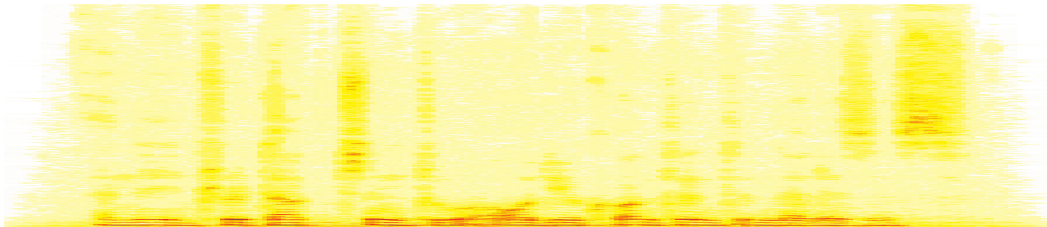


# Introduction to Audio Content Analysis

## Module 8.2: Music Similarity

alexander lerch



# introduction

## overview

### corresponding textbook section

Chapter 8: Musical Genre, Similarity, and Mood (pp. 156–157)

#### ● lecture content

- music similarity and its relation to musical genre
- clustering and visualization of feature space

#### ● learning objectives

- describe potential issues with algorithms for measuring music similarity
- implement a simple k-Means algorithm



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# music similarity

## introduction

- genre classification is just a grouping by specific interpretation of similarity
  - similar set of features
  - ambiguous 'ground truth'
  - unclear value/impact of low level and high level features
- **differences** to genre classification
  - *similarity*: distance measure instead of categorizing into classes

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# audio similarity

## introduction

- **perception** of music similarity
    - multi-dimensional (melodic, rhythmic, sound quality, ...)
    - user dependent
    - associative, may also depend on editorial data
    - may be context dependent
  - genres are **clusters of musical similarity**
- ⇒ genre classification is a *special case* of audio similarity measures
- instead of assigning (genre) labels, the similarity/distance between (pairs) of files is measured

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## K-Means clustering example

- simple k-means example
  - **goal:** minimize intra-cluster variance
  - **distance:** Euclidean
  - **procedure:**
    - 1 *initialization:*  
randomly select  $K$  points in the feature space as initialization.
    - 2 *assignment:*  
assign each observation to the cluster with the mean/centroid of the closest cluster.
    - 3 *update:*  
compute mean/centroid for each cluster.
    - 4 *iteration:*  
go to step 2 until the clusters converge.

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- init randomly
- iteration
  - assign data points to closest centroid
  - update centroids
- terminate when convergence



matlab source: [matlab/displayKMeans.m](https://github.com/GeorgiaTech-Center-for-Music-Technology/matlab/blob/master/displayKMeans.m)

# audio similarity

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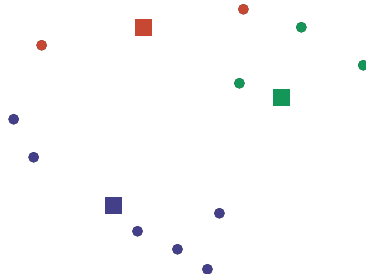
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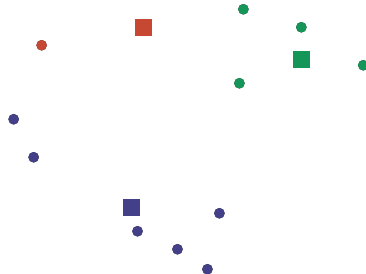
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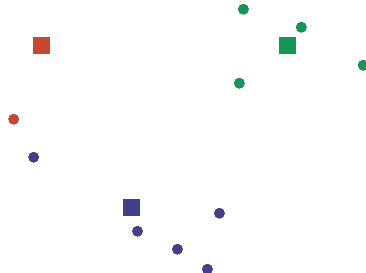




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## visualization in a 2D space

- **problem**
  - feature space is high-dimensional
  - cannot be visualized
- find **mapping** to 2D “preserving” (high-dimensional) distance metrics  
example:
  - Self-Organizing Maps

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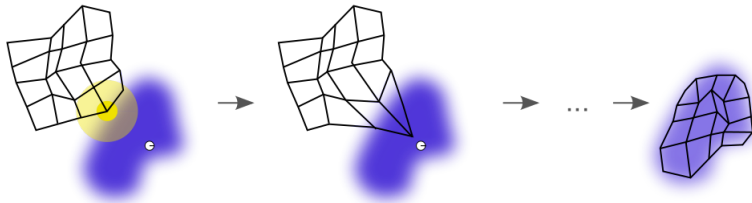
# audio similarity

## visualization example: SOM 1/2

- 1 create a map with 'neurons'
- 2 train
  - for each training sample find BMU (best matching unit)
  - adapt BMU and neighbors toward training sample

$$W_v(t+1) = W_v(t) + \theta(u, v, t)\alpha(t)(D(t) - W_v(t))$$

- $\theta(u, v, t)$ : depends on neighborhood distance from BMU
- $\alpha(t)$ : learning restraint
- $D(t)$  training sample



audio similarity  
SOM 2/2



from<sup>1</sup>

<sup>1</sup>E. Pampalk, "Islands of Music," Diploma Thesis, Technische Universität Wien, 2001.

# summary

## lecture content

- **music similarity**
  - even less clearly defined than music genre
- **processing steps**
  - 1 extract features
  - 2 define some distance metric in feature space
- **clustering algorithms**
  - work to a certain degree with traditional features

