# Introduction to Audio Content Analysis

Module 4.1: Classification

alexander lerch



# corresponding textbook section

#### Section 4.1

#### **■** lecture content

- intuitive intro to machine learning
- classifier examples

# learning objectives

- describe the basic principles of data-driven machine learning approaches
- implement a kNN classifier in Python



Module 4.1: Classification 1 /

## corresponding textbook section

#### Section 4.1

#### lecture content

- intuitive intro to machine learning
- classifier examples

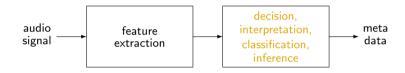
# **■** learning objectives

- describe the basic principles of data-driven machine learning approaches
- implement a kNN classifier in Python



Module 4.1: Classification 1 /

# remember the flow chart of a general ACA system:

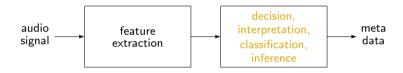


- classification:
  - assign class labels to data
- regression:
  - estimate numerical labels for data
- *clustering*:
  - find grouping patterns in data

Module 4.1: Classification 2 / 8

# classification introduction

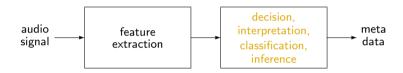
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Module 4.1: Classification 2 / 8

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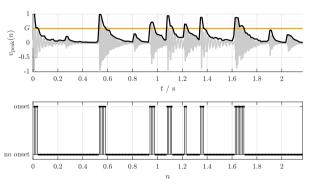


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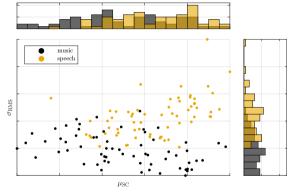
Module 4.1: Classification 2 / 8

# hypothetical system:

- one feature (envelope)
- predefined threshold
  - higher than threshold  $\Rightarrow$  class 1 (onset)
  - lower than threshold  $\Rightarrow$  class 0 (no onset)

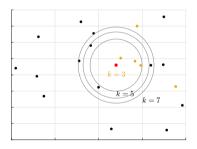


- derive classification parameters from data, e.g.,
- ⇒ learn common feature distributions per class
- $\Rightarrow$  learn separation metrics per class

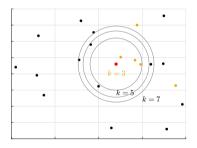


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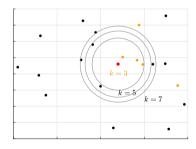
- **training**: extract reference vectors from training set (keep class labels)
- **classifier model**: all training vectors



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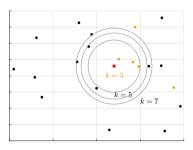


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# classifier examples k-Nearest Neighbor (kNN)

- training: extract reference vectors from training set (keep class labels)
- **classification**: extract test vector and set class to majority of *k* nearest reference vectors
- classifier model: all training vectors

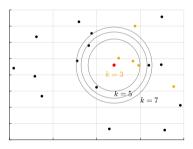


$$k = 3 \Rightarrow \text{gold majority}$$

matlab source: plotKnn.m

# classifier examples k-Nearest Neighbor (kNN)

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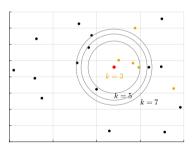


$$k = 5 \Rightarrow \text{black majority}$$

matlab source: plotKnn.m

# classifier examples k-Nearest Neighbor (kNN)

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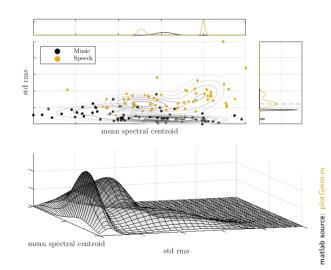
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$$k = 7 \Rightarrow \text{black majority}$$

matlab source: plotKnn.m

model each class distribution as superposition of Gaussian distributions

- classification: compute output of each Gaussian and select class with highest probability
- classifier data: per class per Gaussian: μ and covariance, mixture weight

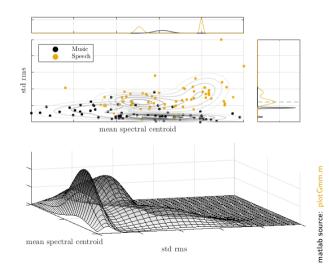


model each class distribution as superposition of Gaussian distributions

#### classification:

compute output of each
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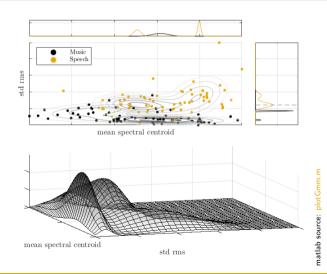
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### ■ classification:

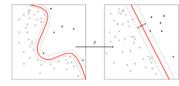
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# classifier data:

per class per Gaussian:  $\mu$  and covariance, mixture weight



map features to high dimensional space



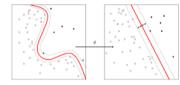
- find separating hyperplane through maximum distance of support vectors (data points)
- classification: apply feature transform and proceed with 'linear' classification
- classifier data: support vectors, kernel, kernel parameters

# classifier examples Support Vector Machine (SVM)

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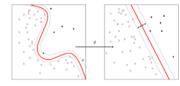
#### ■ training:

map features to high dimensional space



- find separating hyperplane through maximum distance of support vectors (data points)
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• map features to high dimensional space



- find separating hyperplane through maximum distance of support vectors (data points)
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# summary lecture content

## data-driven approach

- 'general' system learns parameters/behavior from data
- human interaction through
  - parametrization and procedures
  - ► data selection

# many classifiers with different levels of complexity

- 1 kNN
- 2 GMM
- 3 SVM
- 4 RandomForest
- 5 DNN
- 6 . . .

