DAY 5

Intelligent Audio Systems:
A review of the foundations and applications of semantic audio analysis and music information retrieval

CCRMA
Center for Computer Research in Music and Acoustics

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Details

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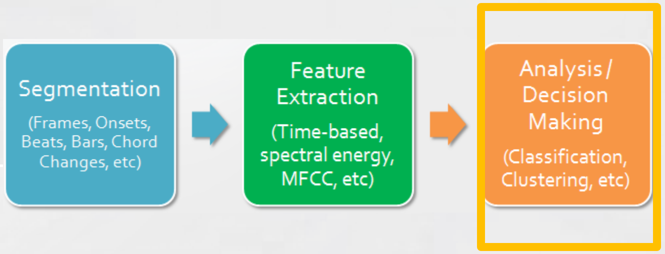
CCRMA Tour (?)



ANALYSIS AND DECISION MAKING: GMMS

Mixture Models (GMM)

- K-means = hard clusters.
- GMM = soft clusters.

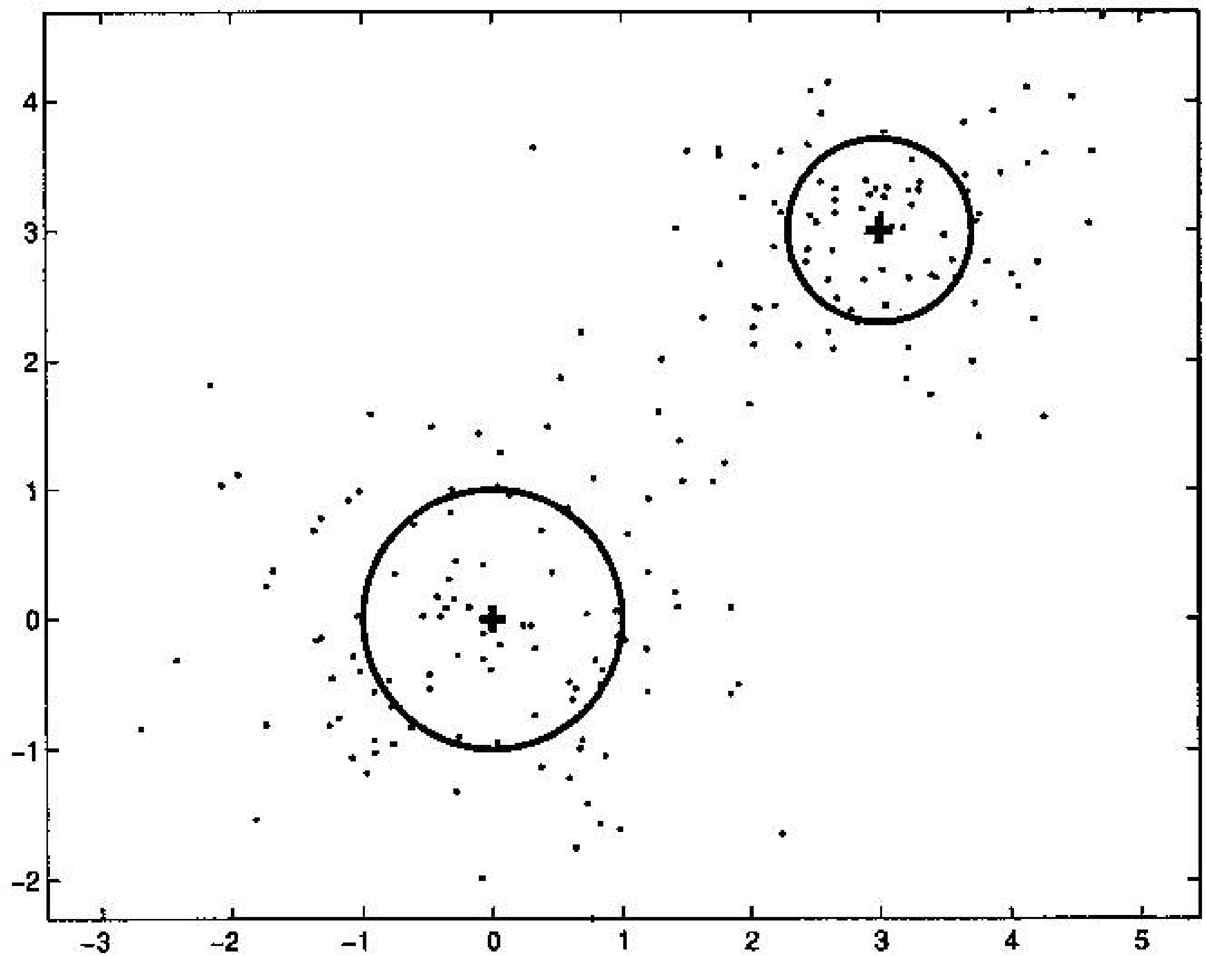


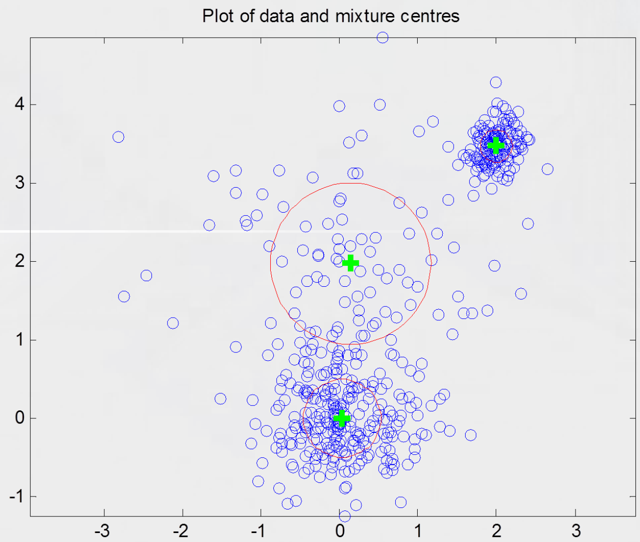
Fig. 3.1. Spherical covariance mixture model. Sampled data (*dots*), **centres** (*crosses*) and one standard deviation error bars (*lines*).

Mixture Models (GMM)

- GMM is good because:
  1. Can approximate any pdf with enough components
  2. EM makes it easy to find components parameters
     - EM - the means and variances adapt to fit the data as well as possible
  3. Compresses data considerably

- Can make softer decisions (decide further downstream given additional information)

GMM Parameters



Input

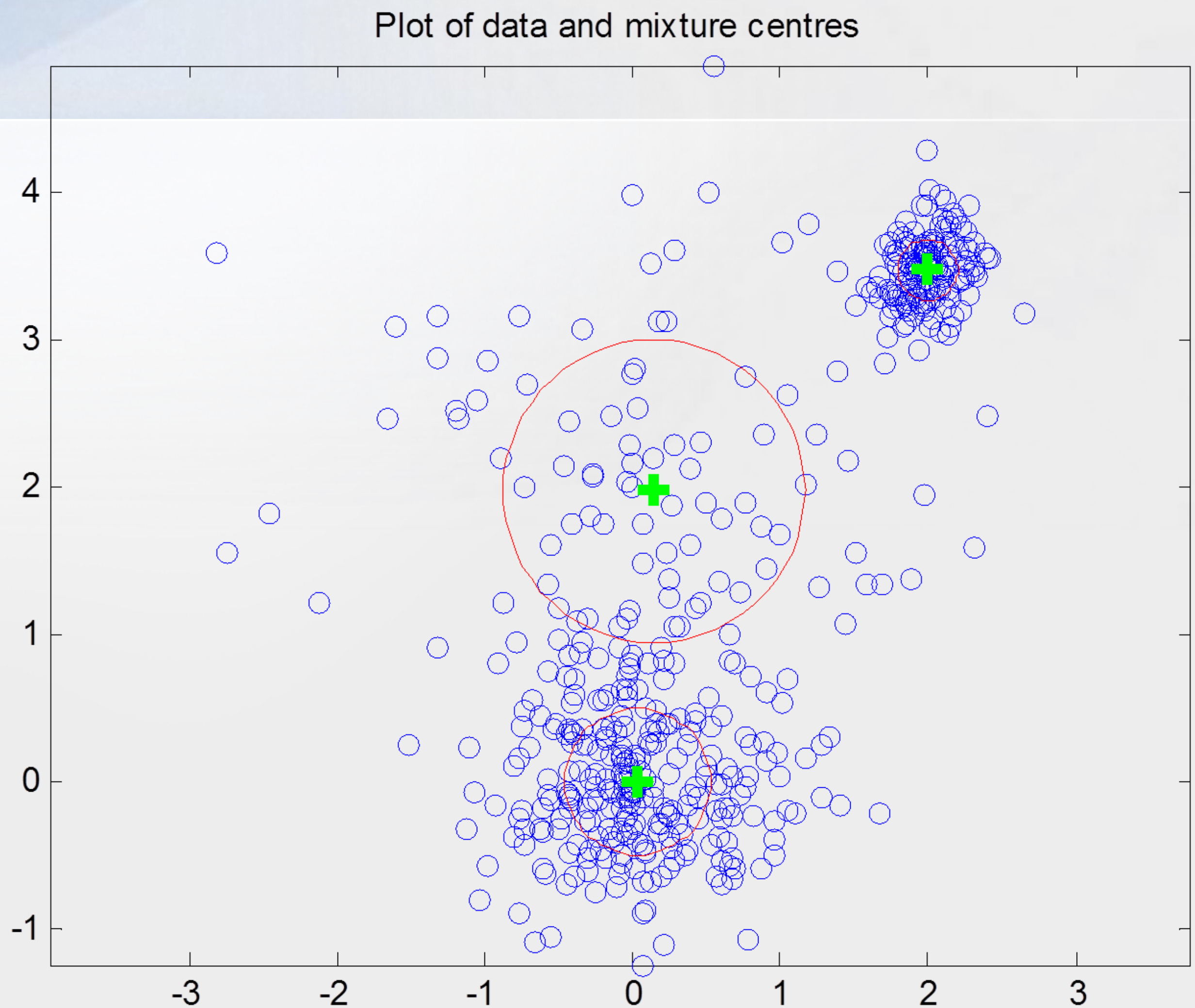
- Number of components (Gaussians)
  - e.g., 3
- Mixture coefficients (sum = 1)
  - e.g., [0.5 0.2 0.3]
  - "Priors" or "Prior probabilities"
  - Priors are "the ***original*** probability that each point came from a given mixture."
  - "A prior is often the purely subjective assessment of an experienced expert."
- Initialized centers, means, variances. (optional)

Output

- Component centers/means, variances, and mixture coeff.
- Posterior probabilities
  - "Posterior probabilities are the responsibilities which the Gaussian components have for each of the data points."

Query

- Obtain similarity via Likelihood


Plot of data and mixture centres
4
3
2
1
0
-1
-3
-2
-1
0
1
2
3

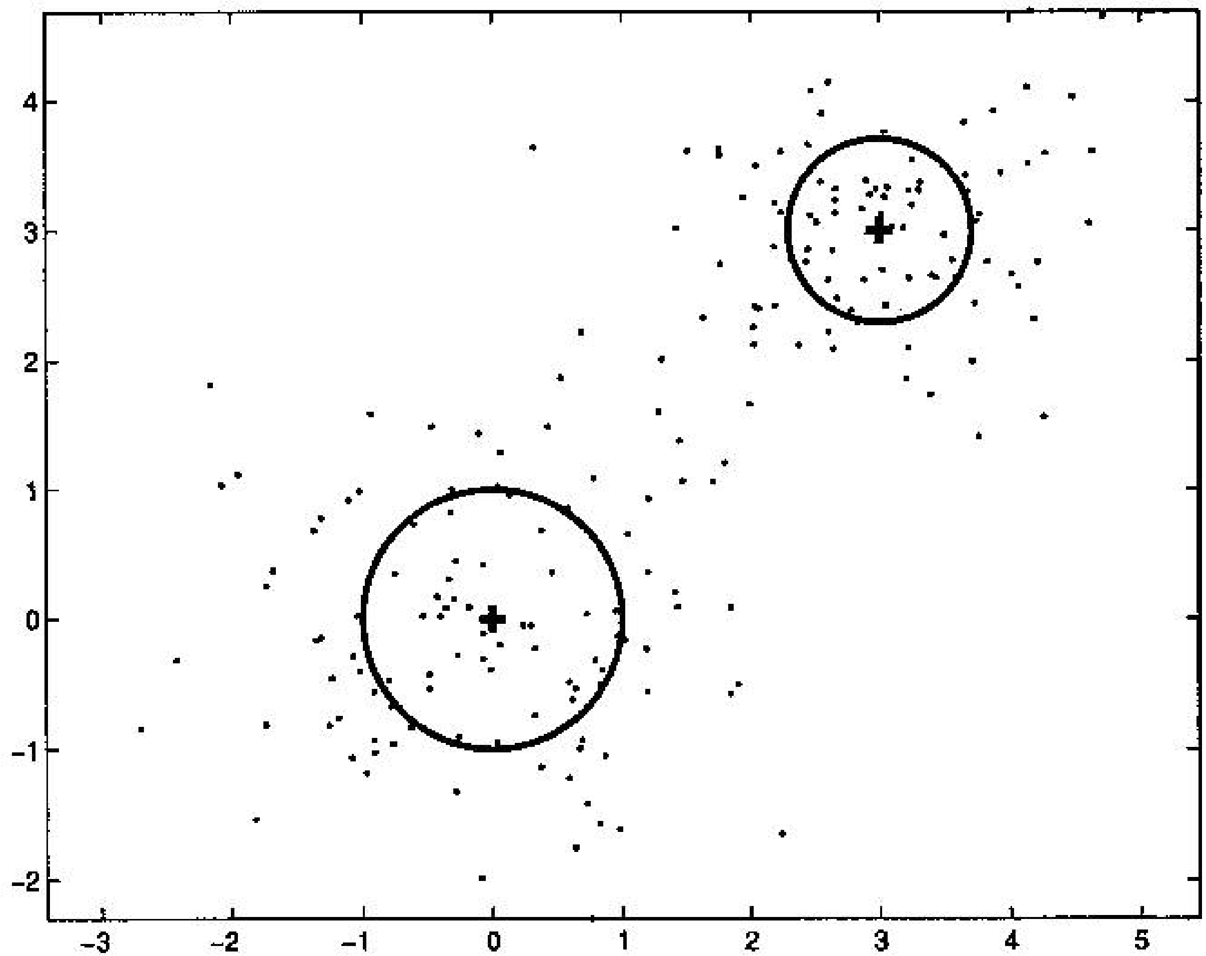
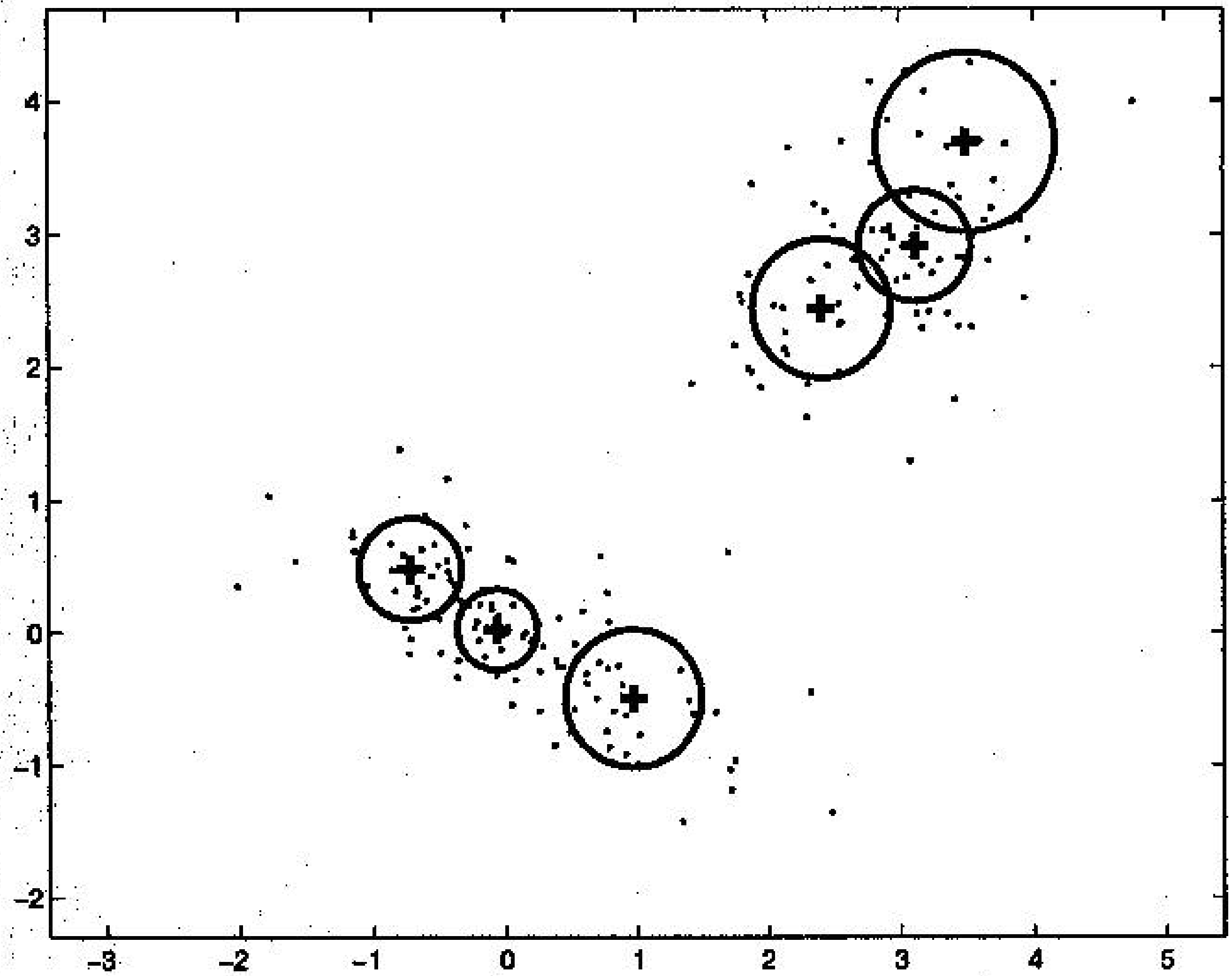


Fig. 3.1. Spherical covariance mixture model. Sampled data (*dots*), **centres** (*crosses*) and one standard deviation error bars (*lines*).



4. Spherical covariance mixture model with six components fitted to the mpled from the full covariance two-component model in Fig. 3.3. Sampled ots), centres (*crosses*) and one standard deviation error bars (*lines*).

- From Netlab (p82-83)

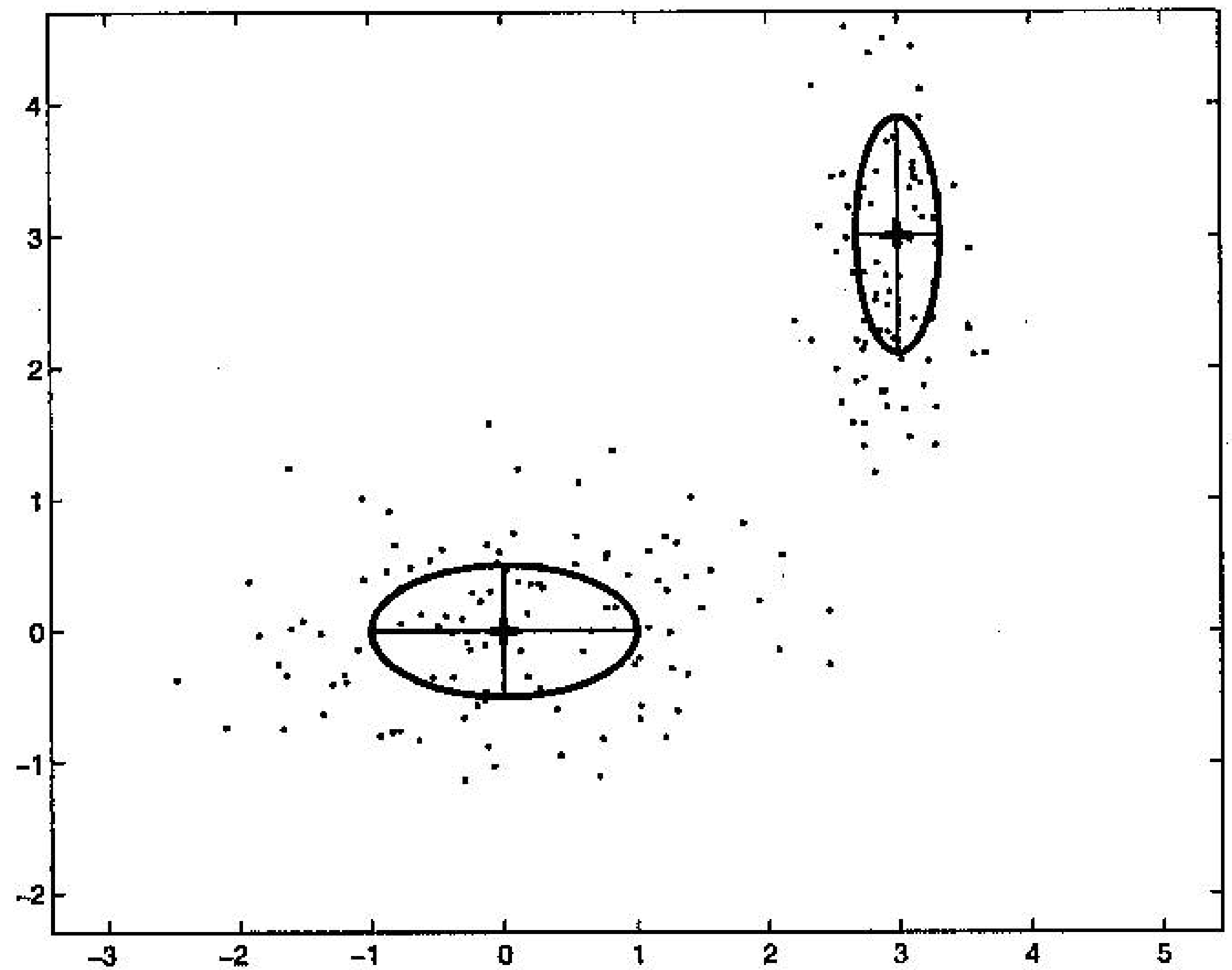
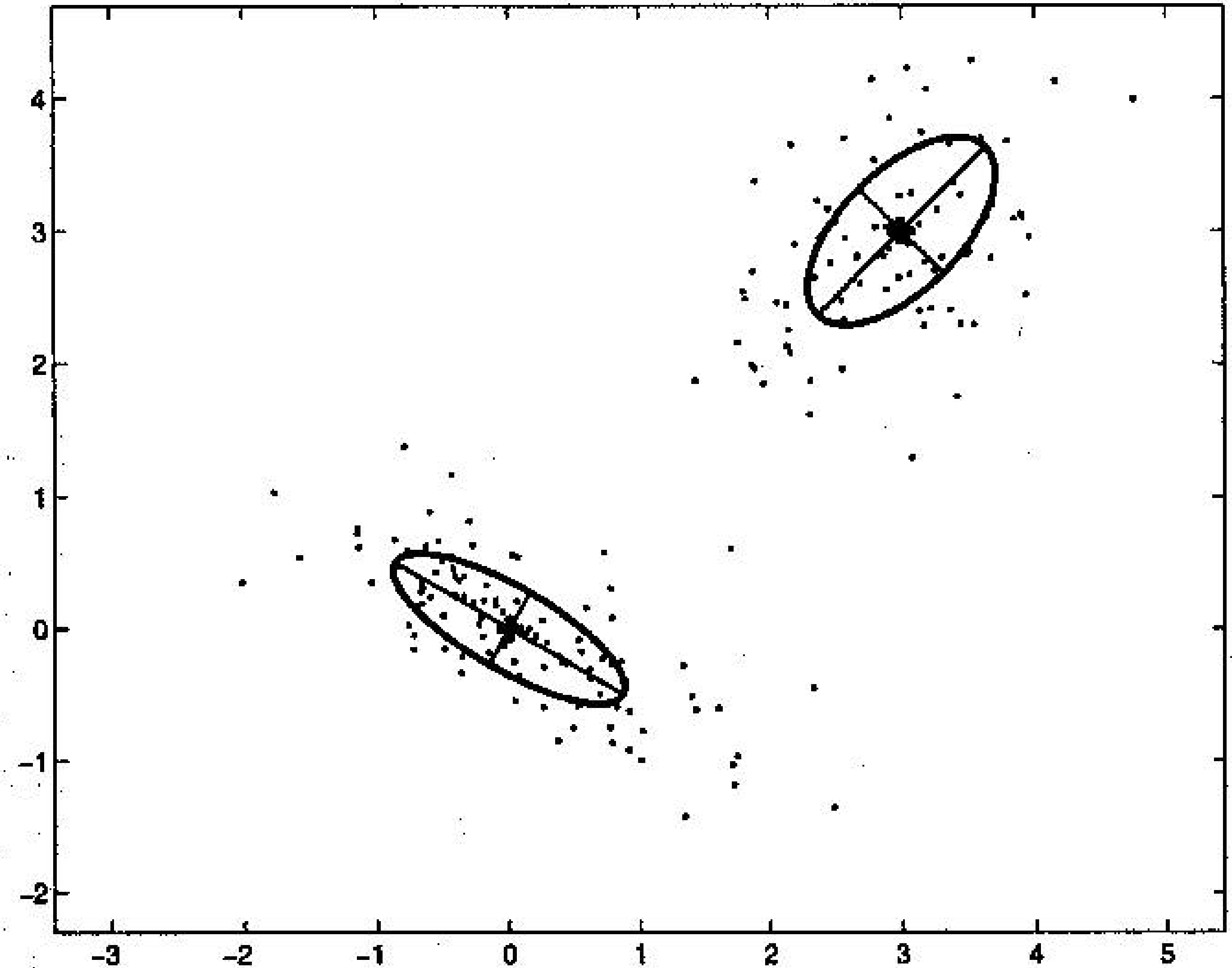


Fig. 3.2. Diagonal covariance mixture model. Sampled data (*dots*), centres (*crosses*), covariance axes (*thin lines*) and one standard deviation error bars (*thick lines*).



3. Full covariance mixture model. Sampled data (*dots*), centres (*crosses*), nce axes (*thin lines*) and one standard deviation error bars (*thick lines*).

GMM: Likelihood

1. Evaluate the probability of that mixture modeling your point.

```
likelihoodgm1 = gmmprob(gm1,testing_features)
likelihoodgm2 = gmmprob(gm2,testing_features);
loglikelihood  = log(likelihoodKick ./likelihoodSnare )
```

- Log-function is “order-preserving” – maximizing a function vs. maximizing its log gives same results

Minimization Problems

>Demgmm1

- EM is gradient-based – it does not find the global maximum in the general case, unless properly initialized in the general region of interest.

- Error wants to be –inf, which occurs when Gaussian is fit for each data point. (mean = data point and variance = 0)

- “There are often a large number of local minima which correspond to poor models. Solution is to build models from many different initialization points and take the best model.”

GMM

- “Pooled covariance" - using a single covariance to describe all clusters (saves on parameter computation)

EXAMPLE OF GMMS: GENRE CLASSIFICATION

Genre

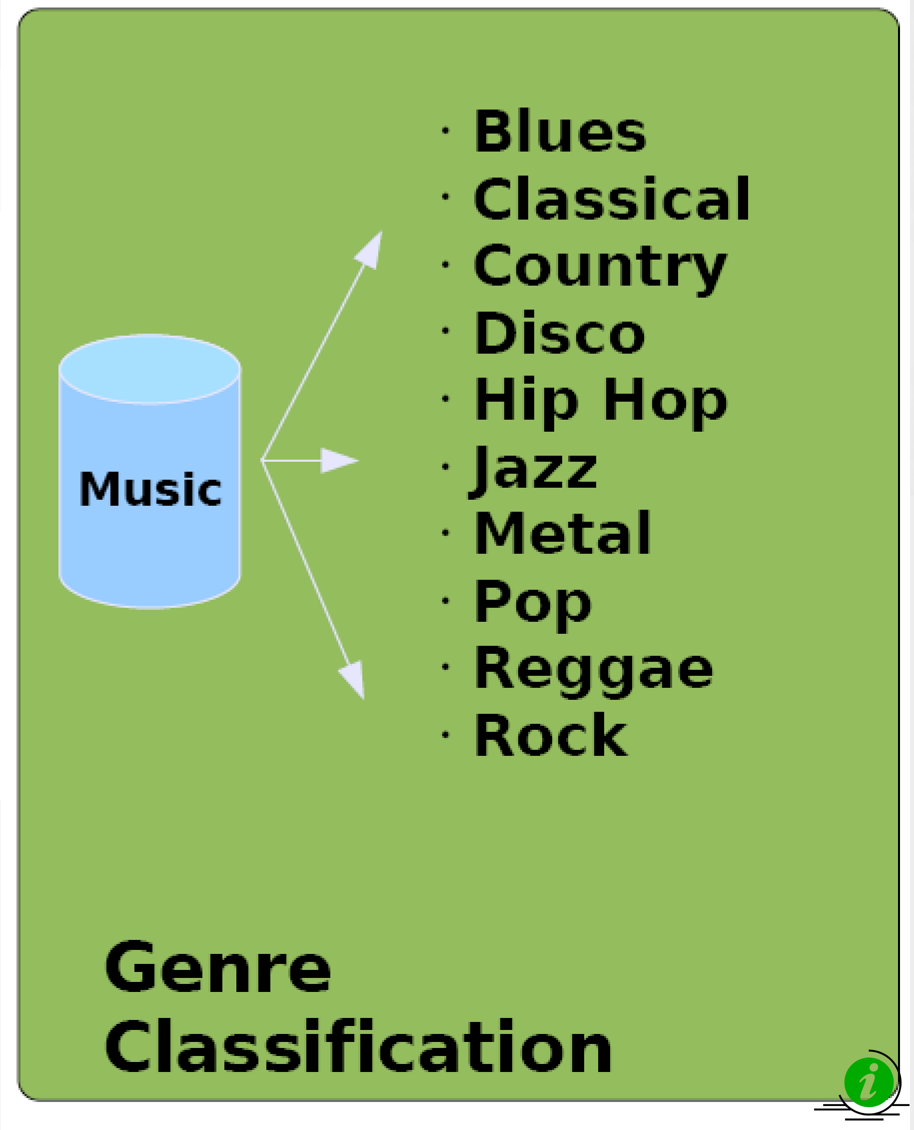
“Because feature vectors are computed from short segments of audio, an entire song induces a cloud of points in feature space.”

“The cloud can be thought of as samples from a distribution that characterizes the song, and we can model that distribution using statistical techniques. Extending this idea, we can conceive of a distribution in feature space that characterizes the entire repertoire of each artist.”

A. Berenzweig, B. Logan, D. Ellis, and B. Whitman. A large-scale evalutation of acoustic and subjective music similarity measures. In Proceedings of 4th International Symposium on Music Information Retrieval, Baltimore, Maryland, 2003.

- **Genre Classification**:
  - Manual : (Perrot/Gjerdigen) 72%
  - Automated (2002) (Tzanetakis) 60%
  - Automated (2005) (Bergstra/Casagrande/Eck) 82%
  - Automated (2007) 76%

From ISMIR 2007 Music Recommender Tutorial (Lamere & Celma)



How?

- Version 1 - One feature vector per song
  - High-level features extracted from data
    - Timbral (MFCCs, etc), Rhythmic content (beat histogram, autocor, tempos), Pitch info
    - Sampling of the frames in the song
  - Statistics of features extracted from a piece (includes means, weights, etc)
  - Representative of MFCC spectral shape
  - Could further use “Anchor space” where classifiers are training to represent musically meaningful classifiers. (Euclidean distance between anchor space)
- Version 2 - Cloud of points
  - Extract audio every *N* frames
  - K-Means or GMM representing a “cloud of points” for song
    - Clusters: mean, covariance and weight of each cluster = signature for song/artist/genre

Training and test data

- An overfit model matches every training example (Now it's "overtrained.")
- Training Error AKA "Class Loss"
- Generalization
  - The goal is to classify new, unseen data.
  - The goal is NOT to fit the training data perfectly.
- An overfit model will not be well-generalized, and ***will*** make errors.
- Rule of thumb: favor simple solutions and more "general" solutions.

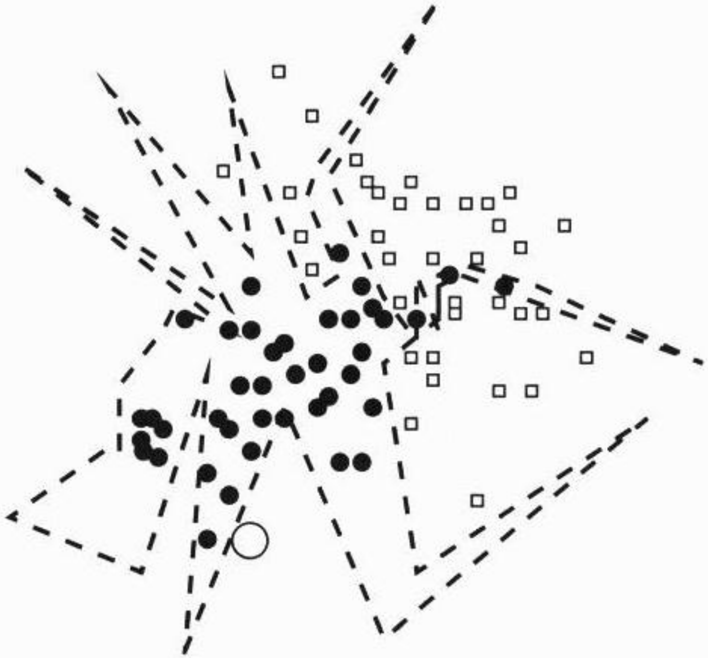


Fig. 2.13. Supervised classification into two classes with 2-dimensional data. In the training set (X, Y), data with label $\mathsf{y} = -1$ are represented with dots, whereas data with label $\mathsf{y} = 1$ are represented with squares. The dotted line is a classification function F such that $\mathsf{R}^{\mathrm{emp}}_{(\mathsf{X},\mathsf{Y})}[\mathsf{F}] = 0$. Though it achieves zero empirical risk, F is not a good classification function, as it makes an error for a new datum which is not in the training set (circle at the bottom, with the true label $\mathsf{y} = -1$).

Evaluation Measures

True+	correct	Classifier correctly predicted something in it's list of known positives
False-	absent	Classifier did not hit, for a known positive result.
False+	incorrect	Classifier said that something was positive when it's actually negative

Evaluation Measures

“Accuracy”

↑ is good

Precision - “Positive Predictive Value”

↓ = high F+ rate, the classifier is hitting all the time

↑ = low F+ rate, no extraneous hits

Recall – “Missed Hits”

↓ = high F- rate, the classifier is missing good hits

↑ = low F- rate, great at negative discrimination – always returns a negative when it should

F-Measure – a blend of precision and recall (harmonic-weighted mean)

↑

Evaluate Measures

P = T+ / (T+ + F+)	[0…1]
R = T+ / (T+ + F -)	[0…1]
F = 2*P*R/(P+R)	[0…1]

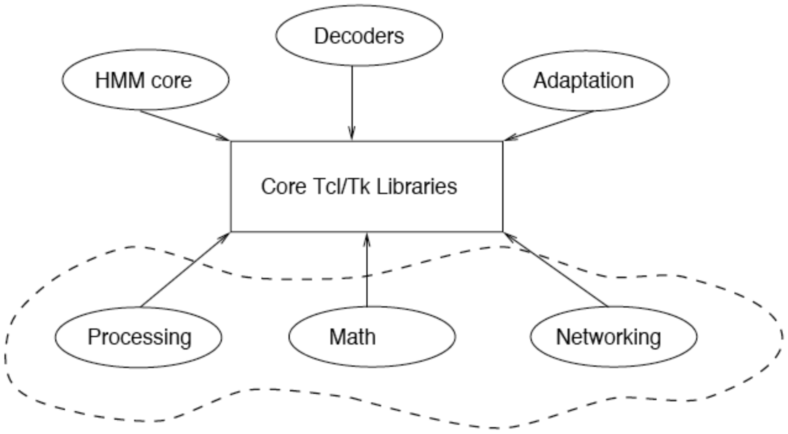
Training and test data

- Cross-validation
- Training, Validation, and Test set
  - Partition randomly to ensure that relative proportion of files in each category was preserved for each set
    - Weka or Netlab has sampling code
- Warnings:
  - Don't test (or optimize, at least) with training data
  - Don't train on test data (no!)

Data preparation

- Examine your data at every chance. (means, max, min, std, “NaN”, “Infs”)
- Try to visualize data when possible to see patterns and see if it makes. Incredible sanity check.
- Eliminate noisy data
- Data preparation
  - Cleaning
    - Open up and examine
    - Handle missing values
  - Relevance / Feature analysis
    - Remove irrelevant or redundant attributes
  - Data Transformation
    - Generalize or normalize data

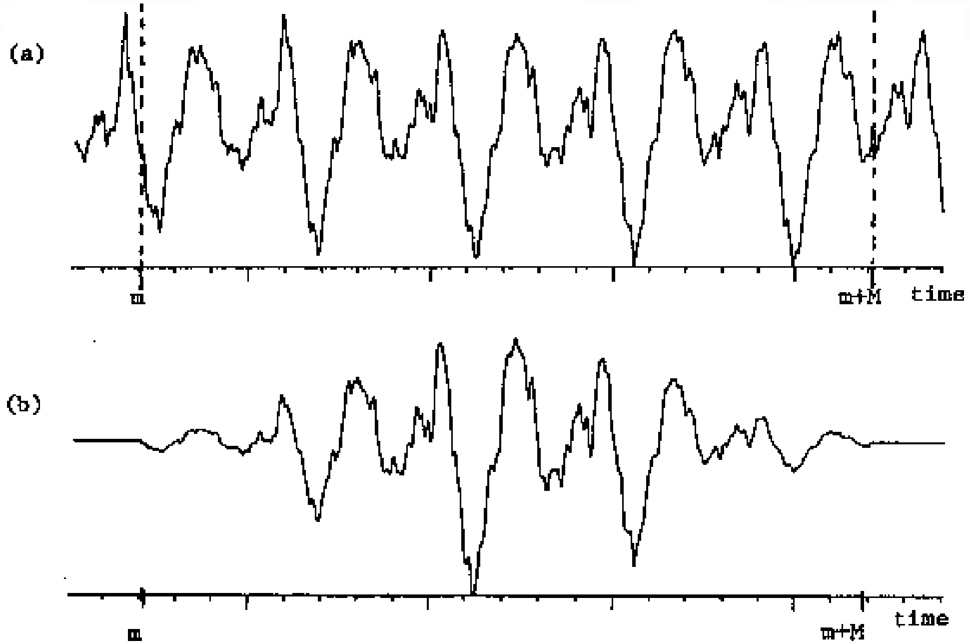
APIs for MIR Tools



- Marsyas: G. Tzanetakis (11), flexible tool set, scripting language, segmentation and classification
- LibOFA: Holm/Pope (00), simple FV for unique ID comparing to a large pre-analyzed database
- D2K/M2K: West/MIREX (06), Java-based GUI related to D2K, many apps.
- LibTSP: P. Kabal (00), C routines for DASP & IO
- CSL: STP/MAT (05), C++ class library for DASP, synthesis, control, spatialization and MIR

APIs - 2

- Libxtract
- Aubio
- SonicVisualizer plug-ins
- Loris
- SPEAR
- CSL
- LibTSP
- Mirtoolbox
- Echonest



Spectral Tools

- SPEAR
- Loris
- Marsyas
- Sonic visualizer

Code Examples

- Buffer, Window classes (see CSL)
- Analyzer class (Marsyas)
- aubio, libxtract
- IO libraries (libSndFile, PortAudio)
- DASP libraries (libTSP, etc.)

Using FFT APIs

- Simple FFT
  - See MAT240B (http://HeavenEverywhere.com/TheBigMATBook)
  - See F. R. Moore’s Elements of Computer Music
- FFTW
  - FFTW data types
  - FFTW plans
  - See CSL Spectral class