DAY 4

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

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These lecture notes contain hyperlinks to the CCRMA Wiki.

On these pages, you can find supplemental material for lectures - providing extra tutorials, support, references for further reading, or demonstration code snippets for those interested in a given topic .

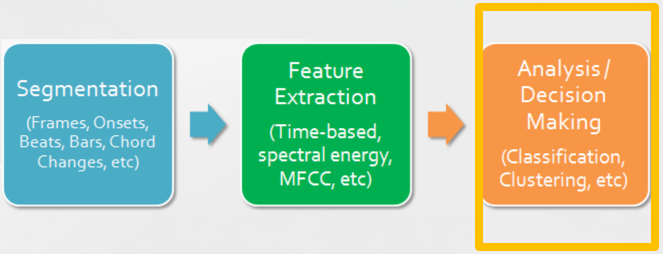
Click on the symbol on the lower-left corner of a slide to access additional resources.

WIKI REFERENCES…

Review from Day 3

- What does it mean to “wrap” a chromagram?
- Why did we use 36 bins per octave in yesterday’s lab?
- True or false – it’s important to carefully chose meaningful features
- What are the 3 major components of a MIR system?

- How did the lab go?



ANALYSIS AND DECISION MAKING: GMMS

Mixture Models (GMM)

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

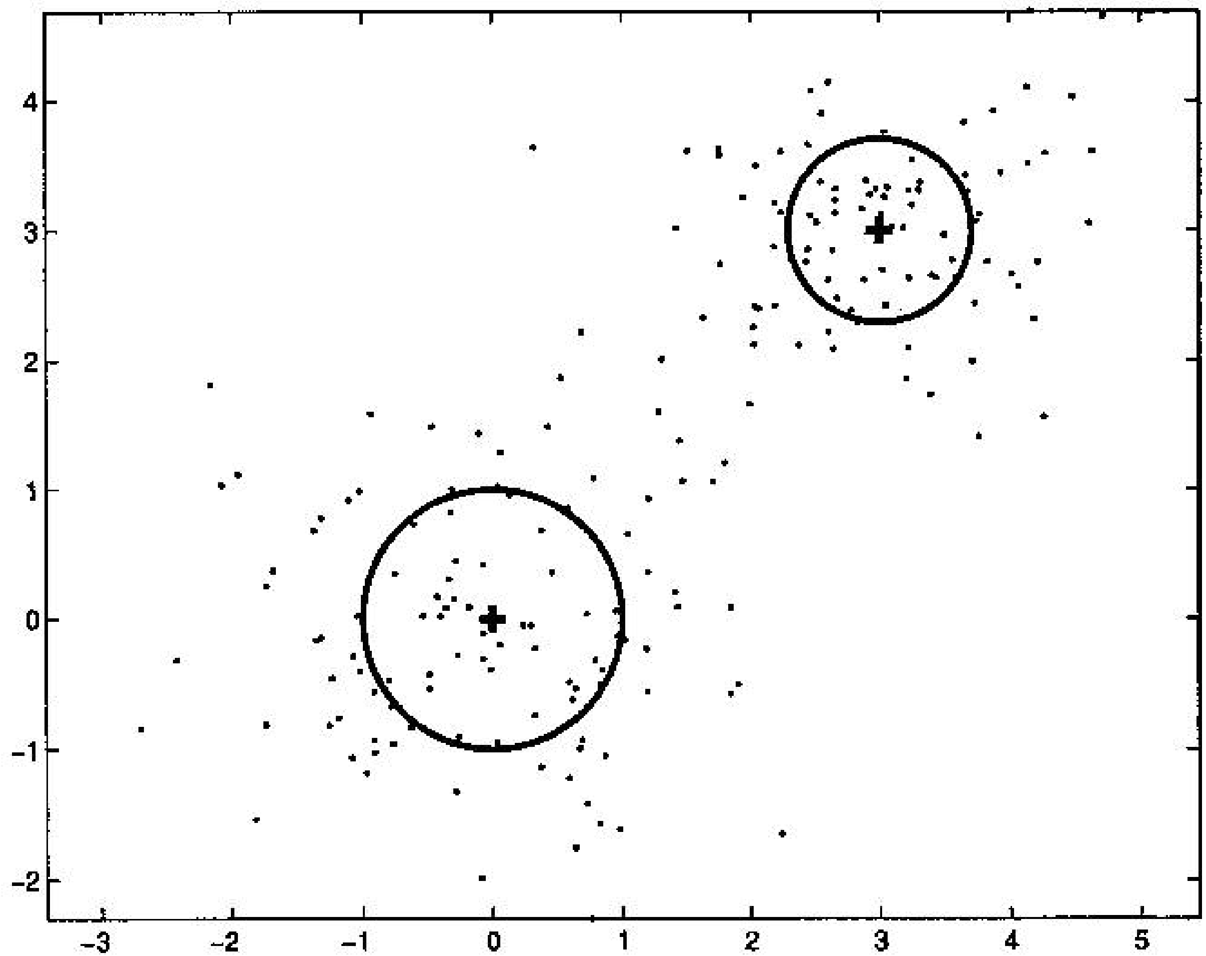


Fig. 3.1. Spherical covariance mixture model. Sampled data (*dots*), **centres** (*crosses*) and one standard deviation error bars (*lines*).

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)

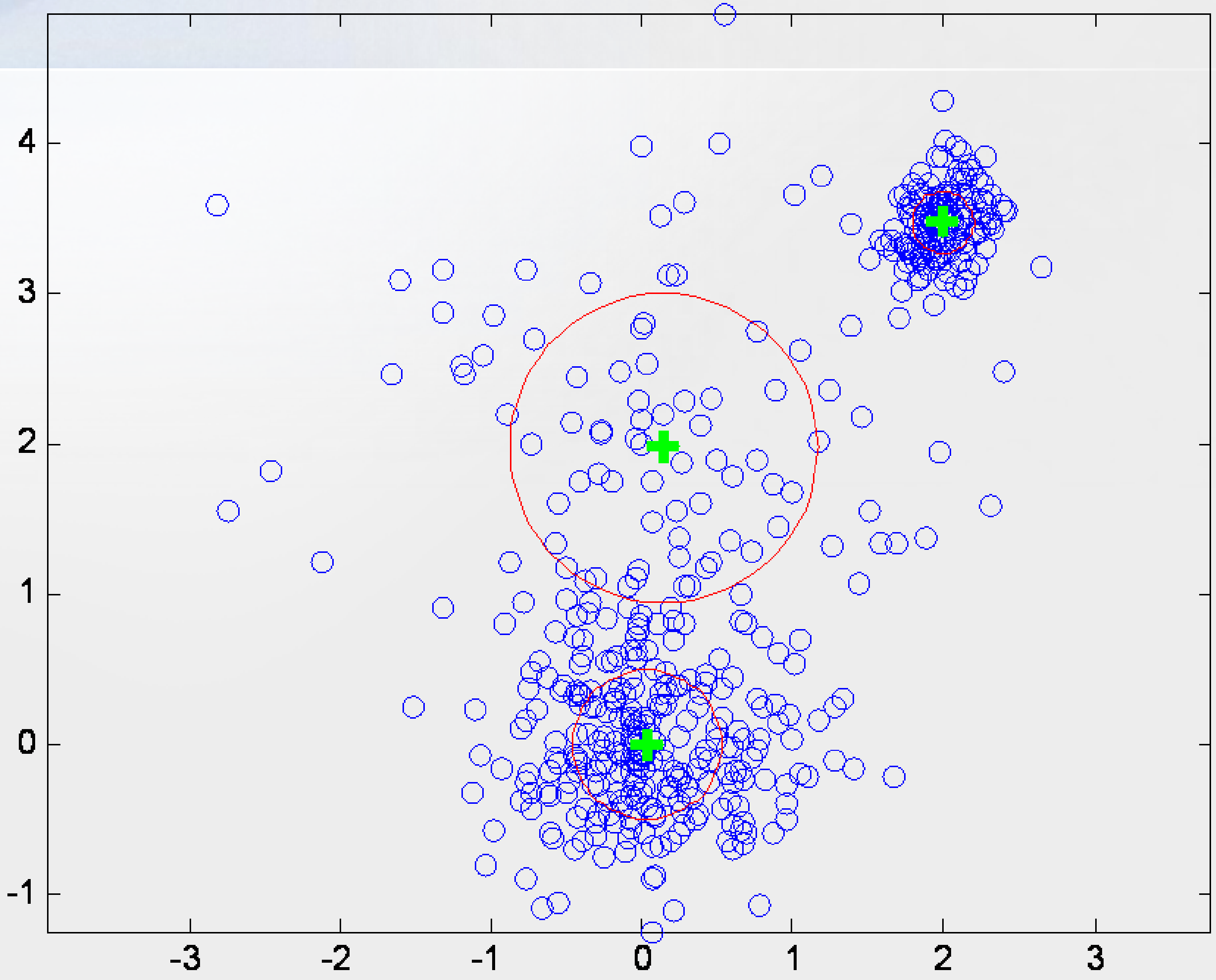
Output

- 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



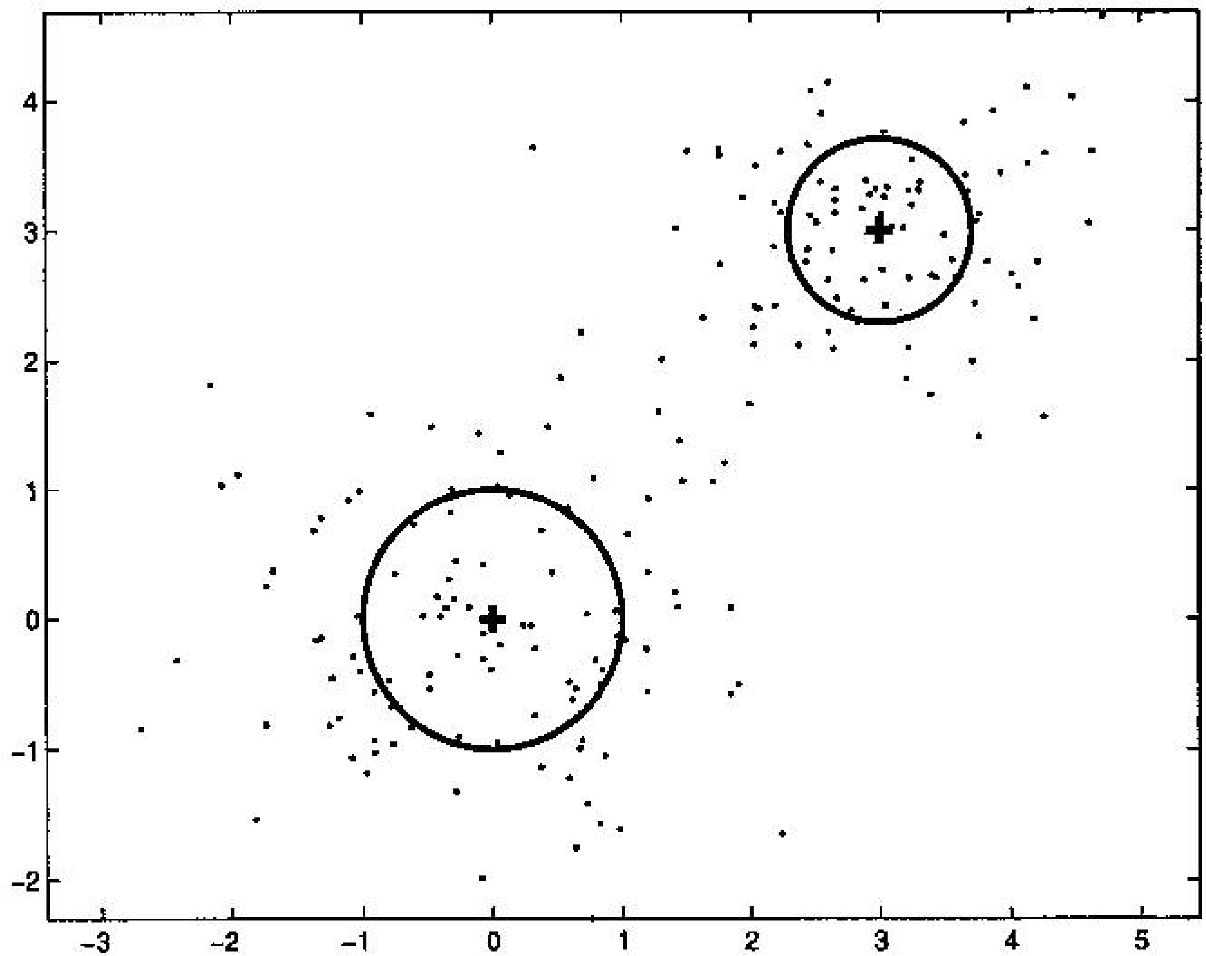
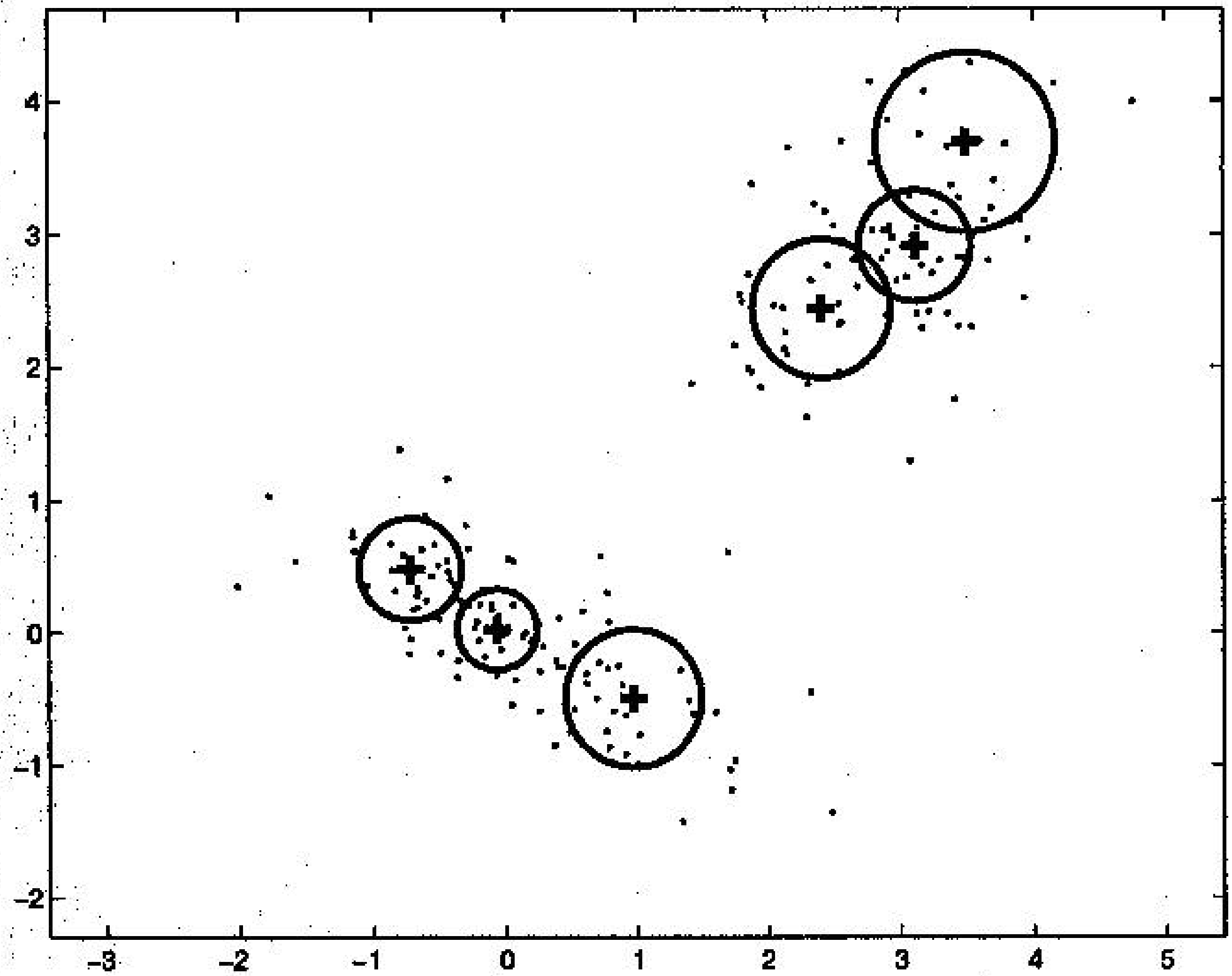


Fig. 3.1. Spherical covariance mixture model. Sampled data (*dots*), **centres** (*crosses*) and one standard deviation error bars (*lines*).



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)

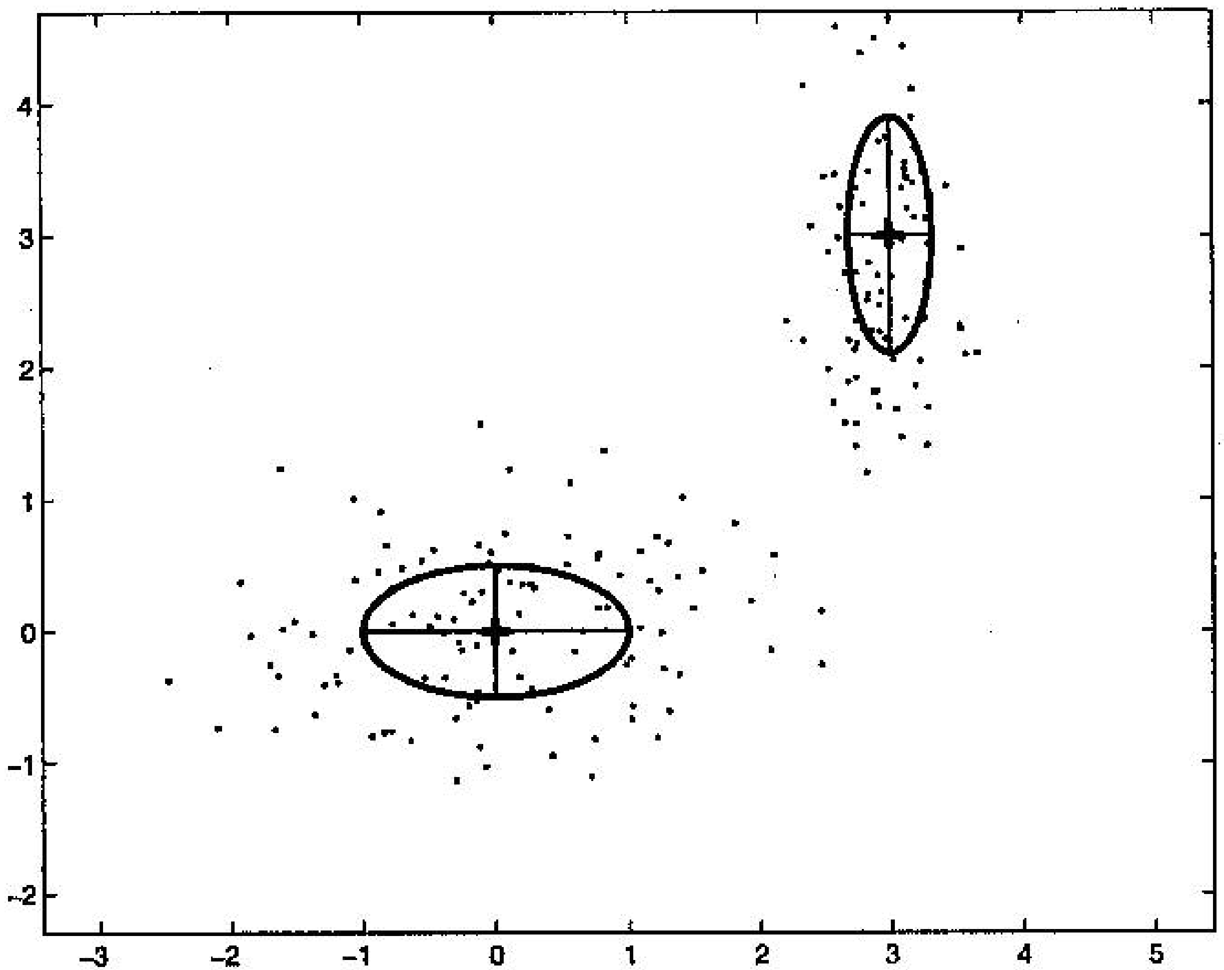
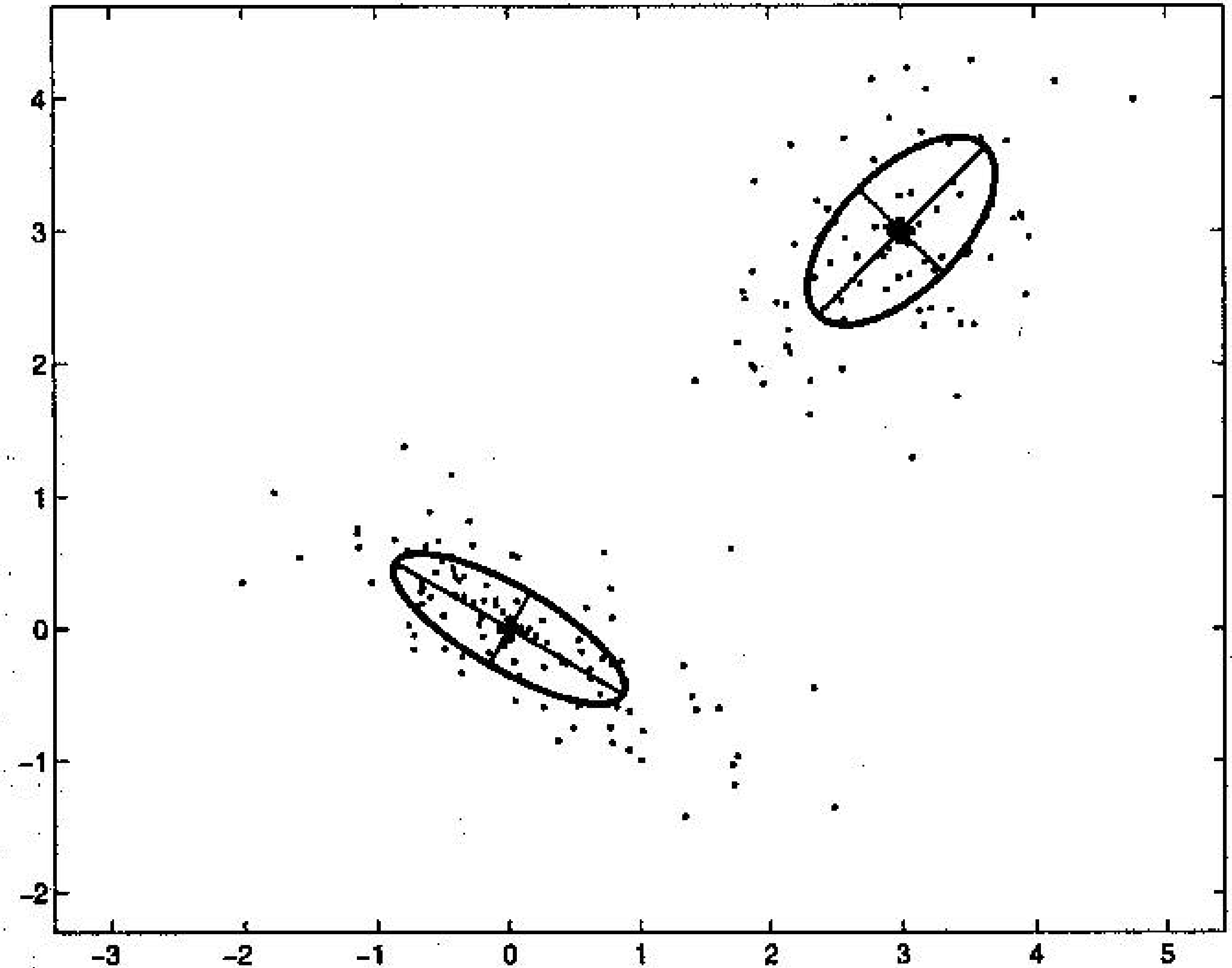


Fig. 3.2. Diagonal covariance mixture model. Sampled data (*dots*), centres (*crosses*), covariance axes (*thin lines*) and one standard deviation error bars (*thick lines*).



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

GMM

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

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

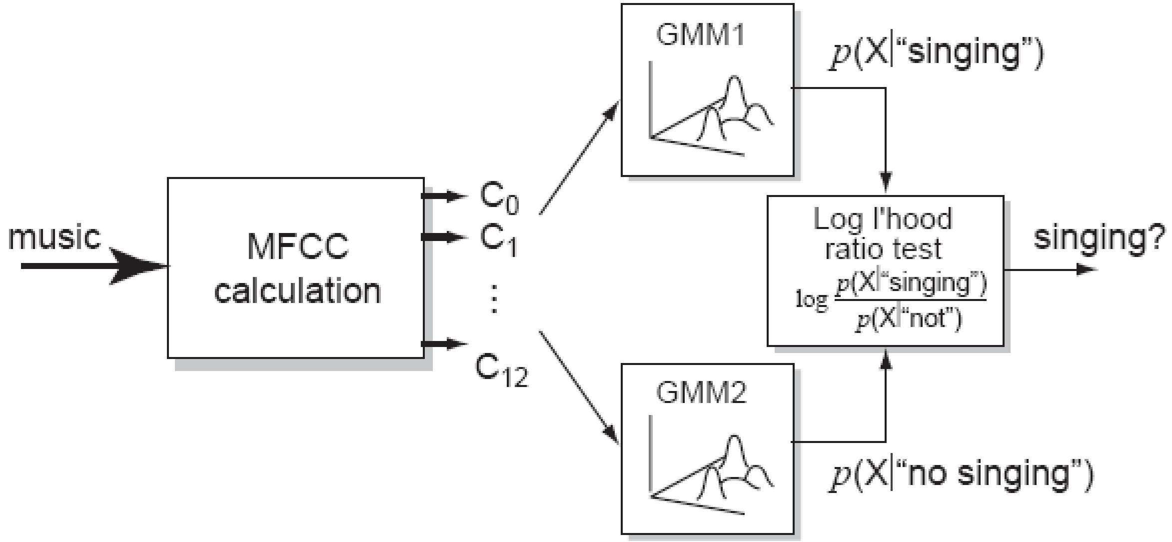
- EM is gradient-based – it does not find the global maximum in the general case, unless properly initialized in the general region of interest.

- 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 System

- **Separate models for $p(x|sing)$, $p(x|no\ sing)$**
  - combined via likelihood ratio test



- **How many Gaussians for each?**
  - say 20; depends on data & complexity
- **What kind of covariance?**
  - diagonal (spherical?)

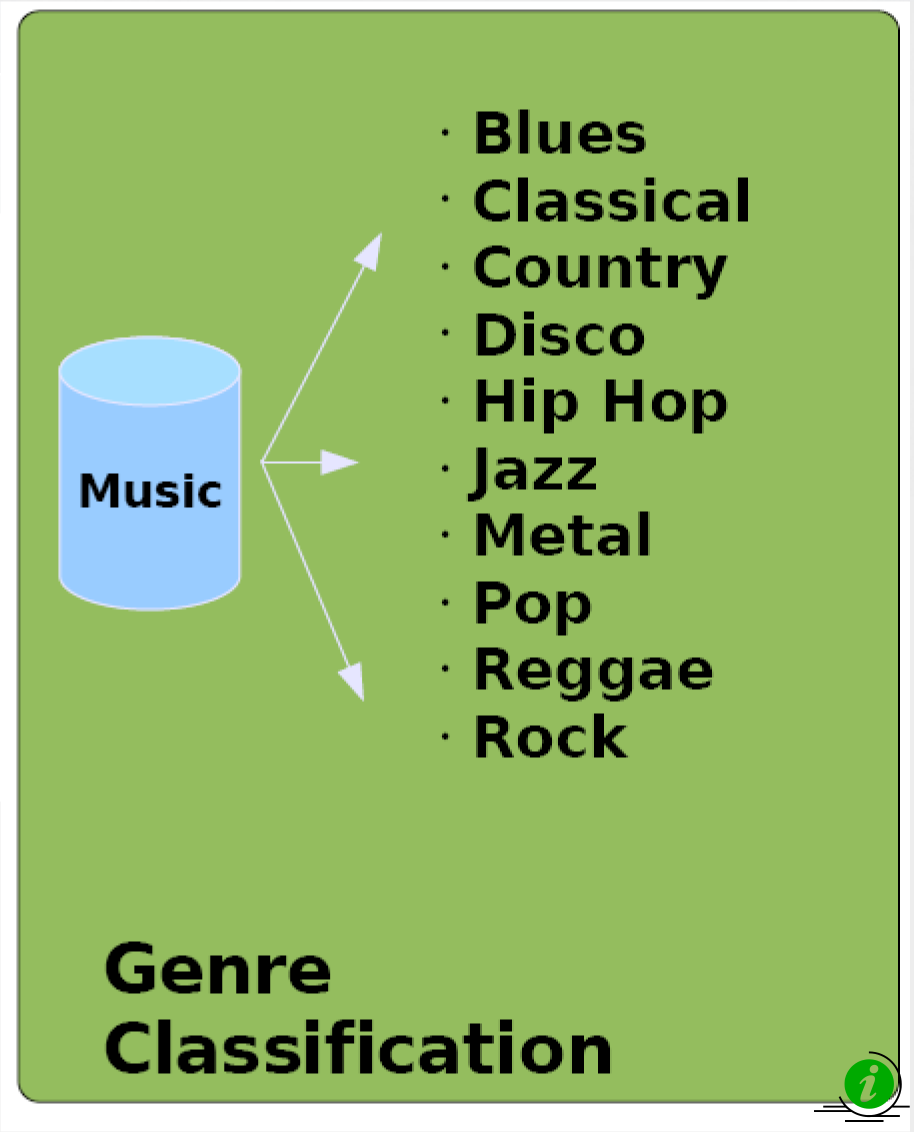
GMM

- Application:
  - State-of-the-art speech recognition systems
  - estimate up to 30,000 separate GMMs, each with about 32 components. This means that these systems can have up to a million Gaussian components!! All the parameters are estimated from (a lot of) data by the EM algorithm.

GENRE

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

From ISMIR 2007 Music Recommender Tutorial (Lamere & Celma)



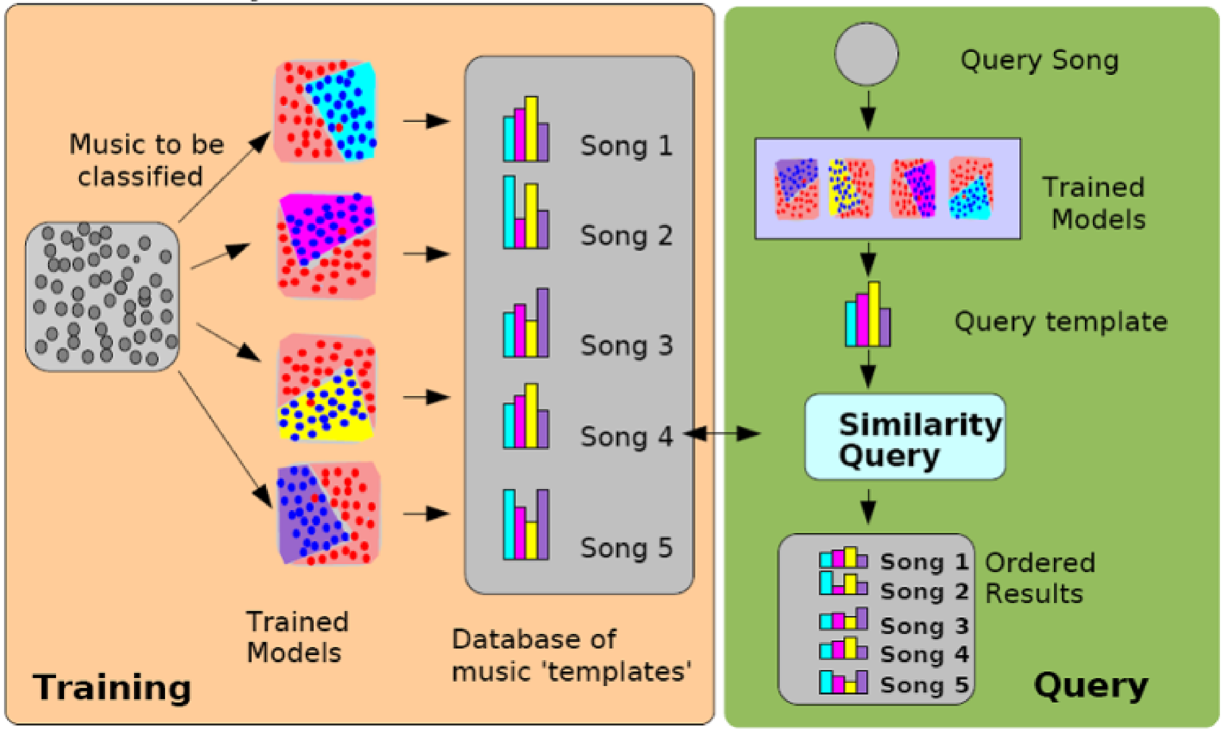
Genre

"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.

- Automatic annotation
  - Similarity based on classification



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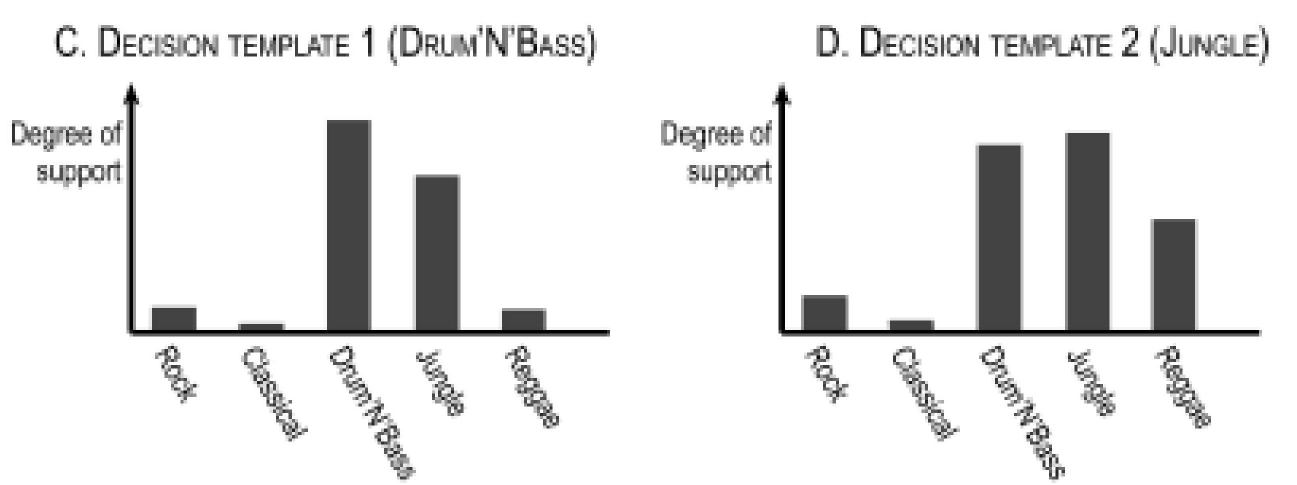

How?

- 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

MORE REAL-WORLD APPLICATIONS

Music Recommendation and Discovery Systems

Today

Tomorrow

- **All music will be on line**
- Billions of tracks
- Millions more arriving every week
- Finding new, relevant music is hard!

If ***everything*** is online, how do we find it?

"A wealth of content creates a poverty of attention"
Herbert A. Simon, Nobel Prize Winner

"iPod **whiplash"**

The Long Tail

Study of 5,000 iPod users:
80% of plays in 23% of songs
64% of songs **never played**

So much feature extraction…

- Features extracted on your host then piped to a server.
- Features only taken on select waveform areas

Tag breakdown

- Social tags
  - Distribution of Tags

Type	Freq	Examples
Genre	68%	Heavy metal, punk
Locale	12%	French, Seattle
Mood	5%	Chill, party
Opinion	4%	Love, favorite
Instrumentation	4%	Piano, female vocal
Style	3%	Political, humor
Misc	3%	Coldplay, composers
Personal	1%	Seen live, I own it

Courtesy: ISMIR 2007 Recommender Tutorial

- Much of last.fm data is currently available via web services, such as:
  - User Profile Data
  - Artist Data
  - Album Data
  - Track Data
  - Tag Data
- http://www.audioscrobbler.net/data/webservices/

Music Recommendation

- Cloud of points from frames of song
  - High-level features extracted from data
  - Classifier: Weighted attribute nearest neighbors or fast distance measures.
  - k-Means or GMM used to create clusters.
  - The mean, covariance and weight of each cluster = signature for the song.

  - Compare distance between other songs (signature) using various techniques to measure distance between probability distributions. (Most similar = closest distance)

>end Day 4

- Mahalanobis
  - Normalize the distance between the test point(s) and the existing cluster set

$$\frac{x - \mu}{\sigma}$$

Distance measures between clusters

- The distances between these clusters are computed using the
  - “Centroid distance”
  - Mahalanobis distance
  - Kullback-Leibler Divergence
  - Earth Movers Distance

GMM

- Sampling