

“Music Information Retrieval” Community

What: Developing systems that retrieve music

When: Late 1990’s to Present

Where: ISMIR - conference started in 2000

**Why: lots of “digital” music, lots of music lovers,
lots of powerful computers**



How can we find find music?

- **Query-by-Metadata** - artist, song, album, year
 - We must know what we want
- **Query-by-(Humming, Tapping, Beatboxing)**
 - Requires talent
- **Query-by-Song-Similarity**
 - We must possess ‘acoustically’ similar songs
- **Query-by-Semantic-Description**
 - Google seems to work pretty well for text
 - Semantic Image Labeling is a hot topic in Computer Vision
 - Can it work for music?

Semantic Music Annotation and Retrieval

Our goal is build a system that can

1. **Annotate** a song with meaningful words
2. **Retrieve** songs given a text-based description

Plan: Learn a probabilistic model that captures a relationship between the **audio content** of a song and **words** that describe the song.

Collecting Semantic Music Data

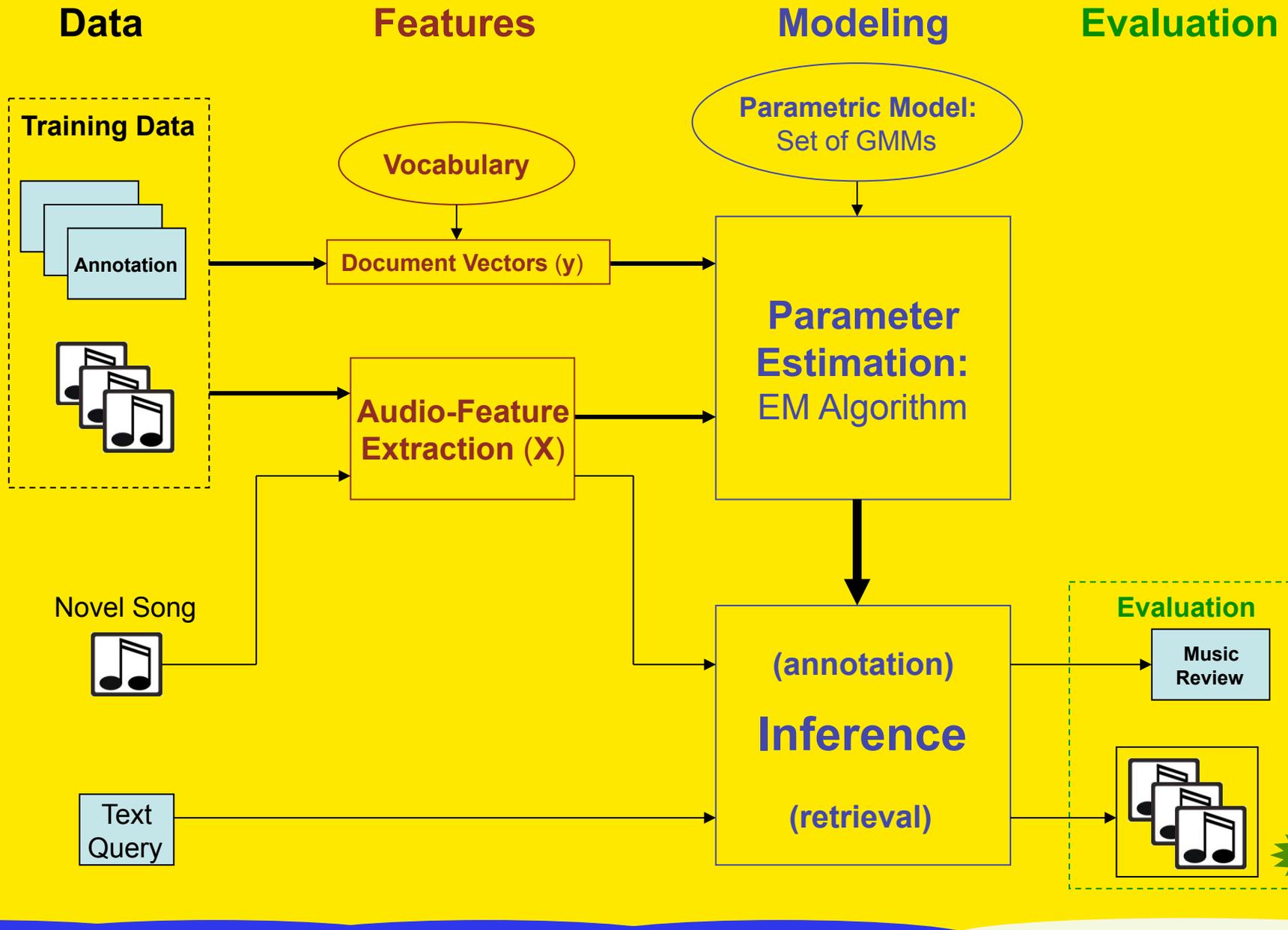
CAL500 Data Set: We have collected 1700 annotations for 500 'western popular' songs by having 55 individuals listen to and evaluate music.

- Each song is annotated by at least 3 individuals.

An annotation reflects the 'strength of association' between a song and 173 words.

- Words relate to Instrumentation, Genre, Emotion, Vocals, Usages, Quality, Tempo, ...
- Collected using a standard survey

System Overview



Our Model

Each song is represented by a time series $X = \{x_1, \dots, x_t\}$

- dynamic Mel-Frequency Cepstral Coefficients [McKinney03]

For each word w , we learn a ‘word-model’ $p(x|w)$ using songs that are associated with the word.

- $p(x|w)$ is modeled using a Gaussian Mixture Model (GMM)

Annotation: Given a novel song, we pick words by comparing the likelihood of the audio features under each word-model.

Retrieval: Given a text query, we pick songs that are likely under the word-models associated with the words in the query.

Annotation: Automatic Music Reviews

Dr. Dre (feat. Snoop Dogg) - Nuthin' but a 'G' thang

This is dance poppy, hip-hop song that is arousing and exciting. It features drum machine, backing vocals, male vocal, a nice acoustic guitar solo, and rapping, strong vocals. It is a song that is very danceable and with a heavy beat that you might like listen to while at a party.

Frank Sinatra - Fly me to the moon

This is a jazzy, singer / songwriter song that is calming and sad. It features acoustic guitar, piano, saxophone, a nice male vocal solo, and emotional, high-pitched vocals. It is a song with a light beat and a slow tempo that you might like listen to while hanging with friends.

Retrieval: Query-by-Semantic-Description

Query	Retrieved Songs
'Tender'	Crosby, Stills and Nash - Guinnevere Jewel - Enter from the East Art Tatum - Willow Weep for Me John Lennon - Imagine Tom Waits - Time
'Female Vocals'	Alicia Keys - Fallin' Shakira - The One Christina Aguilera - Genie in a Bottle Junior Murvin - Police and Thieves Britney Spears - I'm a Slave 4 U
'Tender' AND 'Female Vocals'	Jewel - Enter from the East Evanescence - My Immortal Cowboy Junkies - Postcard Blues Everly Brothers - Take a Message to Mary Sheryl Crow - I Shall Believe

Quantifying Annotation

Our system annotates the Cal-500 songs with 10 words from our vocabulary of 173 words.

- 'Population Annotation' Ground Truth

Metric: 'Word' Precision & Recall

Consider word w ,

$$\text{Precision} = \frac{\text{\# songs correctly annotated with } w}{\text{\# songs annotated with } w}$$

$$\text{Recall} = \frac{\text{\# songs correctly annotated with } w}{\text{\# songs that should have been annotated } w}$$

Mean Word Recall and Word Precision are the averages over all words in our vocabulary.

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Model	Precision	Recall
Random	0.17	0.05
Upper Bound	1.00	0.30
Our System	0.31	0.14
Human	0.34	0.11

Key point: By pooling human annotations, our model can produce annotations that are as consistent as annotations produced by individuals, when compared against a population average.

What's next...

Going Bigger

- Larger Vocabulary
- More Annotation
- Novel Applications

Modeling dependencies

- Words Correlations (e.g., 'Classic Rock' & 'Electric Guitar')
- Audio Features have temporal dependencies
- Modeling individuals rather than populations

Comparing alternative models

- Modeling heterogeneous data is hot topic in Machine Learning
- Many models have been proposed.
- Applications: Image Labeling, Text-Document Classification

Exploring Novel Query Paradigms

- Query-by-semantic-example
- Heterogeneous queries

To learn more...

The mathematics (parameter estimation, inference), a description of the Cal-500 data set, evaluation of annotation and retrieval performance, and much more is available at:

cosmal.ucsd.edu/cal



**“Talking about music is like dancing
about architecture”**

- origins unknown



A biased view of Music Classification

2000-03: Music classification (by genre, emotion, instrumentation) becomes a popular MIR task

- Undergrad Thesis on Genre Classification with G. Tzanetakis

2003-04: MIR community starts to criticize music classification problems

- ill-posed problem due to subjectivity
- not an end in itself
- performance ‘glass ceiling’

2004-06: Focus turns to Music Similarity research

- Recommendation
- Playlist generation

2006-07: We view Music Annotation as a supervised multi-class labeling problem

- Like classification but with large, less-restrictive vocabulary