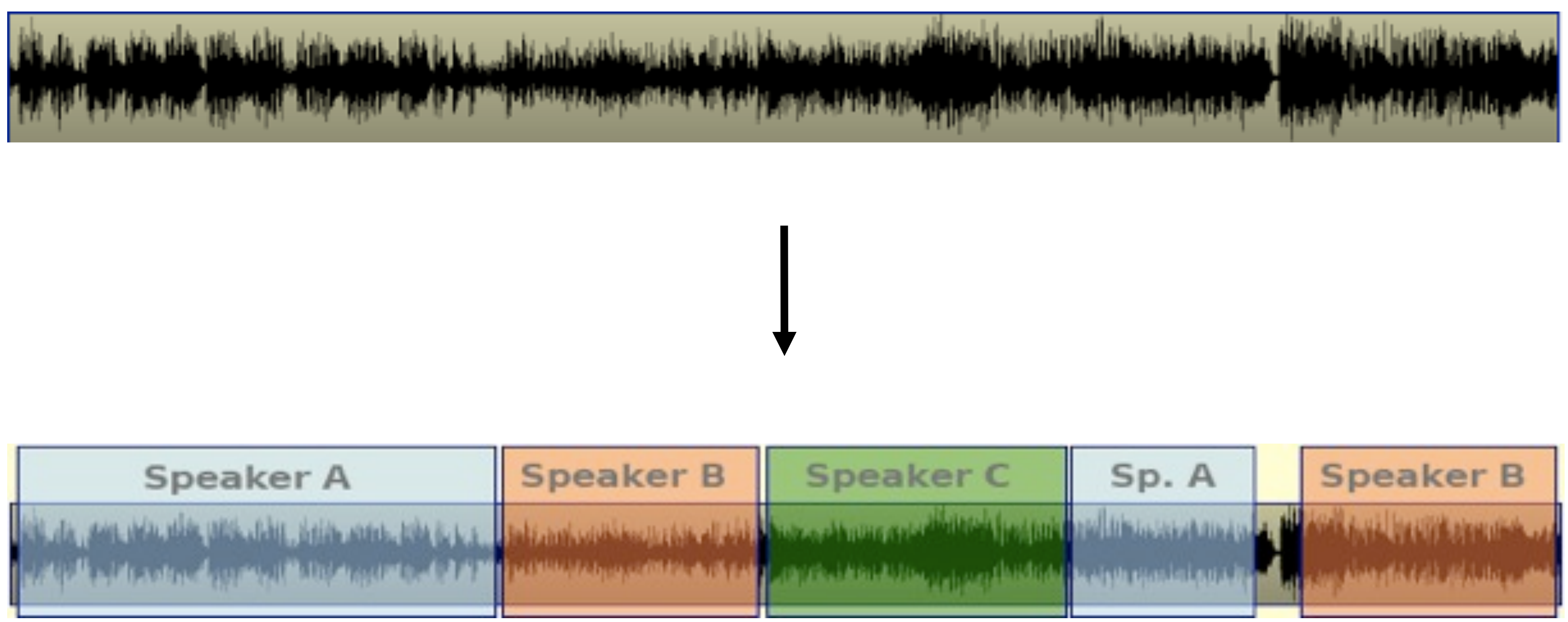
Introduction to Speaker Diarization



Dr. Gerald Friedland
International Computer Science Institute
Berkeley, CA
friedland@icsi.berkeley.edu

Speaker Diarization...

➡tries to answer the question: **“who spoke when?”**

➡using a single or multiple microphone inputs

➡without prior knowledge of anything (#speakers, language, text, etc...)

Visualization

Audiotrack:

Estimate “who spoke when” with no prior knowledge of speakers, #of speakers, words, or language spoken.

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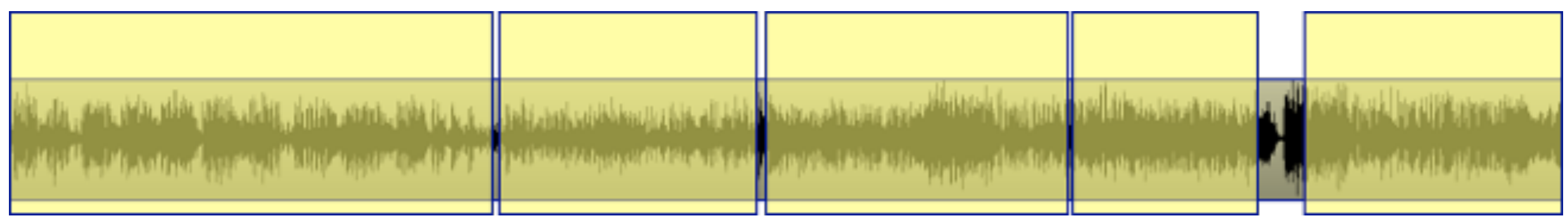

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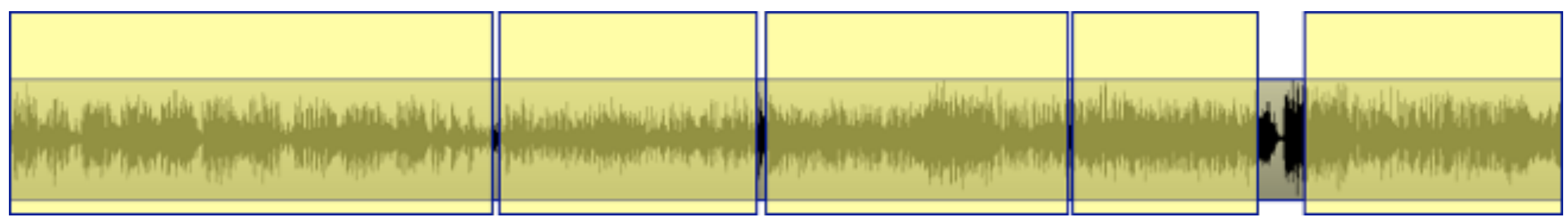

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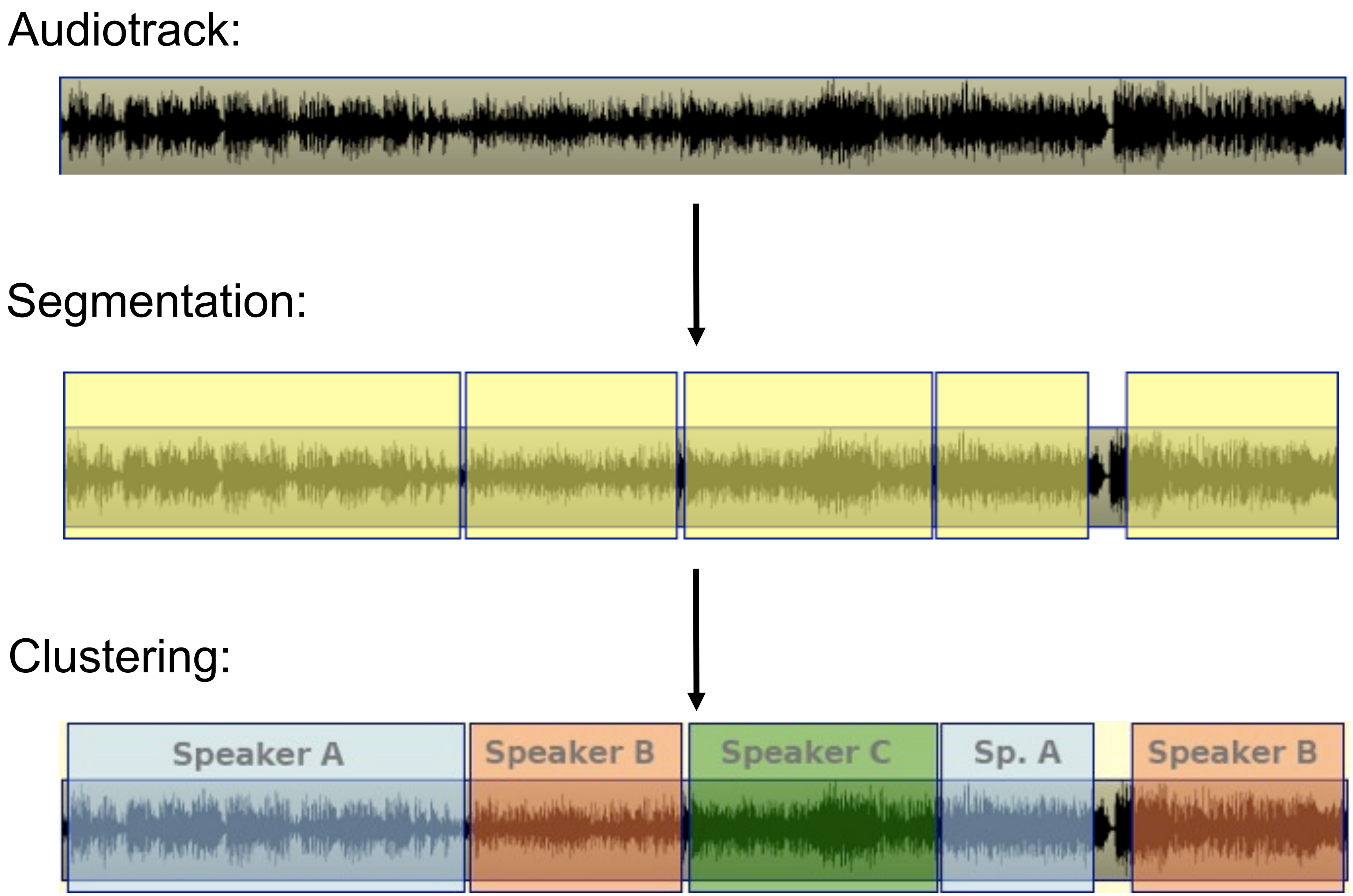

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- Speaker Verification (is supervized and returns yes/no answer)
- Beamforming (as this requires multiple mics, even though beamforming can be used to support diarization)

Why Diarization?

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- Important basic technology for various semantic audio analysis tasks

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- Meeting retrieval, video conferencing, speaker-adaptive ASR, video retrieval, etc...

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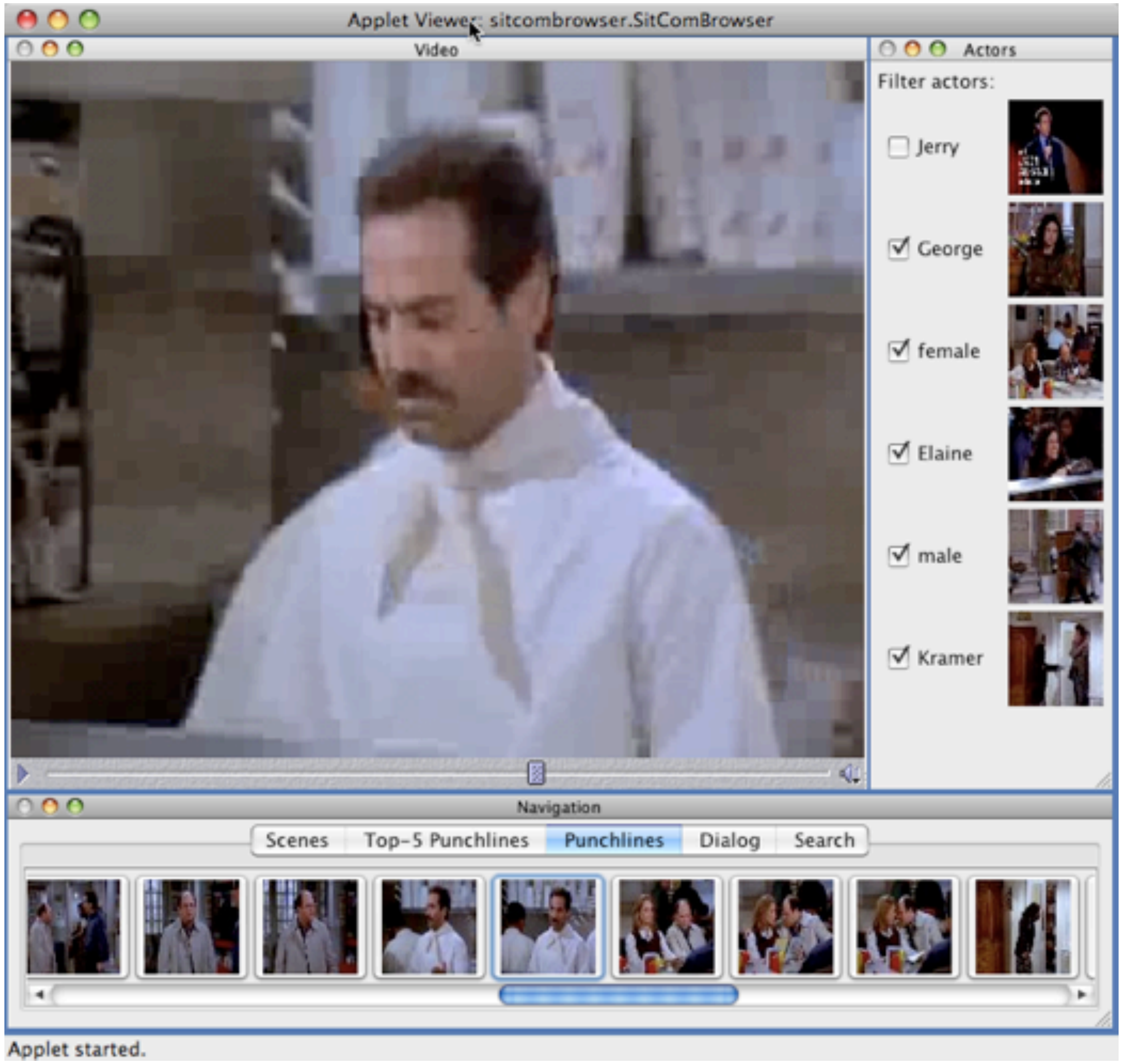
- Let's take a look at some examples

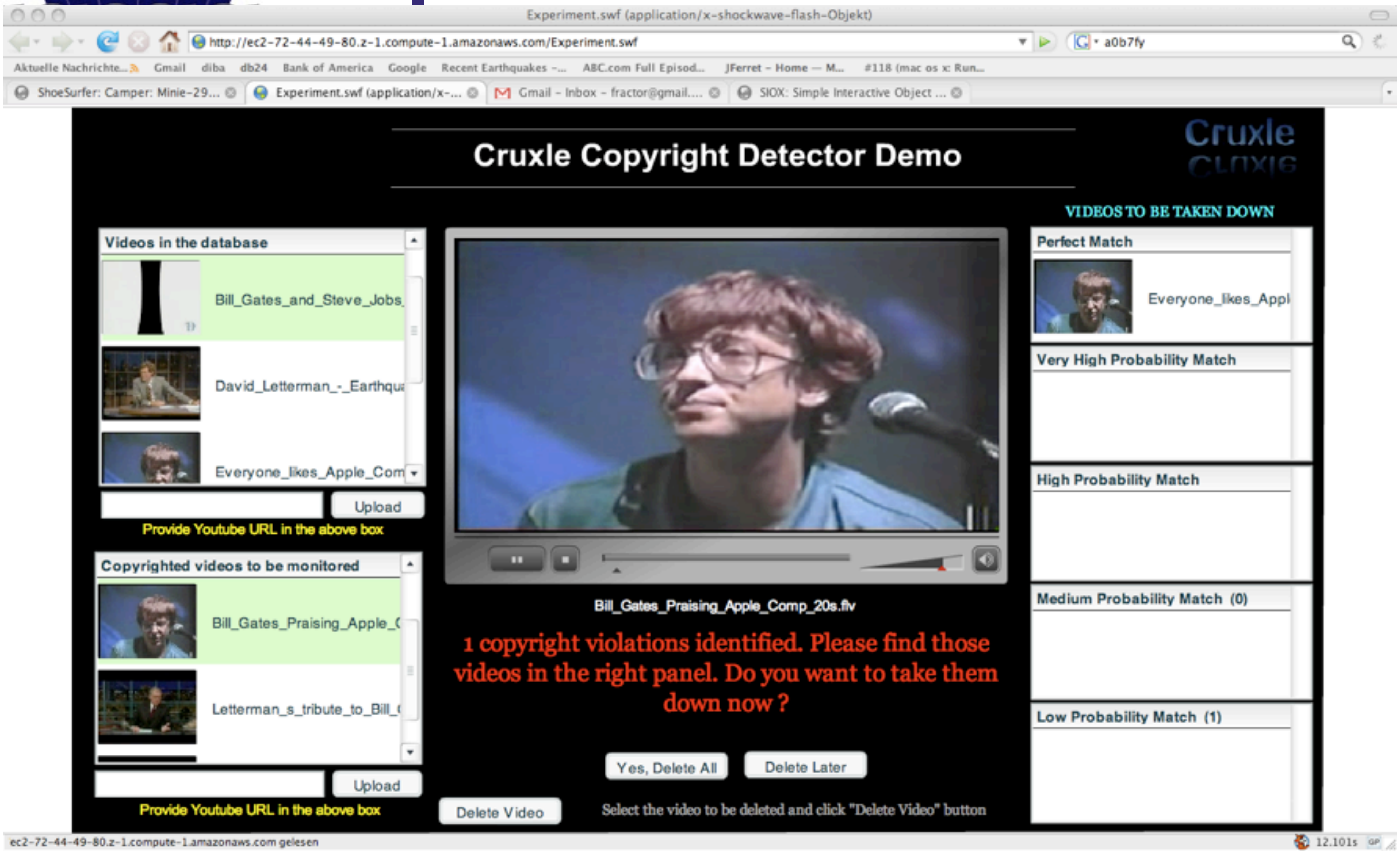
Application: Meeting Browsing

Application: Semantic Navigation



G. Friedland, L. Gottlieb, A. Janin: "Joke-o-mat: Browsing Sitcoms Punchline by Punchline", Proceedings of ACM Multimedia, Beijing, China, October 2009.

Application: Video Duplicate Detection



Other Applications

(Speaker) Diarization is often used as underlying support for...

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- Beamforming
- Visual Localization
- Video Analysis: Object Detection, Event Detection, Scene Detection
- behavior-level analysis tasks, such as dominance detection
- Robotics Applications (e.g. addressing people)
- Support for adaptive speech recognition

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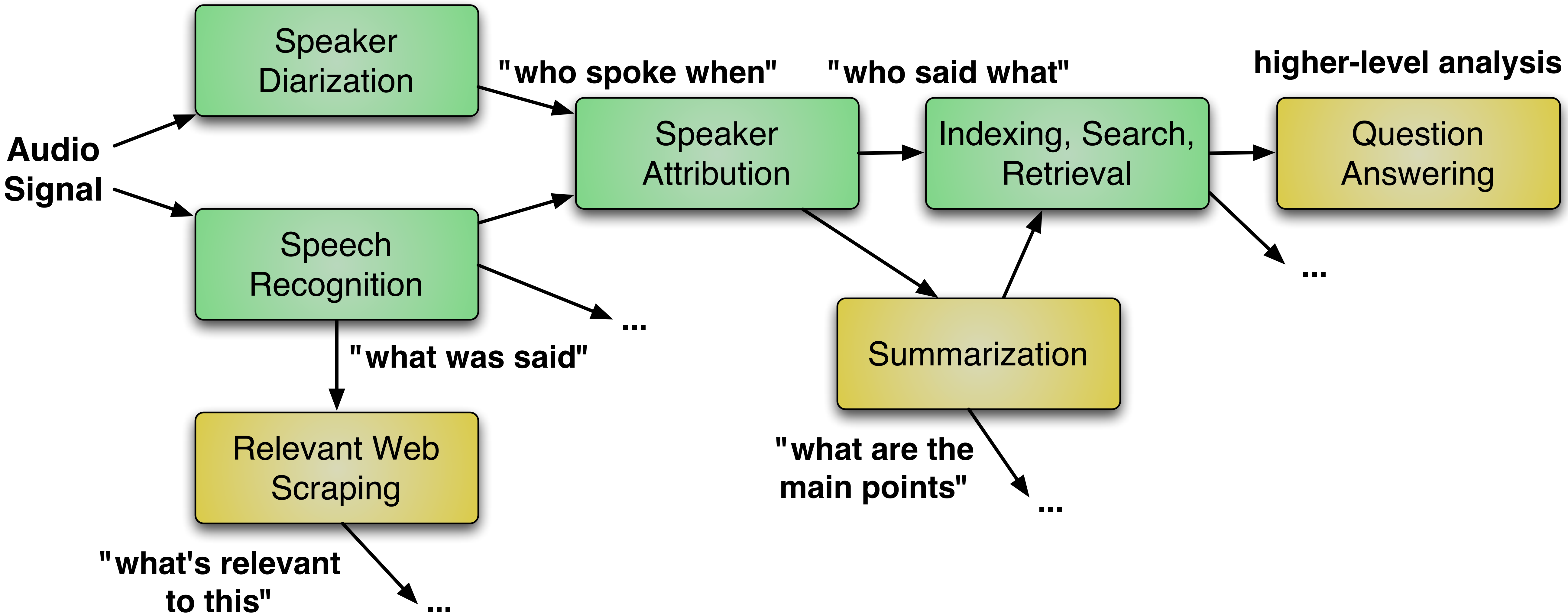
- Idea: Create "Rich Transcripts" of broadcast news, later meetings.
- Evaluated on Real-World data

Typical Component Composition for RT



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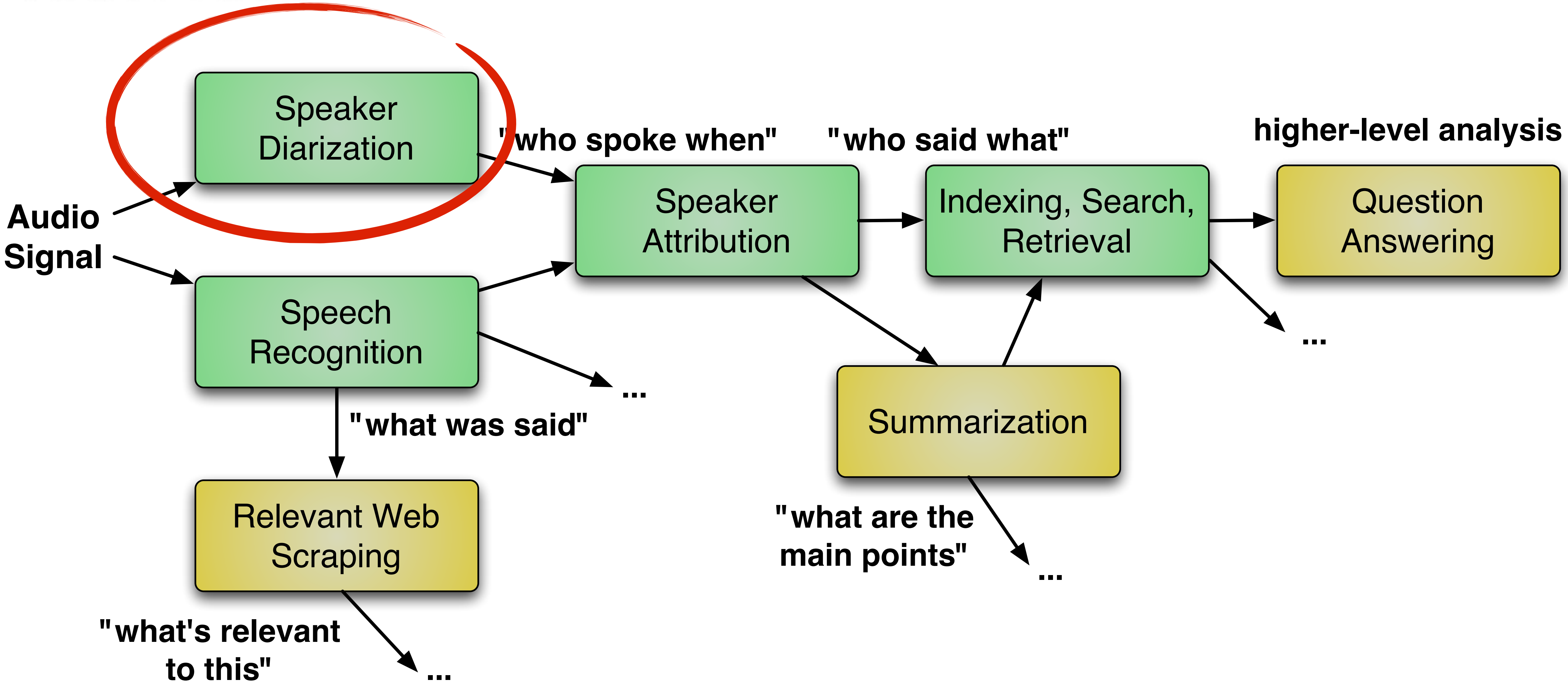
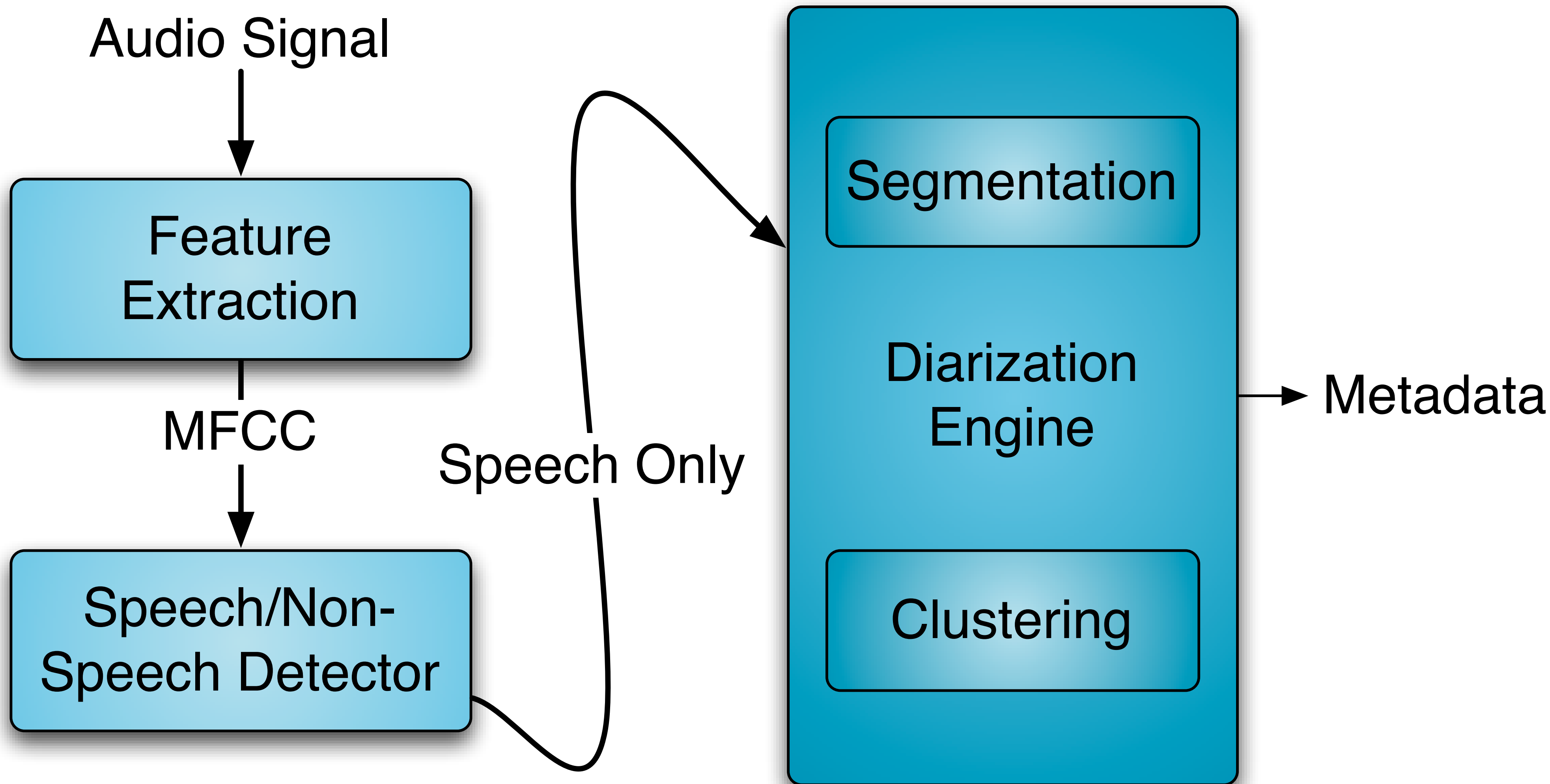


Speaker Diarization: General Overview



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- Large amount of tools available to deal with these files.

Error Measurement

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- All tools available open source

Error Measurement

$$\mathrm{DER} = \frac{T_{FA} + T_{MISS} + T_{SPK}}{T_{SPEECH}}$$

DER = The amounts of time a speaker has been assigned wrongly, missed, assumed when there is none, or assumed solely when there is more than one relative to the length of the audio.

Segmentation & Clustering

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- Originally: Segment first, cluster later

  Chen, S. S. and Gopalakrishnan, P., "Clustering via the bayesian information criterion with applications in speech recognition," Proc. IEEE International Conference on Acoustics, Speech and Signal Processing, 2001, Vol. 2, Seattle, USA, pp. 645-648.

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- More efficient: Top-Down and Bottom-Up Approaches

Segmentation: Secret Sauce

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- How do you distinguish speakers?

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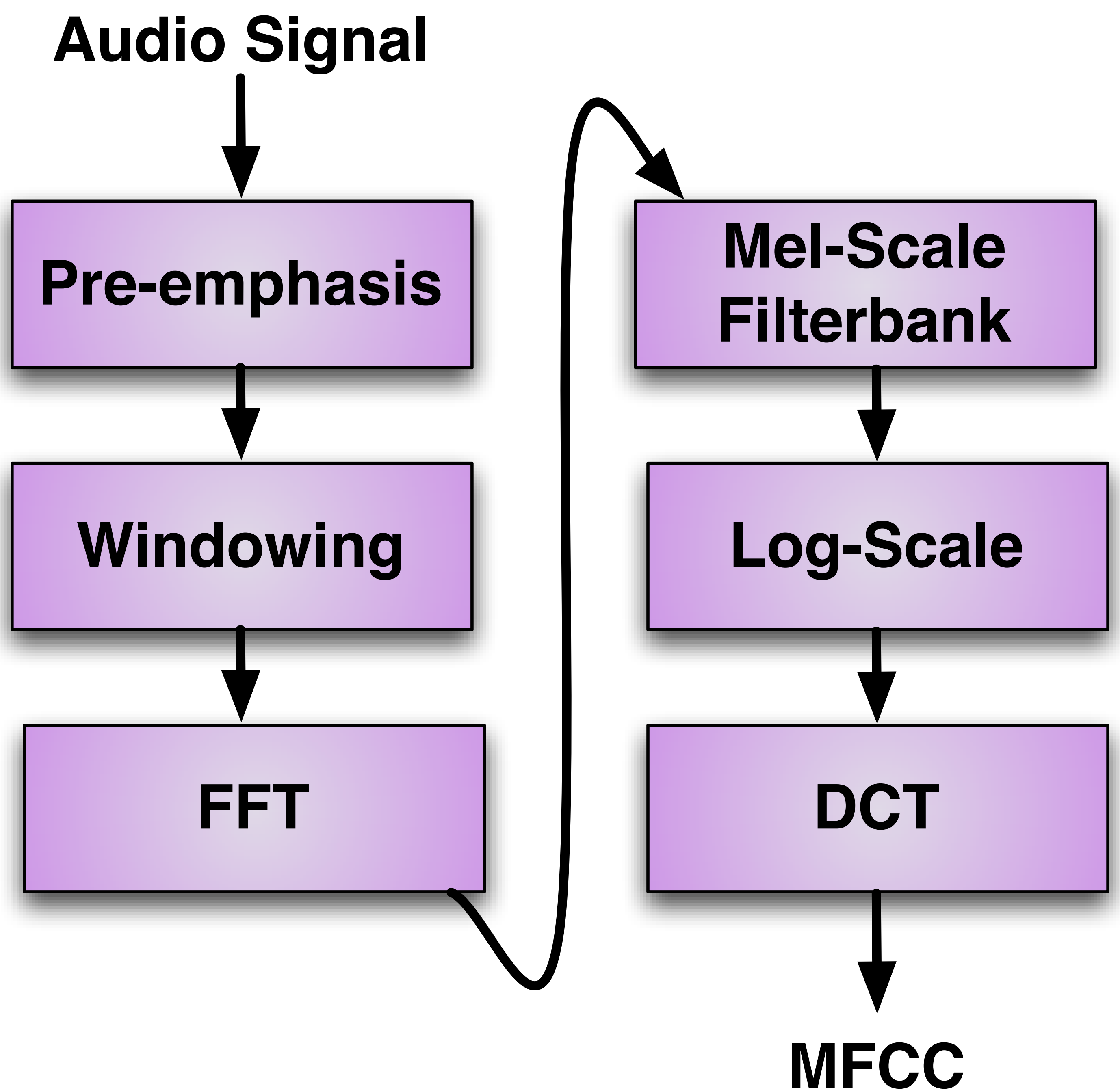
- Combination of MFCC+GMM+BIC seems unbeatable!

Segmentation: Secret Sauce

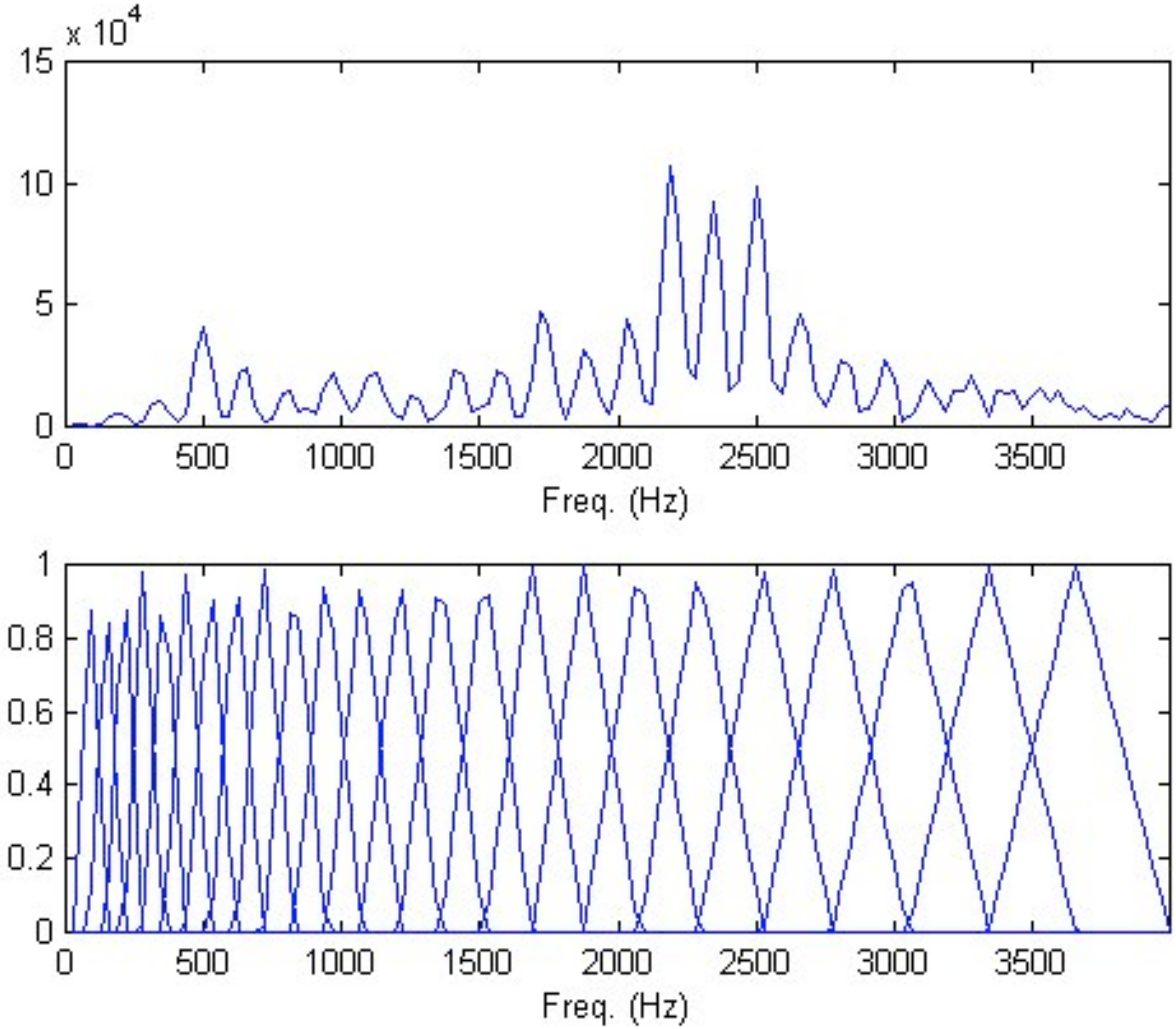
- How do you distinguish speakers?
- Combination of MFCC+GMM+BIC seems unbeatable!
- Can be generalized to Audio Percepts

MFCC: Idea

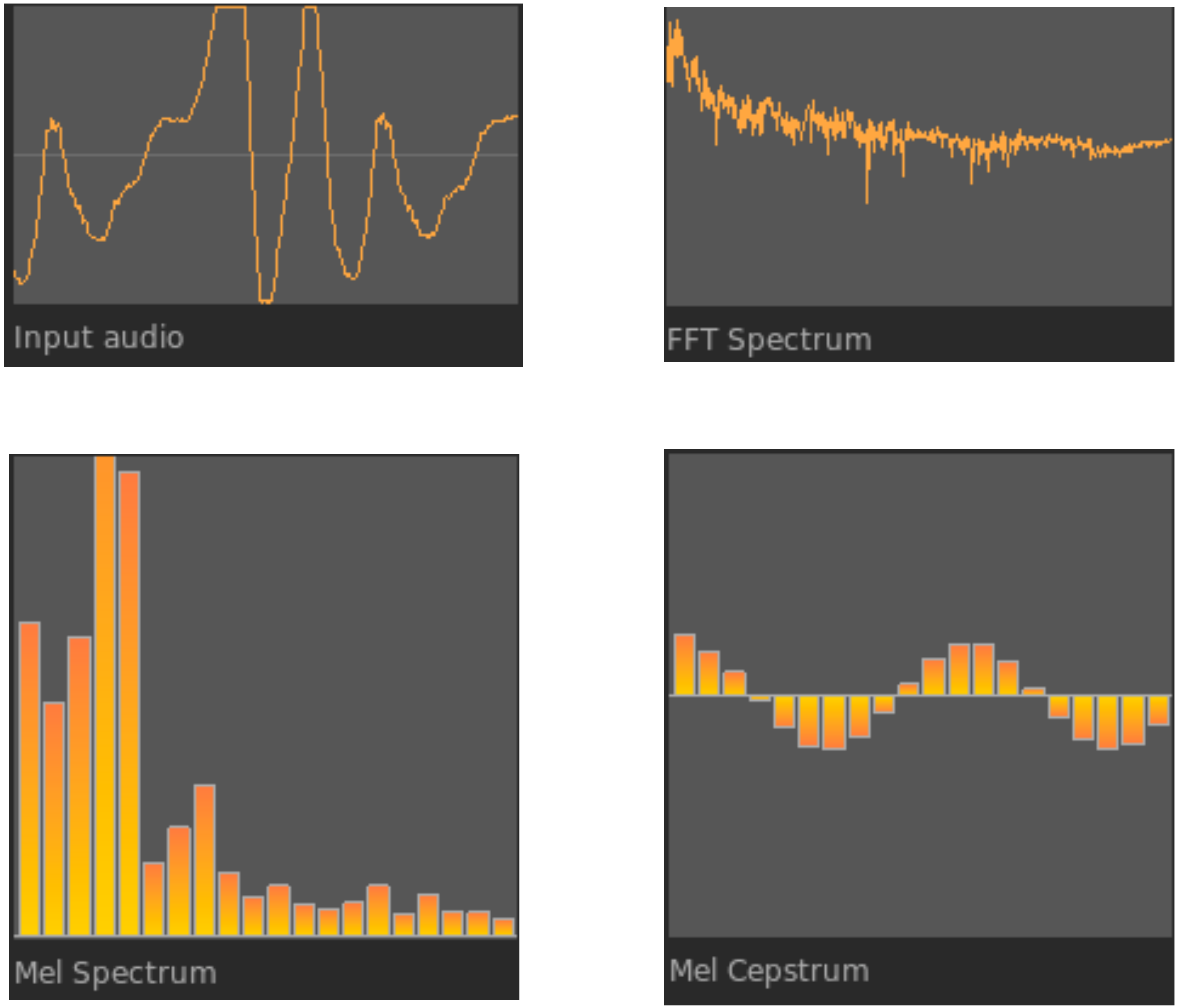


power cepstrum of signal $= \left|\mathbf{F}\left\{\log(|\mathbf{F}\left\{\text{the signal}\right\}|^2)\right\}\right|^2$

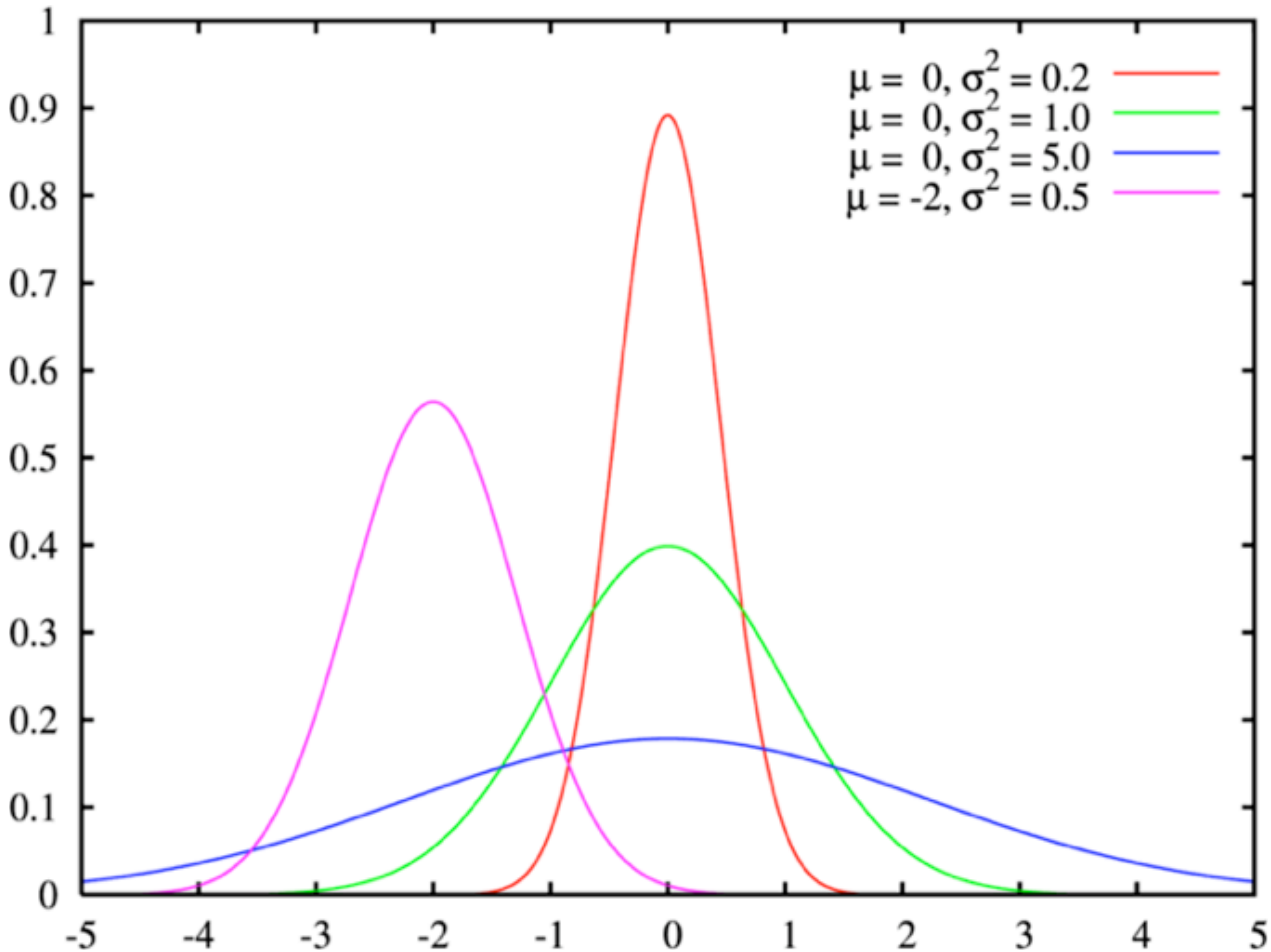
MFCC: Mel Scale



MFCC: Result



Gaussian Mixtures



Training of Mixture Models

Goal: Find a_i for $$f_X(x) = \sum_{i=1}^{n} a_i f_Y(x;\theta_i).$$

Expectation: $$y_{i,j} = \frac{a_i f_Y(x_j;\theta_i)}{f_X(x_j)}.$$

Maximization: $$a_i = \frac{1}{N}\sum_{j=1}^{N} y_{i,j}$$

$$\mu_i = \frac{\sum_j y_{i,j} x_j}{\sum_j y_{i,j}}.$$

Bayesian Information Criterion

$$\mathrm{BIC} = \log p(X|\Theta) - \frac{1}{2}\lambda K \log N$$

where
X is the sequence of features for a segment,
Θ are the parameters of the statistical model for the segment,
K is the number of parameters for the model,
N is the number of frames in the segment,
λ is an optimization parameter.

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- BIC measures the efficiency of the parameterized model in terms of predicting the data.
- BIC is therfore used to choose the number of clusters according to the intrinsic complexity present in a particular dataset.

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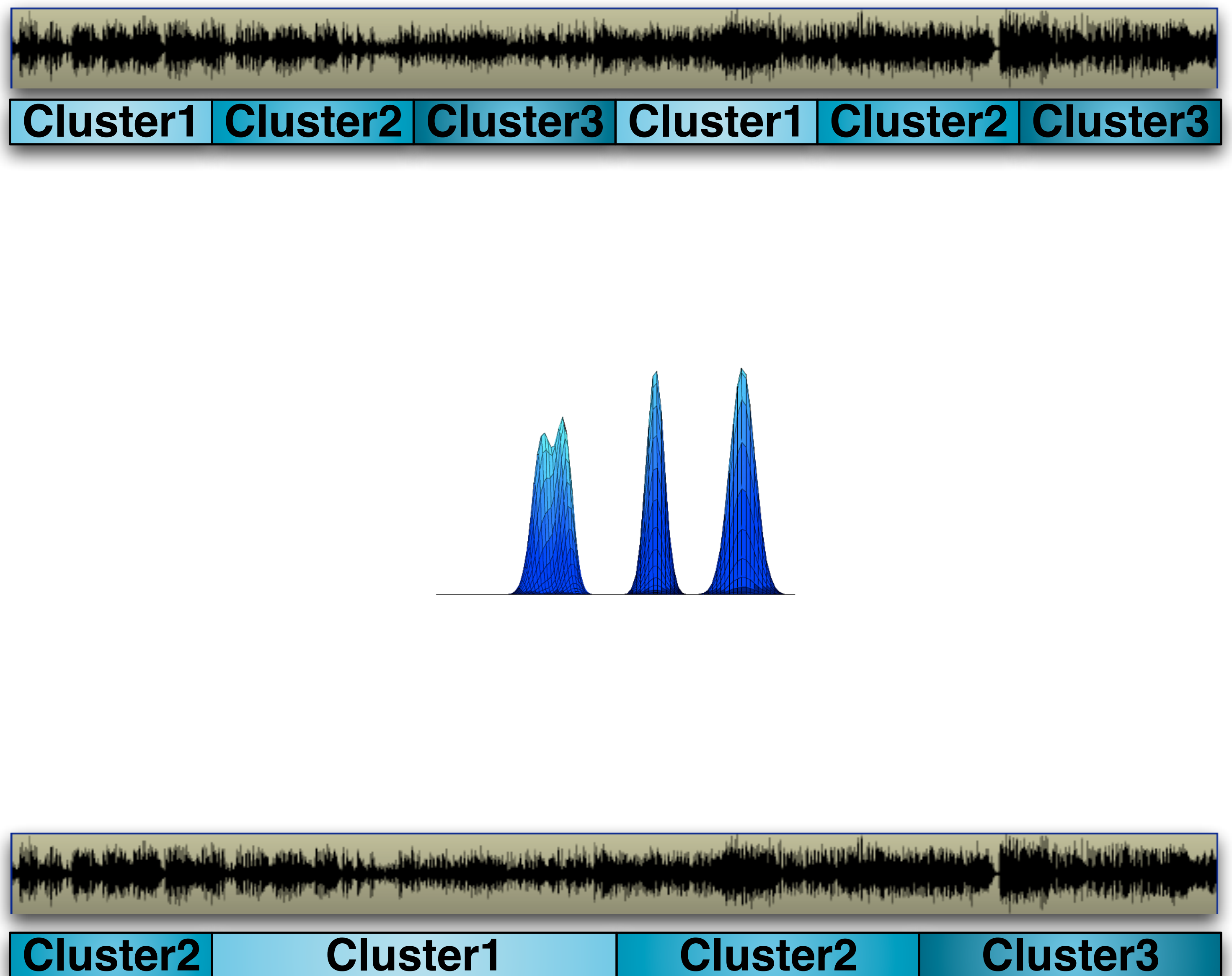
- It is closely related to other penalized likelihood criteria such as RIC and the Akaike information criterion.

Bottom-Up Algorithm



- Start with too many clusters (initialized randomly)
- Purify clusters by comparing and merging similar clusters
- Resegment and repeat until no more merging needed

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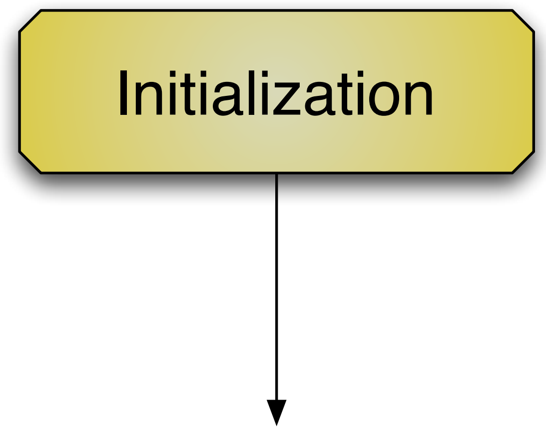

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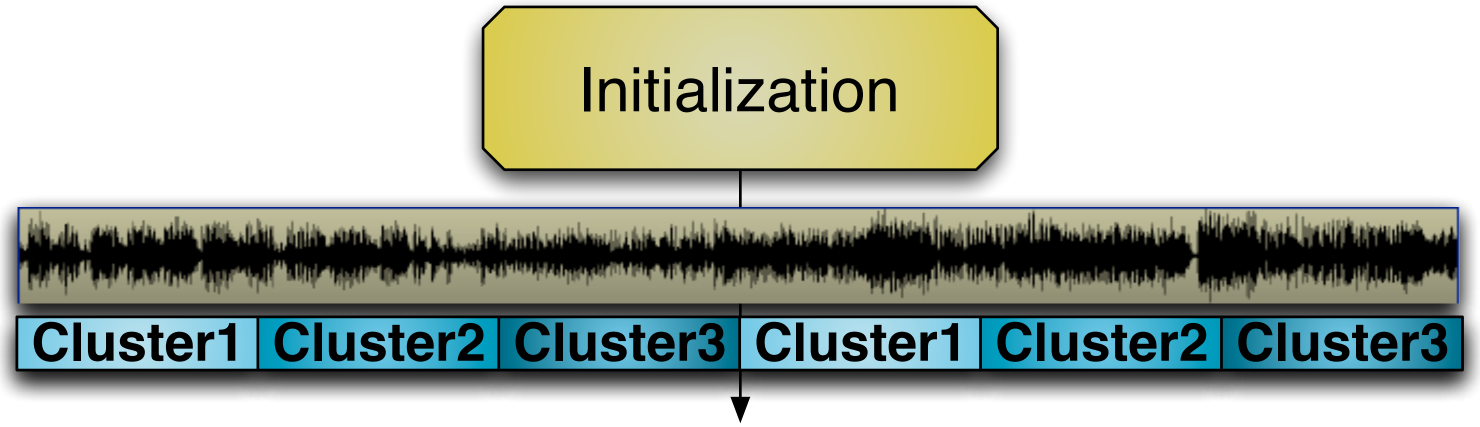

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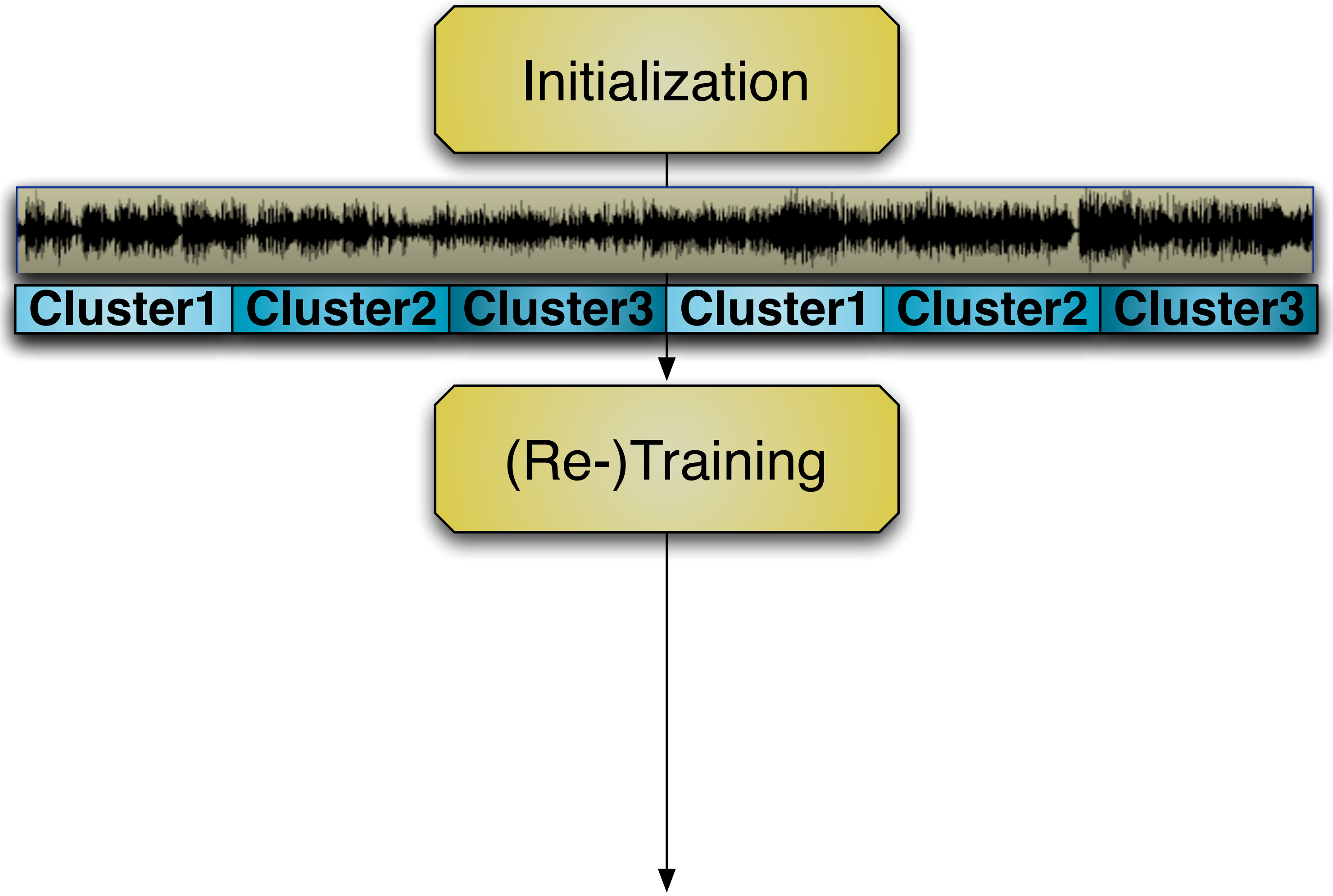

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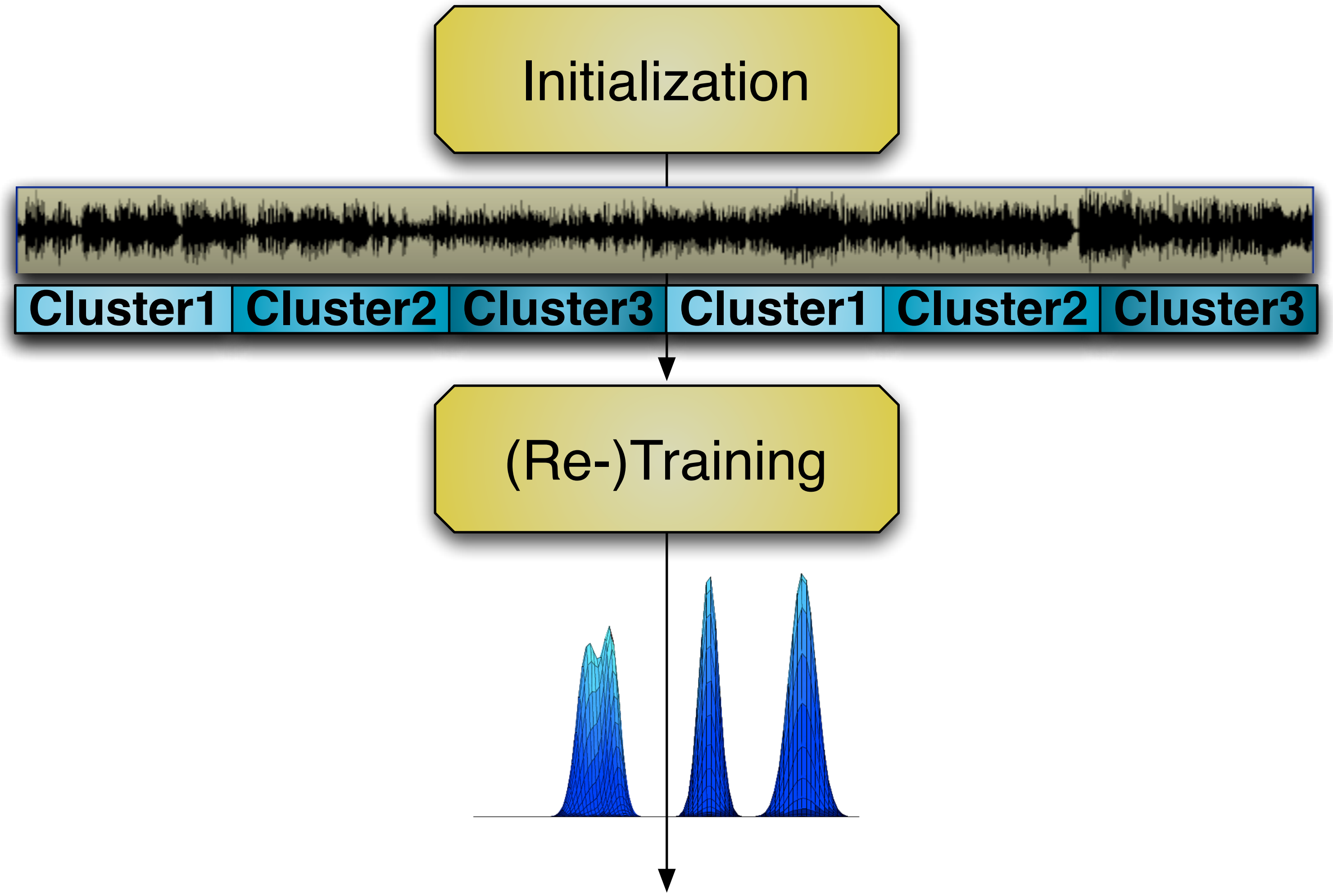

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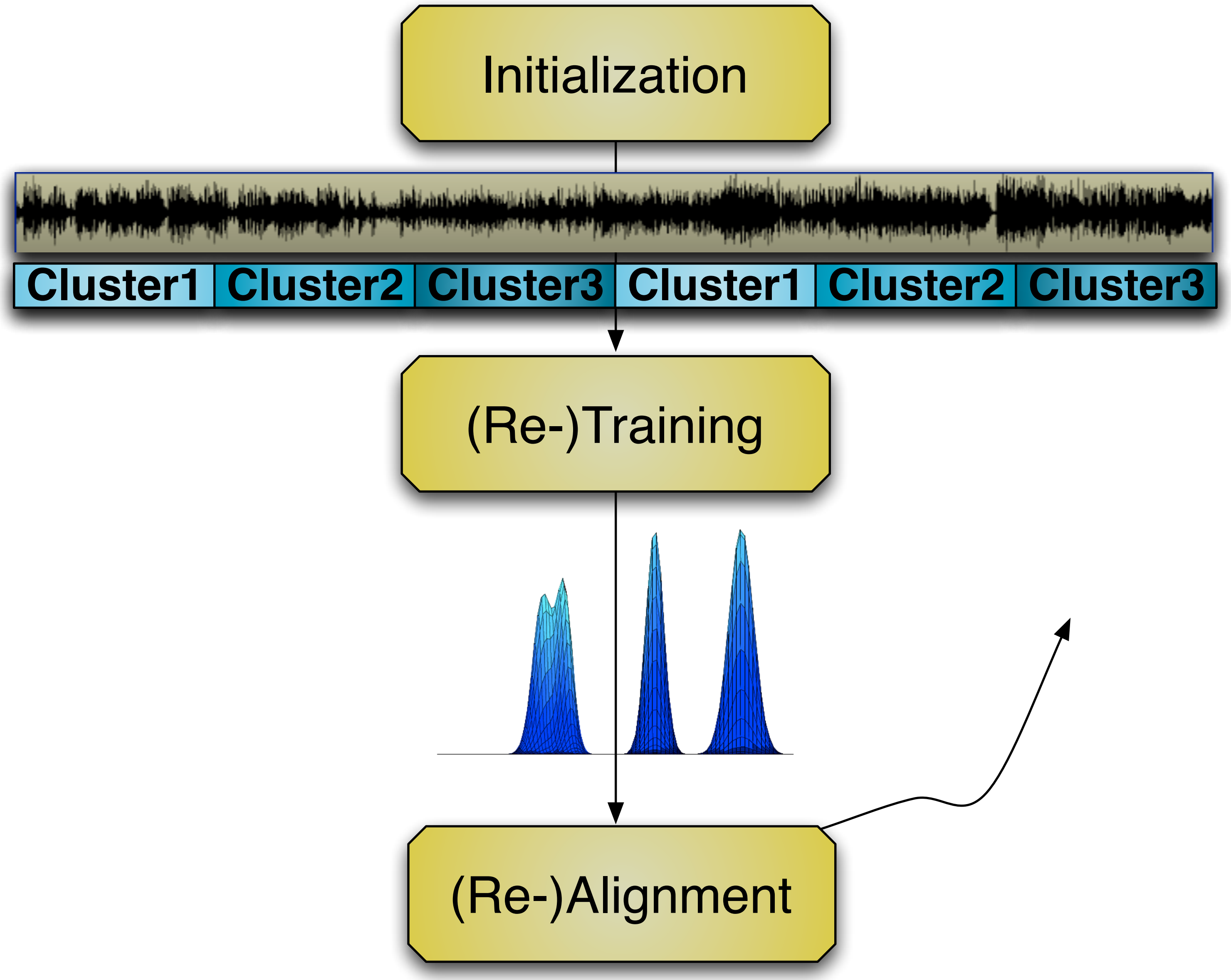

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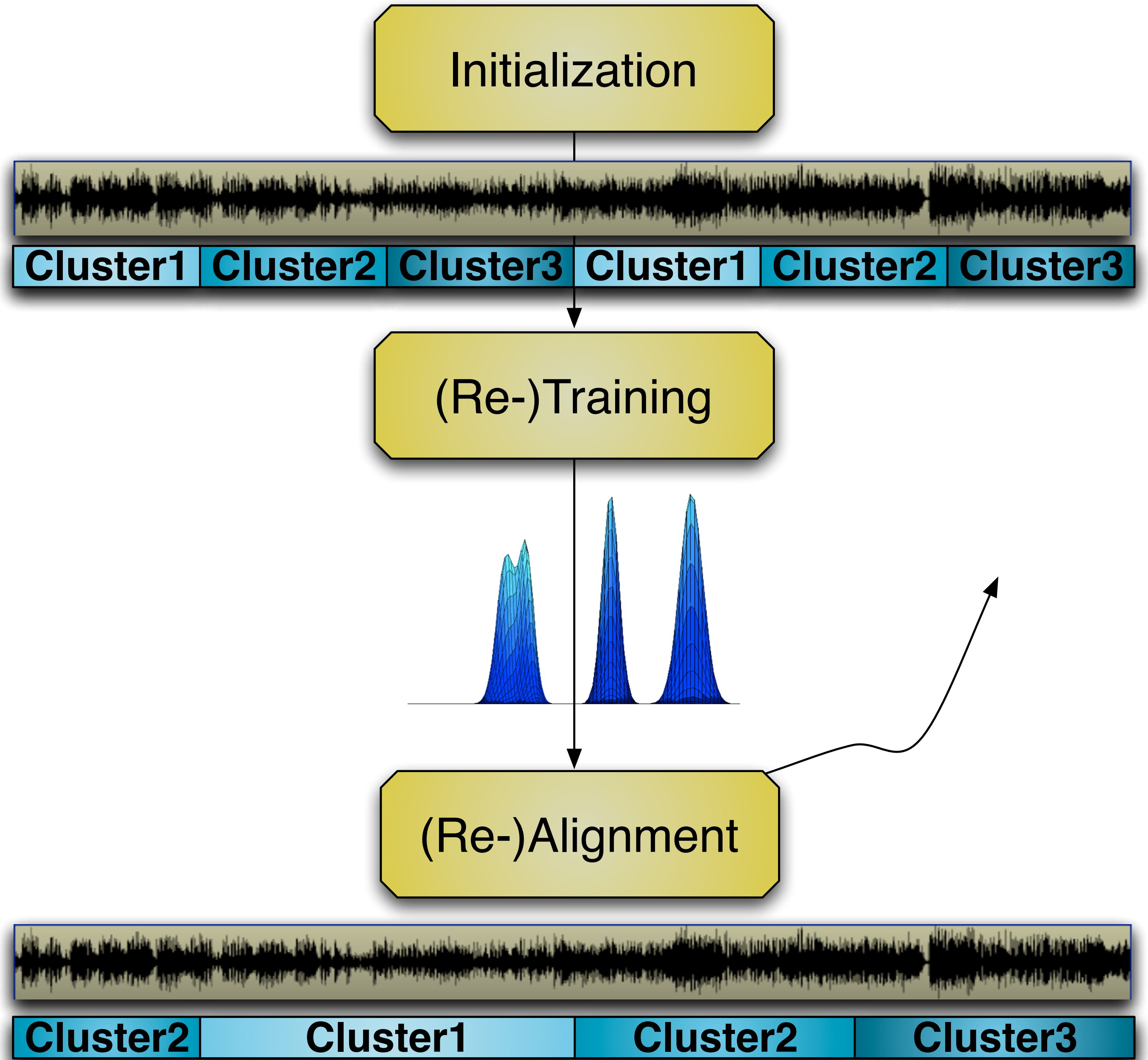

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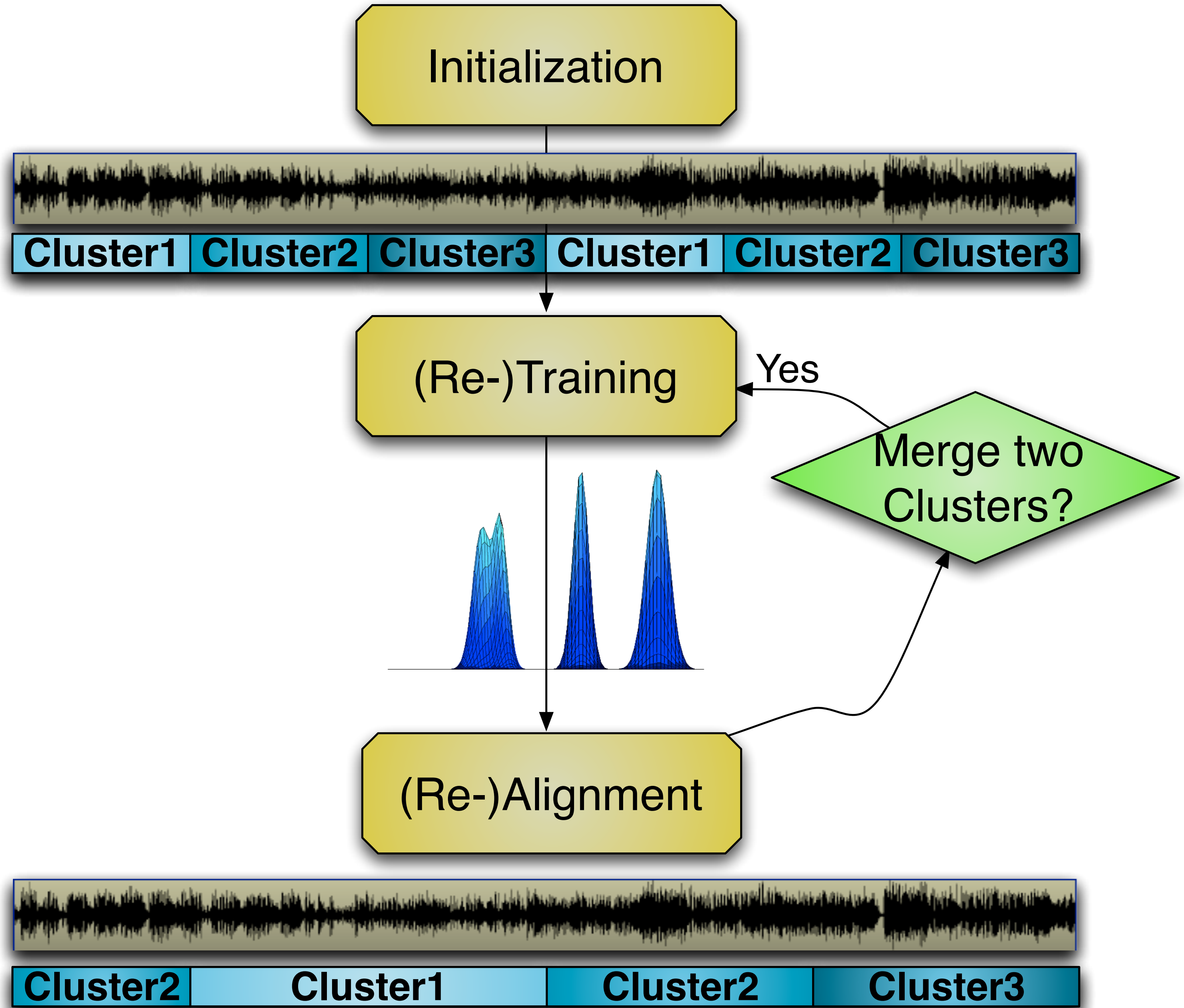

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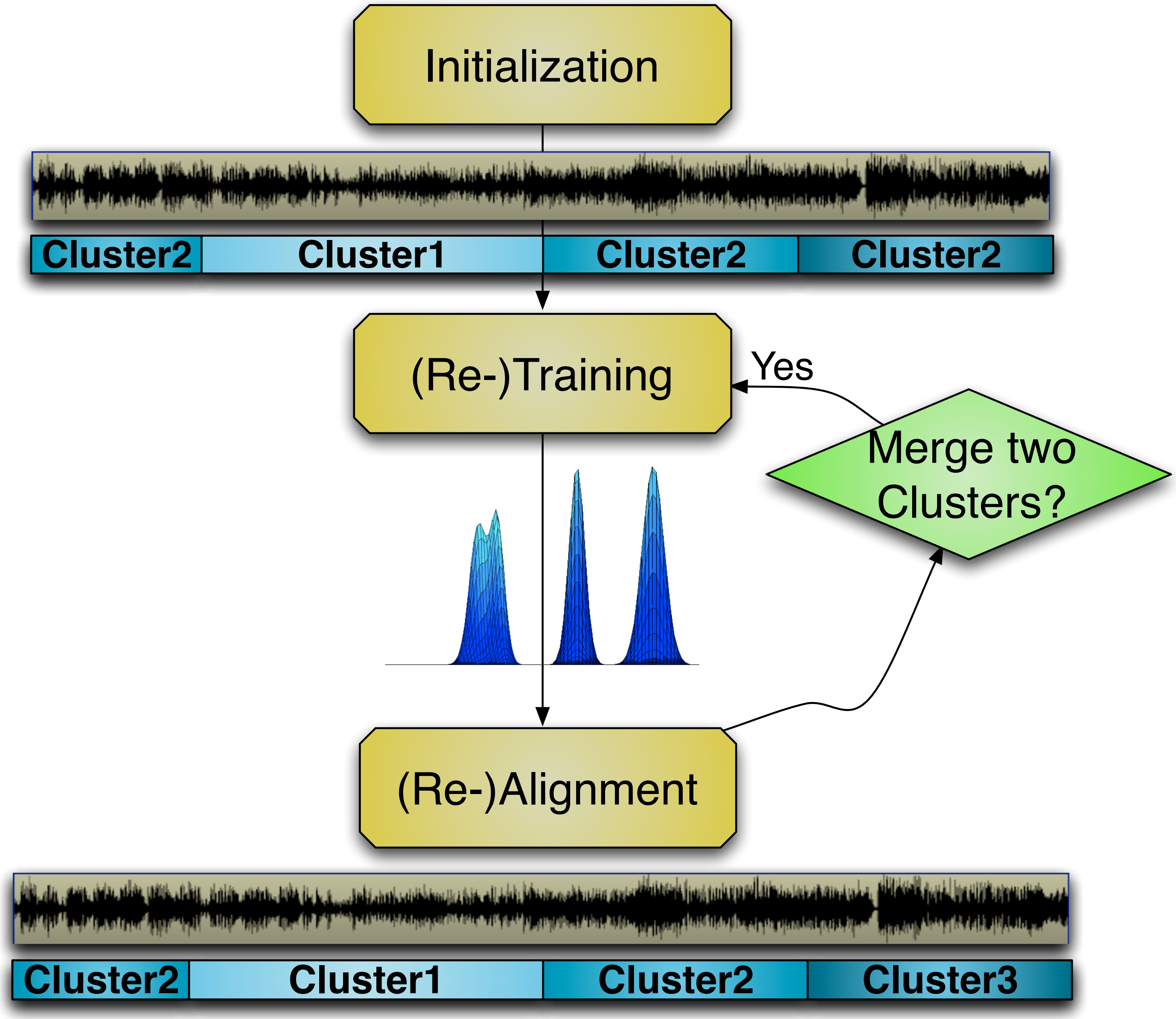

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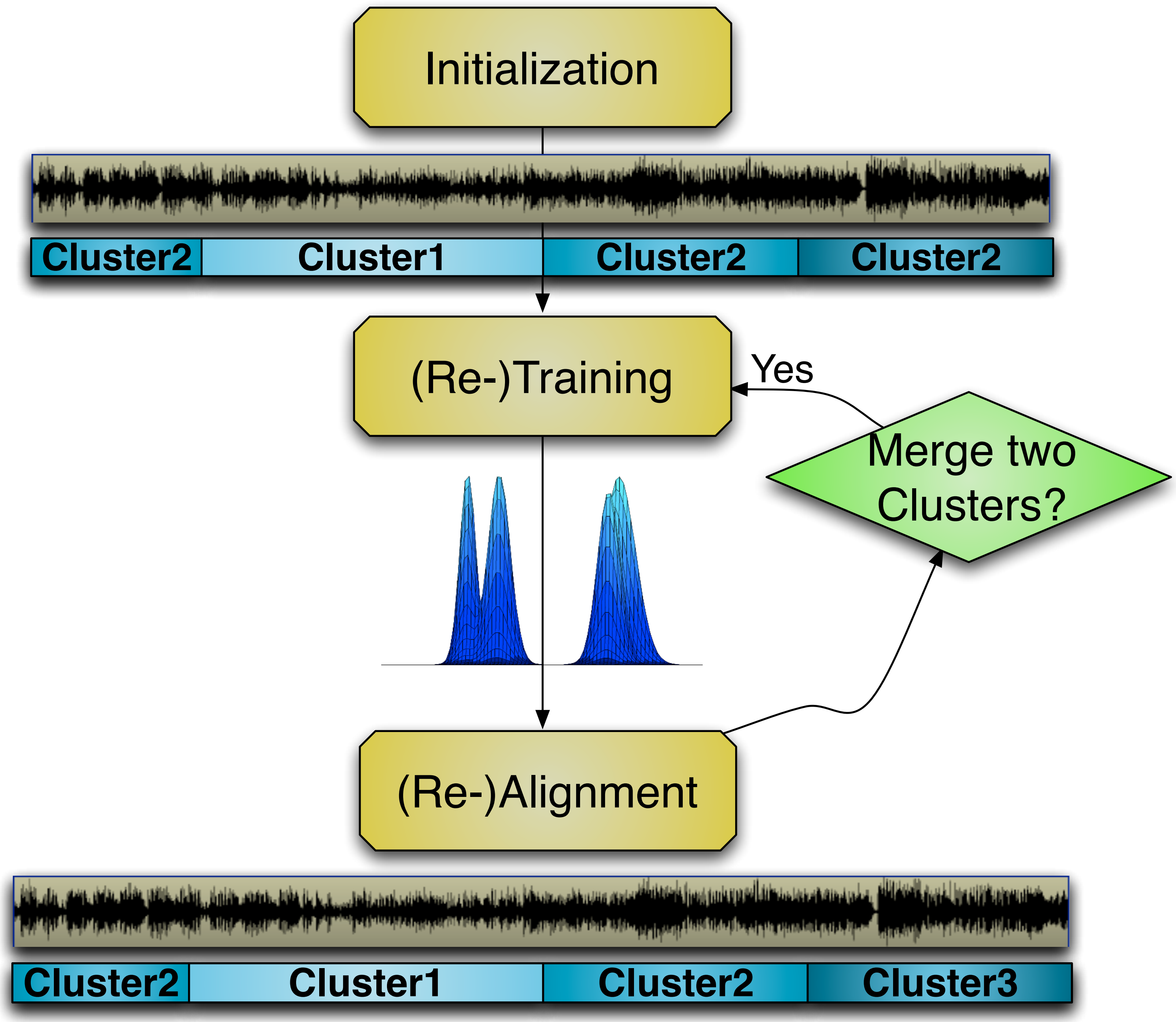

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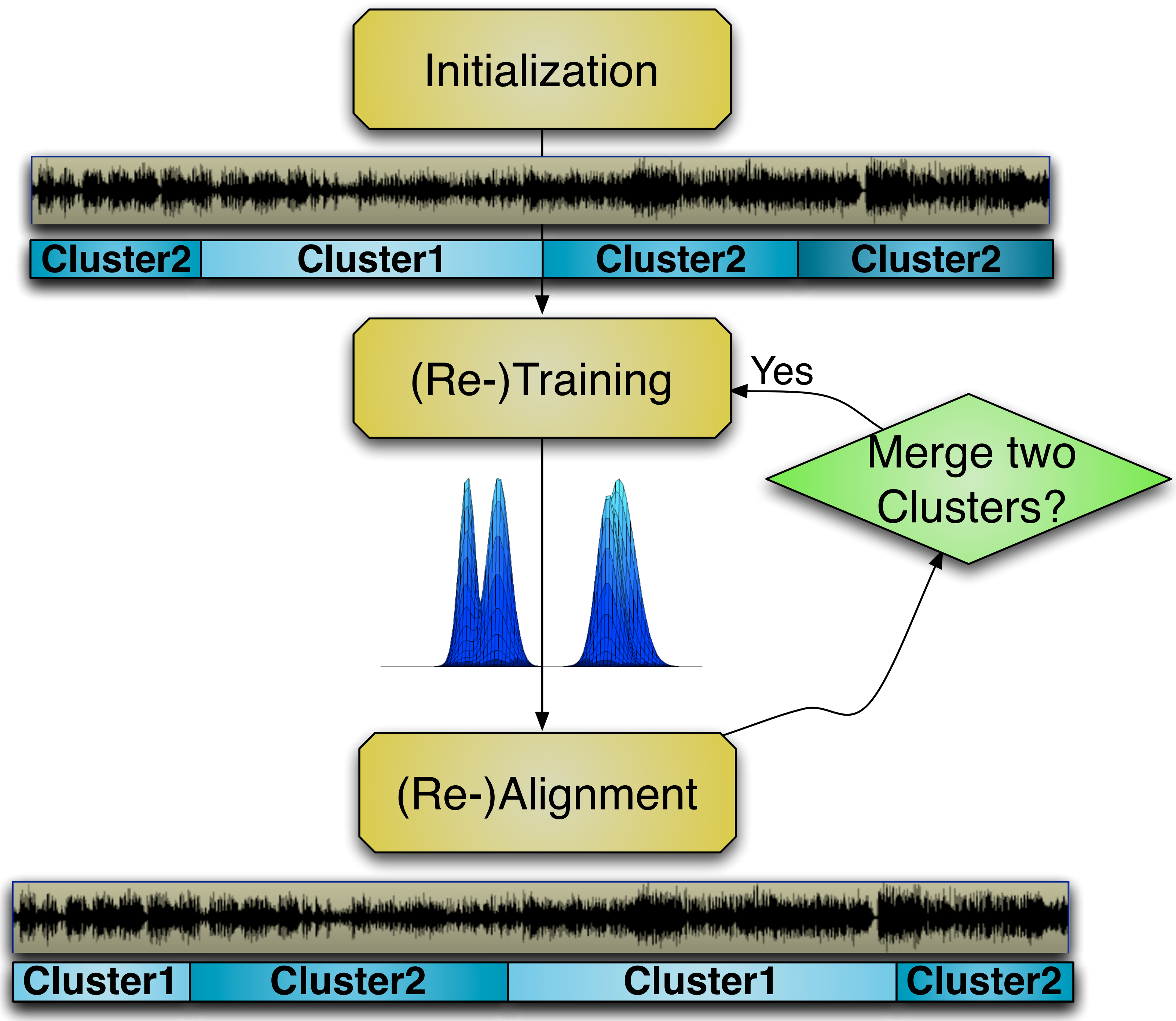

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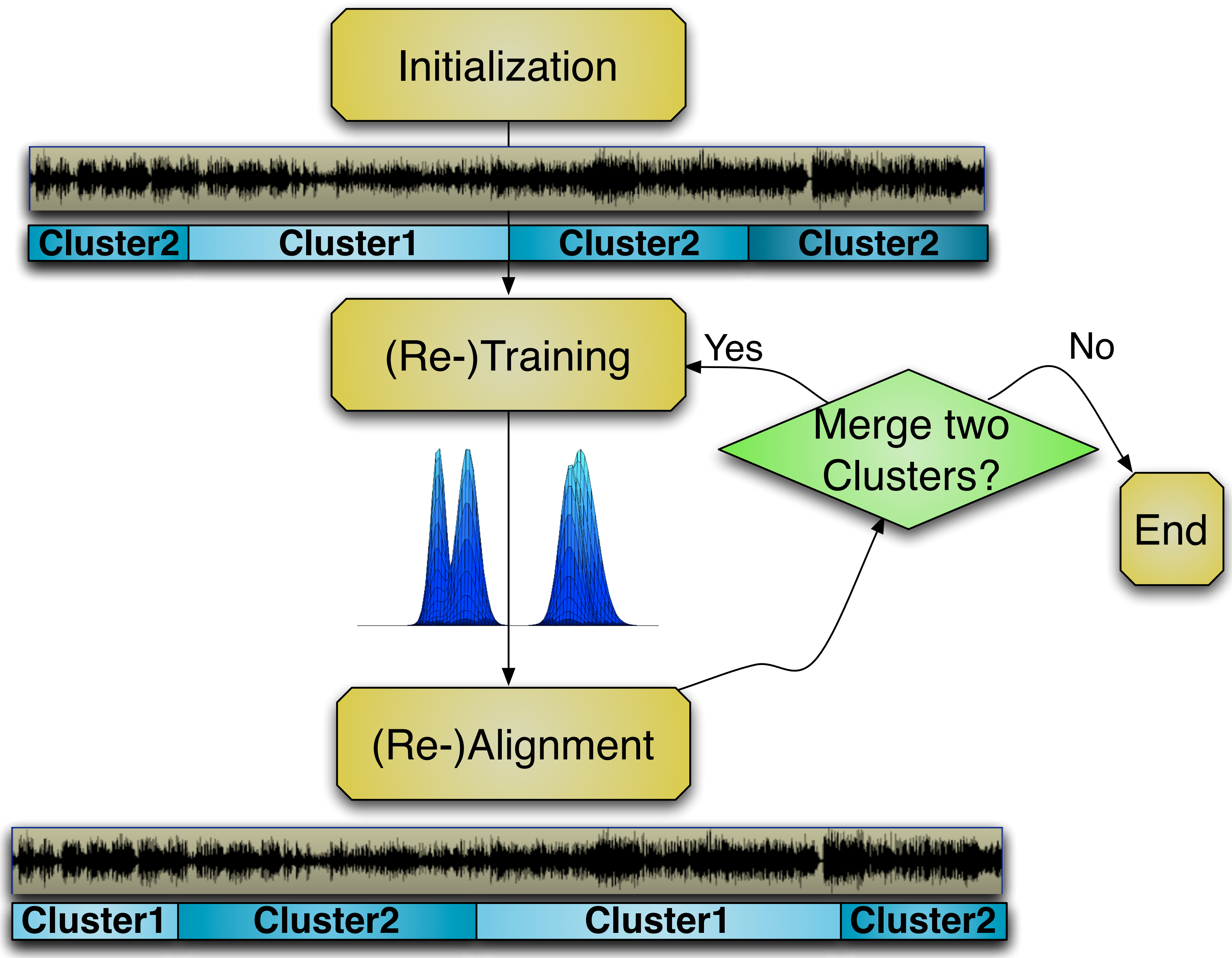

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- Various versions of Diarization Engines developed over the years
- Status: Research code but stable for some applications that are error tolerant

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- Online (single mic, "who is speaking now")

Basic Speaker Diarization: Facts

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- Features: MFCC19, no delta or deltadelta
- Speech/Non-Speech Detector external
- Runtime: ~ realtime (1h audio needs 1h processing on a single CPU, excluding speech/non-speech)

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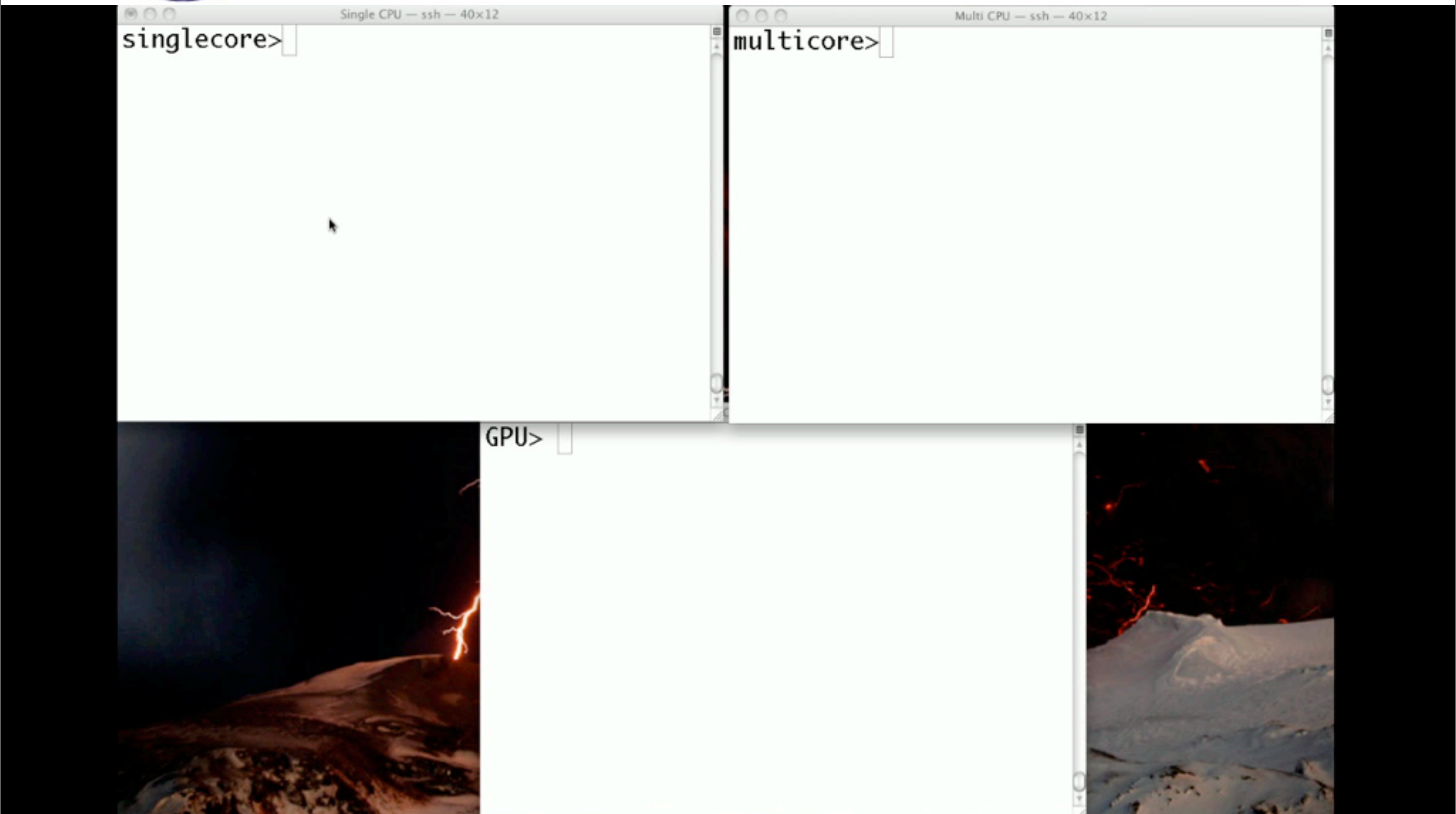
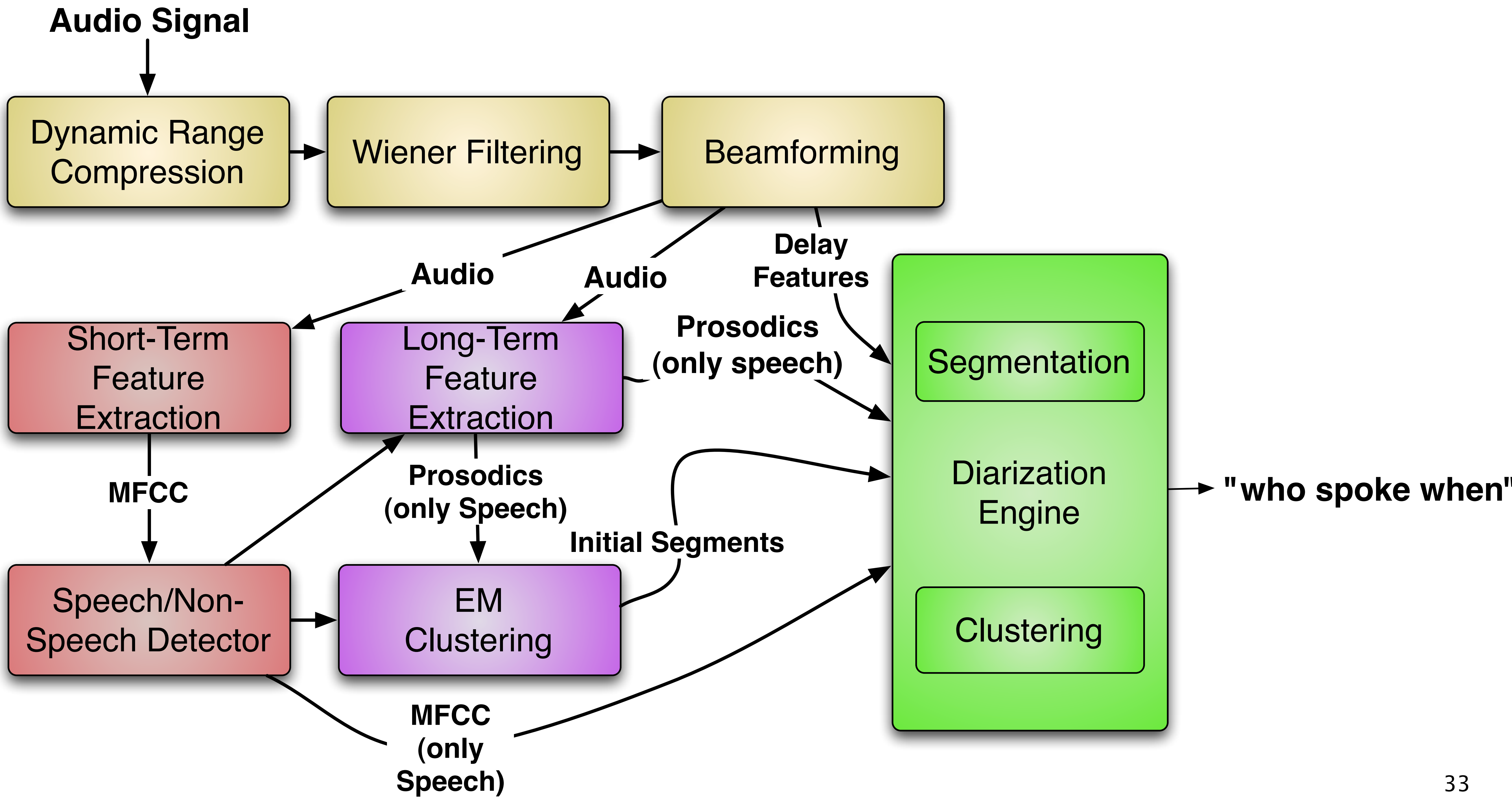
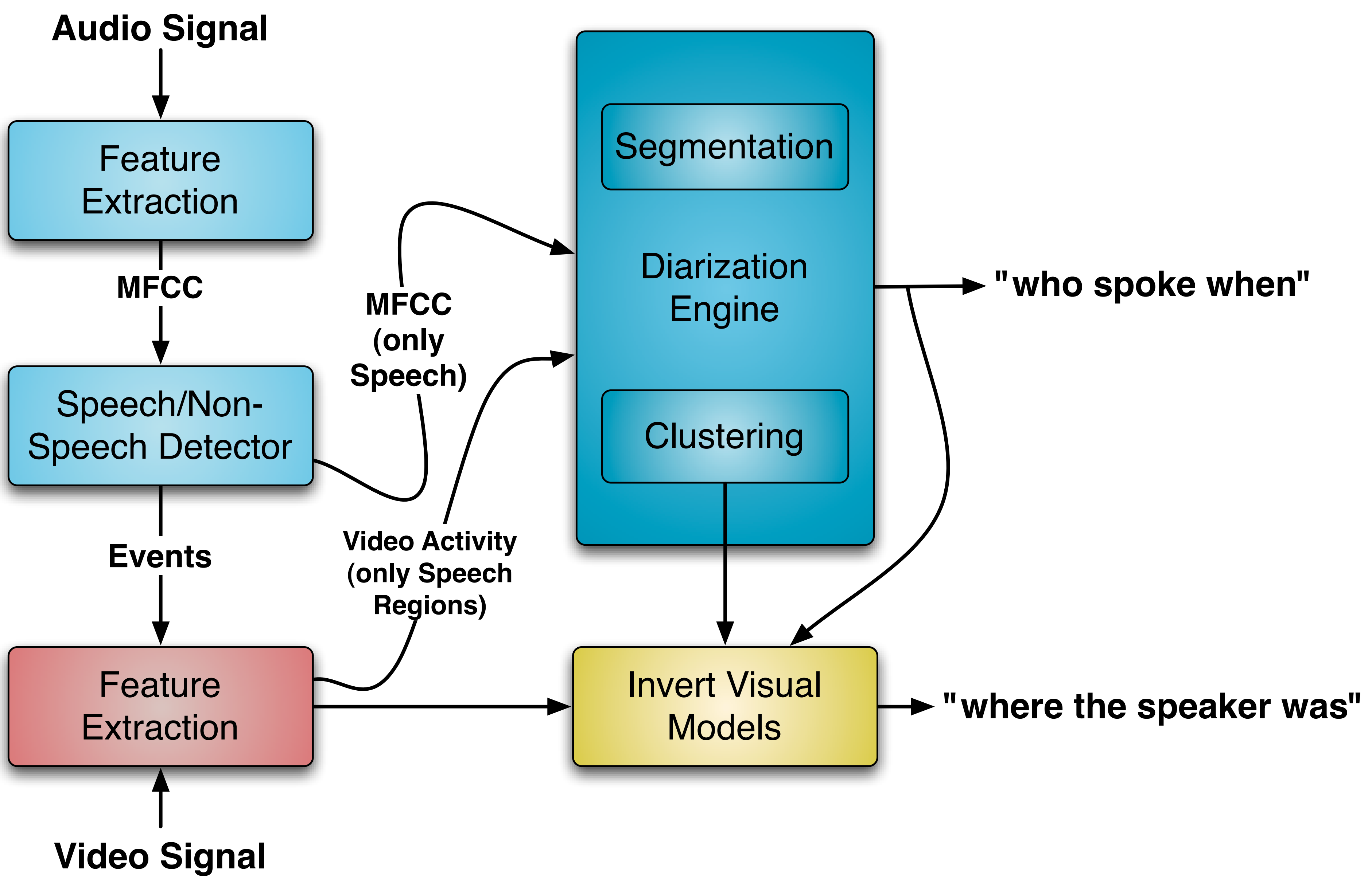
Demo: 1CPU vs 8CPU vs GPU



Most Accurate Speaker Diarization: Overview



Audio/Visual Speaker Diarization: Overview



Video Feature Extraction

MPEG-4 Video → Detect Skin Blocks → Avg. Motion Vectors → Divide Frames into n Regions → **n-dimensional activity vector**

Windowsize: 400ms

Audio/Visual Speaker Diarization: Facts

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- **One** engine for audio and video

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- Scales with n cameras

Audio/Visual Speaker Diarization: Facts

- **One** engine for audio and video
- Scales with n cameras
- Robust against visual changes such as different cloth, occlusions, etc...

  "A voiceprint does not care about somebody dimming the light"

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Audio/Visual Diarization: Example Video

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- Recording is at 16kHz.
- Recording is 15-60 minute length

Current Results using Different Inputs

Error/System	Basic System: 1 Audio Stream	8 Audio Streams	1 Audio Stream + 1 Camera	1 Audio Stream + 4 Cameras
Diarization Error Rate	32.09%	27.55%	27.52%	24.00%
Relative Improvement	baseline	14%	14%	25%
Core Speed (x realtime)	1.0	2.2	1.4	1.3

12 Meeting Recordings from AMI corpus

Most Accurate Results

Error/System	MFCC only (basic system)	Full System	Full System + One Camera
Diarization Error Rate	32.09%	20.33%	18.98%
Relative Improvement	baseline	36%	41%
Core Speed (x realtime)	1.0	2.5	2.9

12 Meetings from AMI corpus "VACE Meetings"

Top Error Sources

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- Overlapped Speech

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- Short Speech Segments (<2s)

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- Low SNR
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- Parameter mismatch, e.g. too few initial clusters

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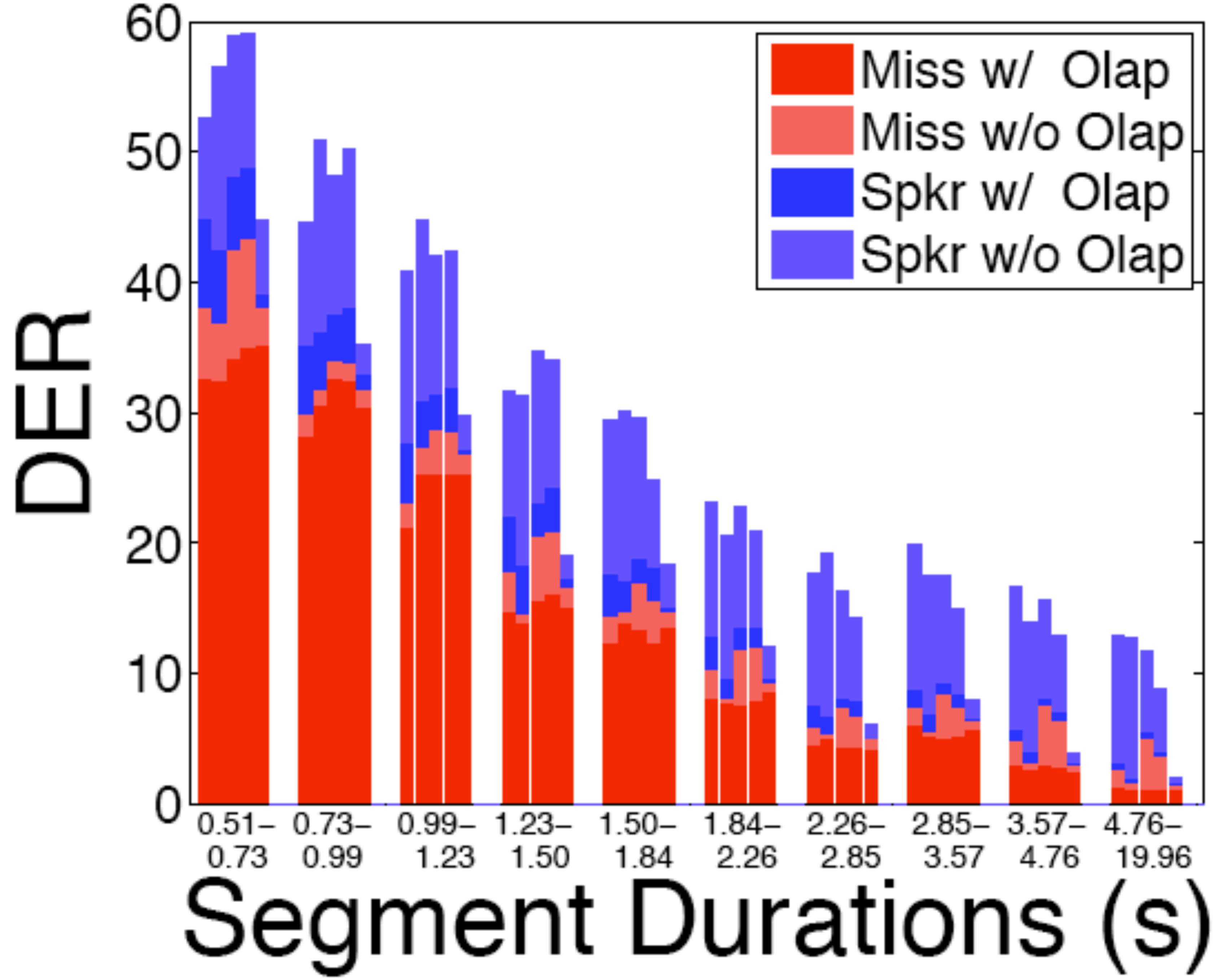
- Limited amount of speakers (4 or so)
- Speaker are well-distinguishable in their voice (e.g. male - female, young - old)
- Speakers are non-emotional
- Recording is at 16kHz or higher.

Future Work!



DER
60
50
40
30
20
10
0
Miss w/ Olap
Miss w/o Olap
Spkr w/ Olap
Spkr w/o Olap
0.51– 0.73
0.73– 0.99
0.99– 1.23
1.23– 1.50
1.50– 1.84
1.84– 2.26
2.26– 2.85
2.85– 3.57
3.57– 4.76
4.76– 19.96
Segment Durations (s)

Thank You!
Questions?

Some of the Presented Work
performed together with:
Mary Knox, Katya Gonina, Adam Janin
and others.