An overview of automatic speaker diarization systems

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Introduction to Speaker Diarization

- Speaker diarization is the task of determining **“who spoke when?”**

- Involve determining **the number of speakers** and identifying **the speech segments corresponding to each speaker**.

- A prepocessing for other downstream application. Such as speech retrieval, speech to text transcription and speaker recognition.

General architecture of Speaker Diarization

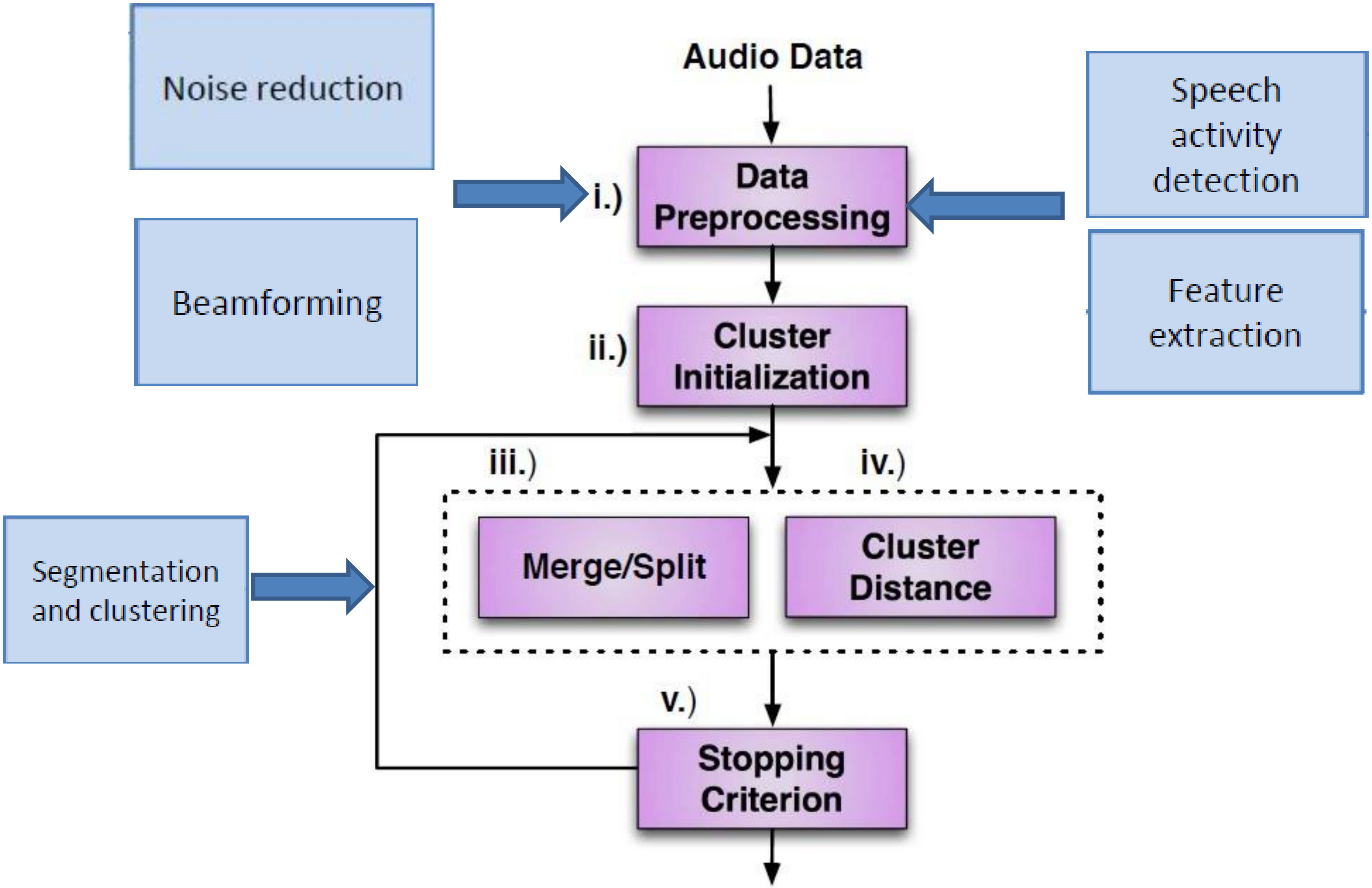


Figure 1 An overview of a typical diarization system

Main approaches for speaker diarization

Bottom-up approach:

● Training a number of clustering, merging and reducing the number of clusters until get the optimum number of clusters.

Top-down approach:

● Start with a single speaker model trained on all speech segment. Then add new speaker until the stop criterion.

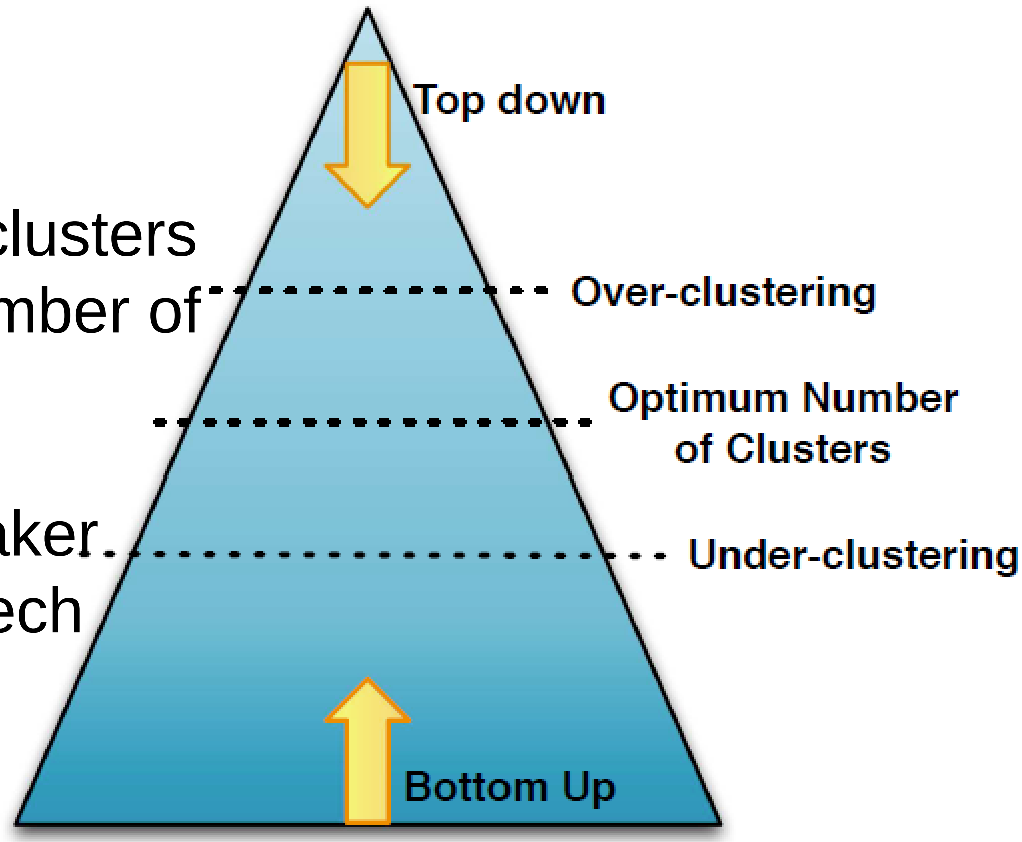
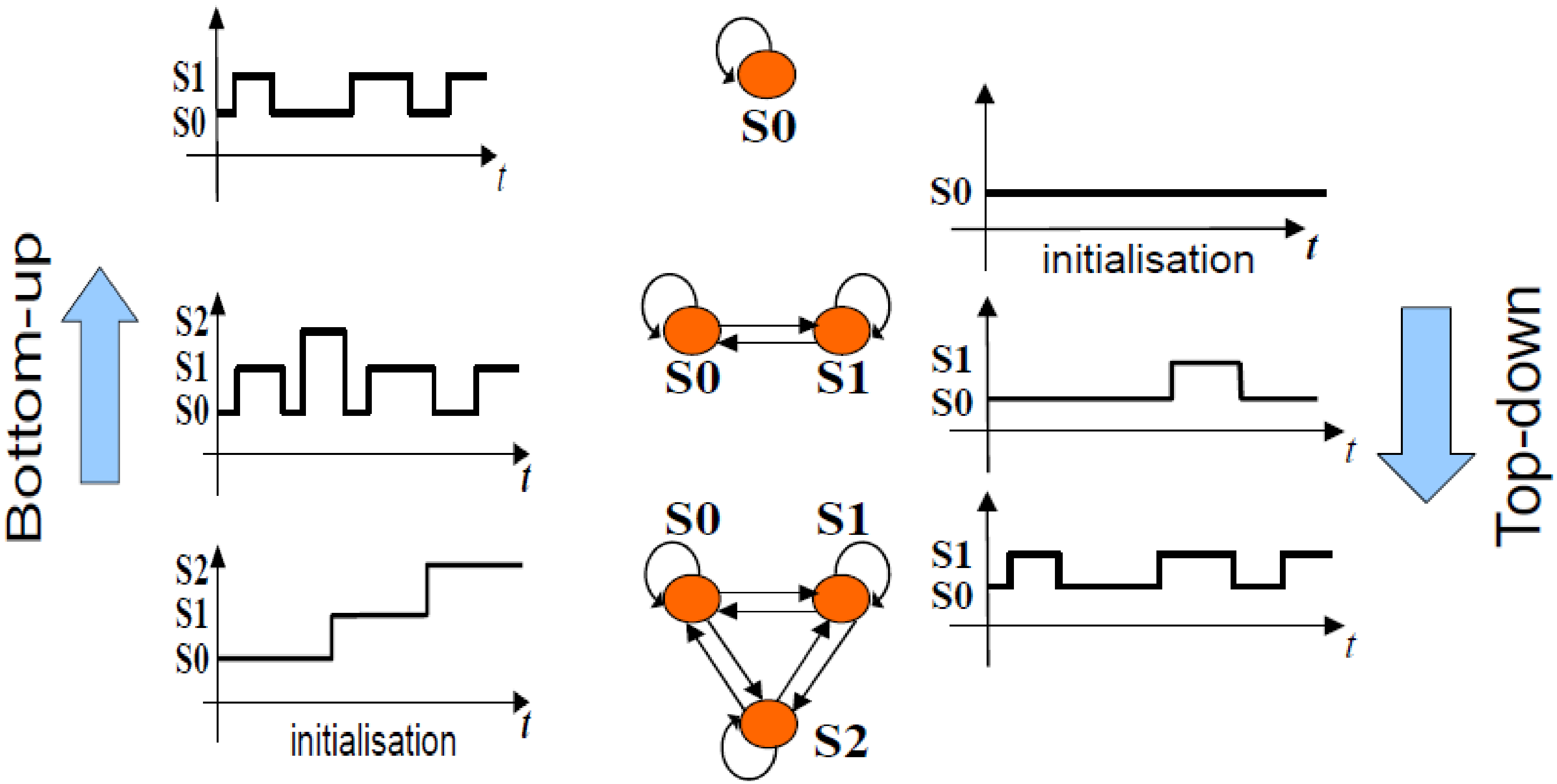


Figure 2 Alternative clustering schemas

Brief Introduction of Algorithm

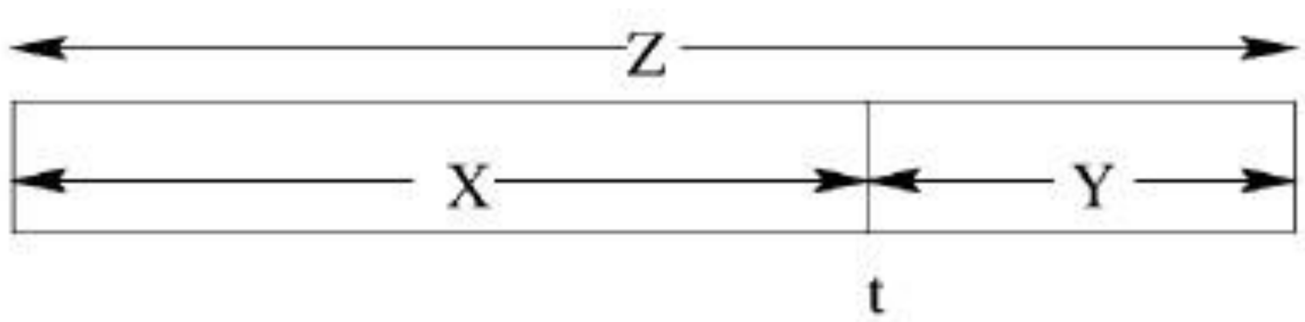


- Initialize clusters with the speech segments.
- Merge/split closet clusters.
- Update distances of remaining cluster to new cluster.
- Iterate until stopping criterion is met.
- Re-segmentation with GMM viterbi decoding.

Comparison and Combination

<table>
<tr><th>Bottom-up approach</th><th>Top-down approach</th><th>Combination</th></tr>
<tr><td>Agglomerative hierarchical clustering.</td><td>Divisive hierarchical clustering.</td><td rowspan="2">Treat top-down output as a base segmentation and apply bottom-up output to purify it.</td></tr>
<tr><td>Use segment to train model is likely to capture more purer models.
Bur it may corresponding to a single speaker or a phone class(short-term feature)</td><td>Use larger data to train small number of models
Normalize both phone class and speaker.
Can be purified.</td></tr>
</table>

Traditional Distance Metrics



0 The null hypothesis is that there is no speaker change at time t.

1 A speaker change point is hypothesized at time t

$$L_0 = \sum_{i=1}^{N_x} \log p(x_i|\theta_z) + \sum_{i=1}^{N_y} \log p(y_i|\theta_z)$$

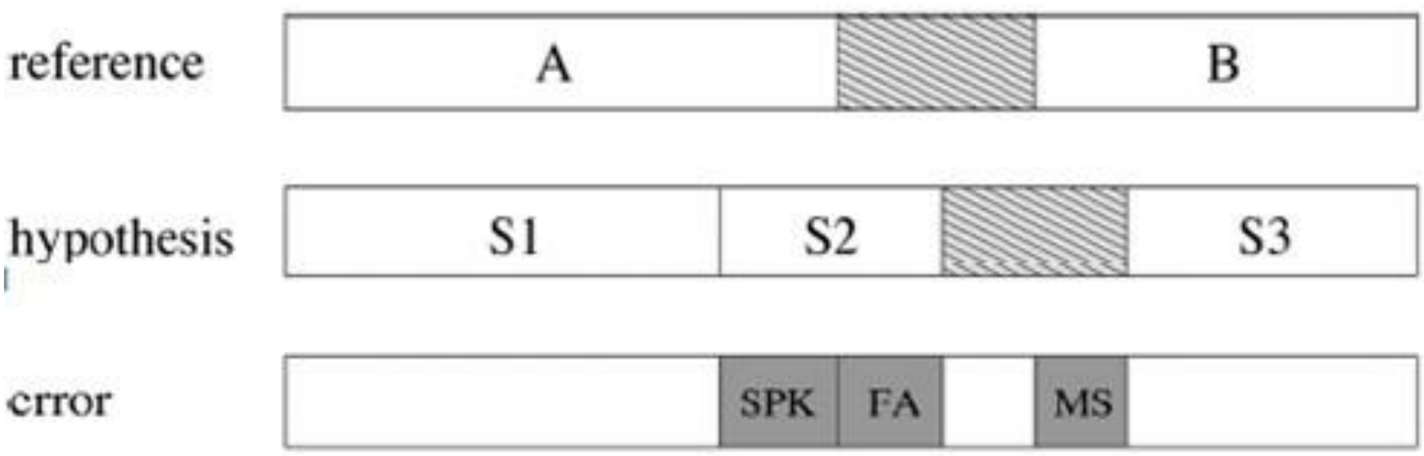
$$L_1 = \sum_{i=1}^{N_x} \log p(x_i|\theta_x) + \sum_{i=1}^{N_y} \log p(y_i|\theta_y).$$

LLR criterion: $d_{\text{llr}} = L_1 - L_0.$

BIC criterion: $d_{\text{bic}} = L_1 - L_0 - \frac{\lambda}{2} \cdot \Delta K \cdot \log N$

Evaluation approach

- Dataset: NIST has organized a series of benchmark evaluations.
- Ground truth: manual labeling of acoustic data.
- DER is used as a results. It is composed as following figure.



DER=Speaker Error+False Alarm/Missed speech error+overlapped error

Large variations
Not robust

Stability SAD

Unsolved problem

Current Research Directions

- From features
  - ◆ time-delay features. Combine acoustic features and inter-channel delay feature.
  - ◆ Prosodic features in diarization.
  - ◆ Fusing short term and long term.
- From models
  - ◆ Use eigenvoice model to represent speaker.
- From metrics
  - Reference Speaker Model proposed by Wang Gang.

Current Research Directions

- New approaches
  - the agglomerative information bottleneck (aIB)
  - the sequential information bottleneck

To finding the most compact representation C of data X that minimizes the mutual information I(X,C) and preserves as much information as possible about Y (maximizing I(C, Y)). It can significant saving in computation.

Current Research Directions

- Bayesian machine learning

  not aim at estimating the parameters of a system (i.e. to perform point estimates), but rather the parameters of their related distribution (hyperparameters).

Bset model

$$m = argmax_m \, p(m|Y) = argmax_m \, p(m)\, p(Y|m)/p(Y)$$

Marginal likehood $$p(Y|m) = \int d\theta \, p(Y|\theta, m) p(\theta|m)$$

Traditional often use MAP to estimate parameter $$\theta_{MAP} = argmax_\theta \; p(\theta) p(Y|\theta)$$

BIC $$log\, p(Y|m) = log\, p(Y|m, \hat{\theta}) - \frac{\nu}{2} log\, N$$

- Monte Carlo Markov Chains (MCMC) sampling method

Current Research Directions

- New approaches
  - Variational Bayes

$$log\, p(Y|m) = log \int d\theta dX\, p(Y, X, \theta|m)$$

Introduce a variational distribution and apply Jensen inequality

to define the upper bound on the marginal log likehood.

$$\begin{aligned} log\, p(Y|m) &\geq \int d\theta dX log\, q(X)q(\theta)\frac{p(Y, X, \theta|m)}{q(X)q(\theta)} = \\ &= \int d\theta q(\theta)[\int dX q(X) log \frac{p(Y, X|\theta, m)}{q(X)} + log\, \frac{p(\theta|m)}{q(\theta)}] = \\ & \int d\theta q(\theta) \int dX q(X) log\, p(Y, X|\theta, m) - \int dX q(X)\, log\, q(X) + \\ &- \quad log\, \frac{q(\theta)}{p(\theta|m)} = F_m(q(X), q(\theta)) \end{aligned}$$

outlook

- Overlapped speech.
- Robust to unseen variations.
- More efficient in order to process increasing dataset sizes.
- Aim at stream audio indexing.

References

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Thanks