Self-Tuning Spectral Clustering for Speaker Diarization

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Unsupervised Speaker Diarization

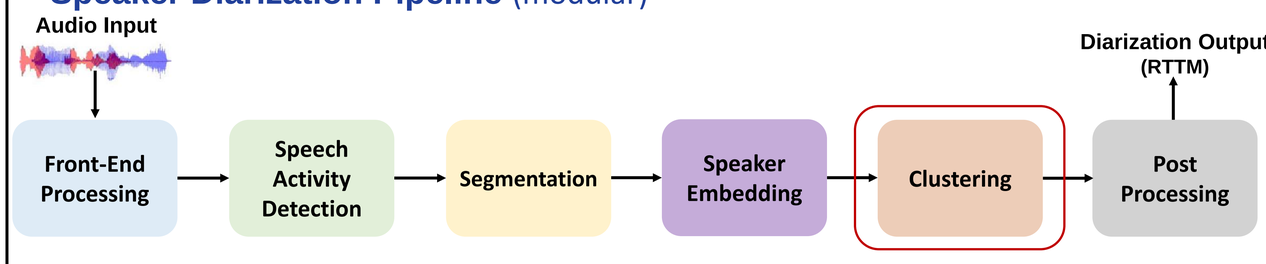
Speaker Diarization answers ***"who spoke when"*** in a multi-speaker audio conversation [1].

Applications Meeting transcription, cocktail party problem, forensics, etc.

Challenges

- ❑ Unknown number of speakers, Overlapping speech, Unbalanced speaker time
- ❑ Acoustic mismatch, Speaker variability, Scenario, etc.

Speaker Diarization Pipeline (modular)



Spectral Clustering Based Speaker diarization

Spectral clustering has proven effective in grouping speech representations for speaker diarization. Post-processing the affinity matrix remains difficult due to the need for careful tuning before the Laplacian.

Semi-supervised: Conventional spectral clustering (CSC)[2]

- ❑ It requires the Dev set to tune the pruning threshold
- ❑ Prunes a fixed number of elements in each row, equal to $\lfloor n(1-\alpha) \rfloor$

Unsupervised: Auto-tuning Spectral Clustering (ASC)[3]

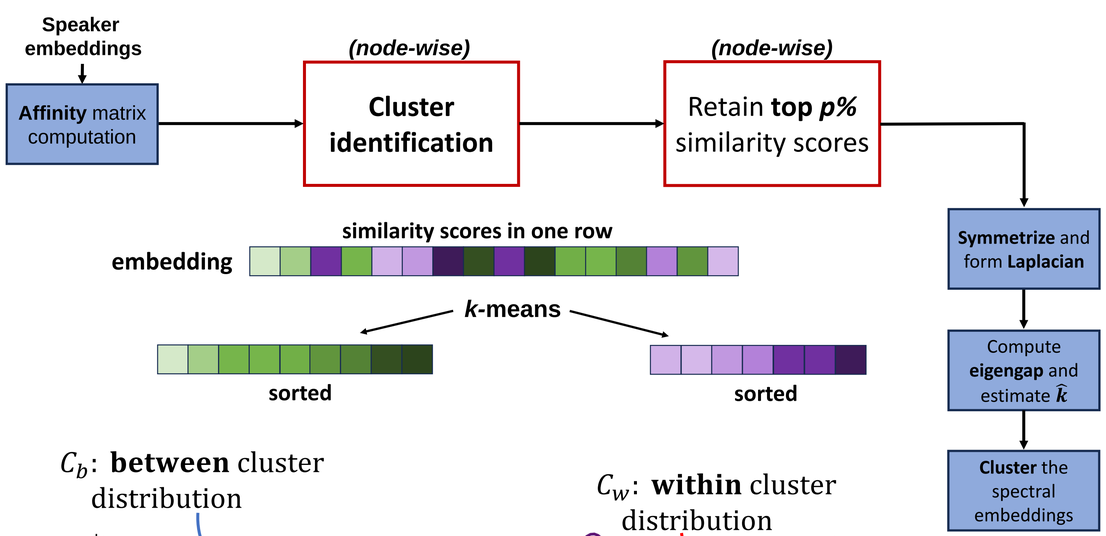
- ❑ It auto-tunes clustering parameters using normalized maximum eigengap (NME) values
- ❑ Eliminate the need for parameter tuning over the Dev set.
- ❑ Prunes a fixed number of elements from in each row.
- ❑ Its complexity is $O(Pn^3) = O(n^4)$,
  where $P = \lfloor n/4 \rfloor$ is the recommended number of binarized similarity matrices.

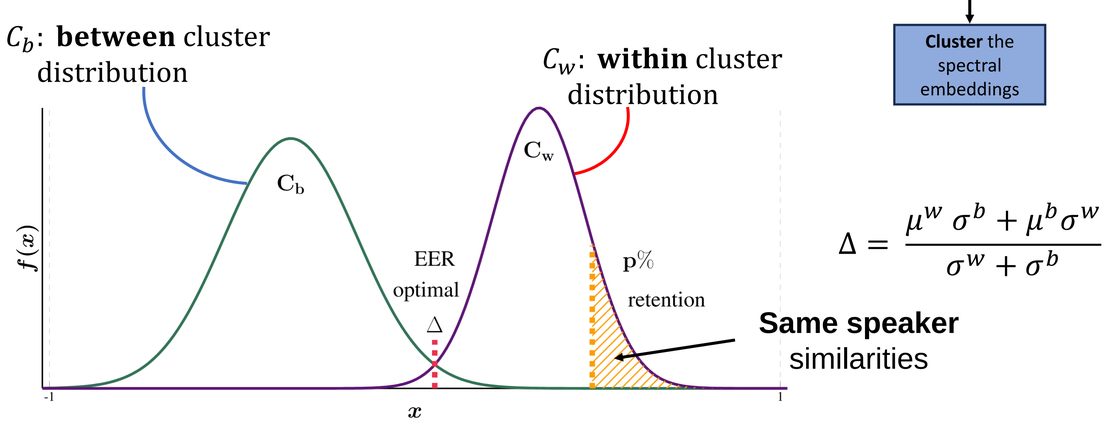
Proposed Methodology

Unsupervised: Spectral clustering with adaptive neighbours

- ❑ Speaker similarities in terms of two gaussian distributions is exploited using *k*-means clustering.
- ❑ A sparse affinity matrix called spectral clustering on p-neighbourhood retained affinity matrix (SC-pNA) is created.
- ❑ Initially, we chose EER-Δ as the pruning threshold.
- ❑ EER-Δ points where the false rejection rate and the false acceptance rate coincide, inspired from the equal error rate (EER).
- ❑ Later, we chose a more aggressive threshold over EER- Δ, by retaining top p% within speaker similarities.
- ❑ p = 20% is identified as the best selection for p.
- ❑ The complexity of SC-pNA is $O(n^3)$, more efficient than ASC.

SC-pNA Algorithm





$$\Delta = \frac{\mu^w \sigma^b + \mu^b \sigma^w}{\sigma^w + \sigma^b}$$

Experimental Setup

Dataset

DIHARD-III. It comprise data from 11 diverse domains.

Metric

Diarization error rate (DER) = $\frac{\textbf{Missed speech} + \textbf{False alarm} + \textbf{Speaker error}}{\textbf{Total speaking time}}$

SD system

SpeechBrain: an open source speech toolkit.

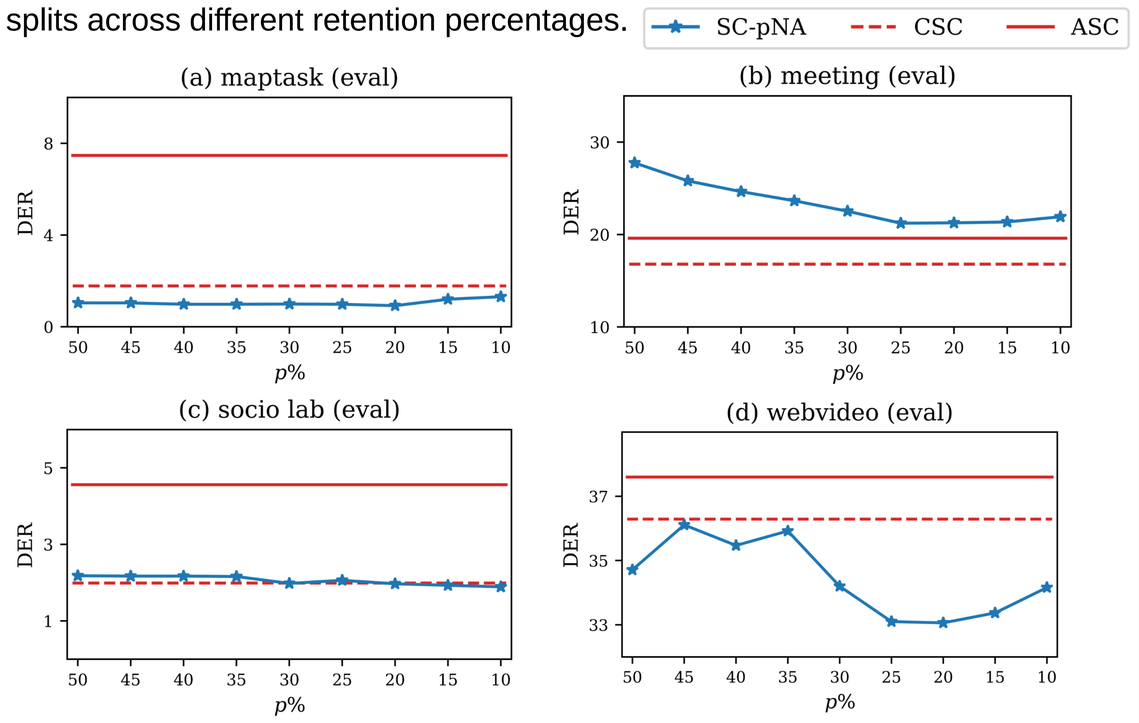
Results and Discussion

Speaker diarization system performance in terms of DER **(lower is better).** The semi-supervised CSC acts as a baseline along with unsupervised ASC, EER-Δ and the SC-pNA over DIHARD-III dataset Eval split.

	Semi-supervised (baseline)	Unsupervised		
Domain	**CSC**	**ASC**	**EER-Δ**	**SC-pNA**
broadcast interview	3.58	**3.67**	6.82	4.77
court	2.09	**2.73**	17.51	7.15
cts	6.58	7.3	12.66	**6.63**
maptask	1.78	7.47	5.25	**0.92**
meeting	16.79	**19.60**	40.84	21.26
socio lab	1.99	4.56	8.66	**1.97**
webvideo	36.29	37.60	36.52	**33.06**
restaurant	29.93	**33.35**	59.78	38.81
Audiobooks	0.50	27.53	0.18	**0.09**
clinical	4.34	10.62	31.23	**3.31**
socio field	5.18	10.30	16.57	**3.79**
Overall	9.97	13.11	20.08	**10.27**

Hyper-parameter selection

The variation in the speaker diarization performance in terms of DER across four data splits across different retention percentages.



Acknowledgements

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References

1. Dawalatabad, N., Ravanelli, M., Grondin, F., Thienpondt, J., Desplanques, B., Na, H. (2021) ECAPA-TDNN Embeddings for Speaker Diarization. Proc. Interspeech 2021.
2. Tae Jin Park, Naoyuki Kanda, Dimitrios Dimitriadis, Kyu J. Han, Shinji Watanabe, Shrikanth Narayanan, A review of speaker diarization: Recent advances with deep learning, Computer Speech & Language, 2022.
3. T. J. Park, K. J. Han, M. Kumar and S. Narayanan, "Auto-Tuning Spectral Clustering for Speaker Diarization Using Normalized Maximum Eigengap," in IEEE Signal Processing Letters.