HIGHLY EFFICIENT REAL-TIME STREAMING AND FULLY ON-DEVICE SPEAKER DIARIZATION WITH MULTI-STAGE CLUSTERING

Quan Wang^{*}, Yiling Huang^{*}, Han Lu, Guanlong Zhao, Ignacio Lopez Moreno

Google LLC, USA

{ quanw, yilinghuang, luha, guanlongzhao, elnota }@google.com

ABSTRACT

While recent research advances in speaker diarization mostly focus on improving the quality of diarization results, there is also an increasing interest in improving the efficiency of diarization systems. In this paper, we propose a multi-stage clustering strategy, that uses different clustering algorithms for input of different lengths. Specifically, a fallback clusterer is used to handle short-form inputs; a main clusterer is used to handle medium-length inputs; and a pre-clusterer is used to compress long-form inputs before they are processed by the main clusterer. Both the main clusterer and the pre-clusterer can be configured with an upper bound of the computational complexity to adapt to devices with different constraints. This multi-stage clustering strategy is critical for streaming on-device speaker diarization systems, where the budgets of CPU, memory and battery are tight.

Index Terms— Speaker diarization, clustering, efficiency, multi-stage, FLOPs

1. INTRODUCTION

Research advances in the speaker diarization community have been tackling various challenges in the past decade. Different clustering algorithms including agglomerative hierarchical clustering (AHC) [1], K-means [2] and spectral clustering [3] had been explored. Specifically, many works had been proposed to further improve the spectral clustering algorithms for speaker diarization, such as auto-tune [4], speaker turn constraints [5], and multi-scale segmentation [6]. To better leverage training datasets that are annotated with timestamped speaker labels, supervised diarization approaches have been explored, including UIS-RNN [7], DNC [8], and EEND [9, 10]. Approaches such as TS-VAD [11] and EEND-SS [12] had been proposed to solve the speech separation and diarization problems jointly [13, 14]. Various other advances are described and discussed in literature reviews and tutorials [15, 16].

Despite these advances, another challenge that prevents speaker diarization systems from being widely used in production environments is the efficiency of the system, which is also a relatively less discussed topic in the speaker diarization community. In this paper, we are particularly interested in streaming on-device speaker diarization for mobile phones, such as annotating speaker labels in a recording session. The requirements for such applications are multifaceted:

 The diarization system must perform well on audio data from multiple domains. Since supervised diarization algorithms such as UIS-RNN [7] and EEND [9] are highly dependent on the domain of the training data, and often suffer from insufficient training data, we prefer to use unsupervised clustering algorithms in such applications.

- 2. The diarization system must perform well on input audio of variable lengths, from a few seconds to a few hours.
- The system must work in a streaming fashion, producing realtime speaker labels while audio being recorded by the microphone on the device.
- 4. The diarization system must be optimized to be highly efficient, to work within the limited budget of CPU, memory and power. Particularly, the computational cost of the clustering algorithm must be upper bounded to avoid out-of-memory (OOM) or excessive battery drain issues on mobile devices, even if the input audio is hours long.

To meet these requirements, we propose a multi-stage clustering strategy that combines AHC and spectral clustering, and leverage the strength of both algorithms. Based on our experiments, AHC is good at identifying single speaker versus multiple speakers, but often ends up with too many small clusters, especially for long-form speech. Spectral clustering is great at estimating the number of speakers with the eigen-gap approach, but usually under the assumptions that there are at least two different speakers, and there are sufficient data points to be clustered. At the same time, the computational cost of spectral clustering is too expensive for long-form speech, mostly due to the calculation and eigen decomposition of the Laplacian matrix. Based on the above observations, we use different clustering algorithms for inputs of different lengths. When input audio is short, we use AHC to avoid the insufficient data problem of spectral clustering; when input audio is of medium length, we use spectral clustering for better speaker count estimate; when input audio is long, we first use AHC as a pre-clusterer to compress the inputs to hierarchical cluster centroids, then use spectral clustering to further cluster these centroids. We enforce an upper bound on the number of inputs to the AHC pre-clusterer by caching and re-using previous AHC centroids, such that the overall computational cost of the entire diarization system is always bounded.

2. SYSTEM DESCRIPTION

2.1. Recap of baseline system

Our speaker diarization system is largely built on top of the Turnto-Diarize system described in [5], which consists of a speaker turn detection model, a speaker encoder model, and unsupervised clustering. The speaker turn detection model is a Transformer Transducer (T-T) [17] trained to output automatic speech recognition (ASR) transcripts augmented with a special token <st> to represent a speaker turn. This T-T model has $\sim 13M$ parameters in total. The speaker encoder is a text-independent speaker recognition

^{*}Equal contribution.



Fig. 1. Diagram of the multi-stage clustering strategy. L and U_1 are the lower bound and upper bound of the main clusterer, respectively. U_2 is the upper bound of the pre-clusterer.

model trained with the generalized end-to-end extended-set softmax (GE2E-XS) loss [18, 19], which consists of 12 conformer [20] layers each of 144-dim, followed by an attentive temporal pooling module [21]. The speaker encoder model has \sim 7.4M paramters in total.

To reduce the length of the sequence to be clustered, the speaker encoder produces only one embedding for each speaker turn, or every 6 seconds if a single turn is longer than that. To achieve great performance and streaming diarization at the same time, we run spectral clustering in an online fashion: every time when we have a new speaker embedding, we run spectral clustering on the entire sequence of all existing embeddings. This means it's possible to correct previously predicted speaker labels in a later clustering step.

This baseline system has shown great potential in many applications, but still have several constraints when deploying to mobile applications:

- Spectral clustering uses the eigen-gap criterion to estimate the number of speakers. But this approach usually assumes there are at least two speakers. It often fails to distinguish single speaker versus multiple speakers.
- Spectral clustering works best when there are sufficient inputs to be clustered. This means for the first few minutes during the streaming diarization, the quality of the streaming outputs can be significantly lower, resulting in low user retention.
- 3. The computational cost of spectral clustering on N embeddings is $O(N^{\omega})$, where ω depends on the specific implementation and the desired precision [22]. Similar to matrix multiplication, ω has a theoretical lower bound of $\omega \ge 2.37$ [23]. The high cost will result in huge latency when the input is long-form, *e.g.* when user attempts to diarize hours-long recordings, thus is not acceptable for streaming applications.

2.2. Multi-stage clustering

A high-level diagram of the multi-stage clustering strategy is illustrated in Fig. 1. Assume the input sequence consists of N speaker embeddings from the speaker encoder model. The clustering algorithm being used will vary based on different values of N, as described below.

2.2.1. Speaker turn detection

The speaker encoder model will produce a new speaker embedding both at detected speaker turns and when reaching a maximal length of a segment (*i.e.* 6 seconds). If no speaker turn token <st> was detected for the N speaker embeddings, we directly output a single speaker without running any clustering algorithm.

2.2.2. Fallback clusterer

Since spectral clustering cannot handle small inputs very well, we could use a different fallback clustering algorithm when N < L, where L is the lower bound of the number of inputs to spectral clustering. In this paper, we use AHC with the average linkage type as our fallback clusterer. The stopping criterion of the AHC is based on a threshold pre-determined on dev datasets.

2.2.3. Main clusterer

If the input size N is between the lower and upper bounds of the spectral clustering algorithm, *i.e.* $L \leq N < U_1$, the main clusterer (*i.e.* spectral clustering) is used to cluster the inputs directly. With this upper bound, the computational cost of spectral clustering will not exceed $O(U_1^{\omega})$ [22]. Since auto-tune [4, 5] is used to improve the quality of spectral clustering results, the computational cost needs to be multiplied by the number of search steps.

2.2.4. Pre-clusterer

If $U_1 \leq N < U_2$, we use a pre-clusterer to reduce the size of the clustering inputs first. Here we use AHC with the complete linkage (*a.k.a.* farthest neighbor) type as our pre-clusterer. When the number of clusters reduces to U_1 , the AHC pre-clusterer will stop, and we compute the centroids of these U_1 pre-clusters. Then we feed these U_1 centroids as the input to the main clusterer to get the final speaker labels of all original inputs.

2.2.5. Dynamic compression

With the pre-clusterer, we upper bounded the cost of spectral clustering to $O(U_1^{\omega})$. However, the AHC pre-clusterer itself has a computational cost of $O(N^2)$ or larger, depending on implementation. When the input audio is very long, this cost will still be unacceptable. Thus we propose a dynamic compression approach to also enforce an upper bound U_2 for the AHC pre-clusterer.

During the streaming diarization process, when $N = U_2$, we trigger the AHC pre-clusterer, and compress the U_2 inputs to U_1 pre-cluster centroids. We store these U_1 centroids and the mapping between these centroids to original inputs in an internal cache. For future clustering steps when $N > U_2$, the first U_2 inputs are replaced

 Table 1. A list of our evaluation datasets. Some of the datasets had been filtered or processed due to license issues.

| Dataset | Domain | Num. | Num. | Avg. | Avg. |
|----------|-----------|------|-------|---------|--------|
| | | utt | hours | spk/utt | length |
| AMI | Meeting | 16 | 9.1 | 4 | 34min |
| Callhome | Telephone | 20 | 1.7 | 2 | 5min |
| DIHARD1 | Mixed | 114 | 16.2 | 3.3 | 8.5min |
| Fisher | Telephone | 172 | 28.7 | 2 | 10min |
| ICSI | Meeting | 13 | 5 | 6.4 | 23min |
| Inbound | Telephone | 250 | 21 | 4.3 | 5min |
| Outbound | Telephone | 450 | 45.6 | 2 | 6.1min |

by the cached U_1 centroids, and the AHC pre-clusterer will only run on $N' = U_1 + (N - U_2)$ inputs.

As N increases, N' will hit the upper bound U_2 again. Thus we need to update the cached centroids and the centroid-to-input mapping every $U_2 - U_1$ steps. The number of cached centroids is always U_1 , and it maps to $U_2 + (K-1) \cdot (U_2 - U_1)$ original inputs, where K is the number of times that the input to AHC clusterer reached U_2 previously. For each individual step, the cost of AHC pre-clusterer is upper bounded to $O(U_2^2)$.

2.2.6. Cost analysis

With the mutli-stage clustering strategy described above, the input size to the spectral clustering algorithm is upper bounded to U_1 , and the input size to the AHC algorithm is upper bounded to U_2 . Thus the overall computational cost of an individual clustering step is upper bounded to $O(U_1^{\omega}) + O(U_2^2)$, where $2.37 \le \omega \le 3$ depends on the specific implementation. At the same time, due to the dynamic compression, we only need to store at most U_2 embeddings/centroids in memory, instead of all the previous N embeddings. Thus both the time complexity and space complexity of the clustering algorithm are upper bounded to a configurable constant.

3. EXPERIMENTS

3.1. Metrics

To evaluate the impact of different components that we proposed in the multi-stage clustering strategy, we perform a careful ablation study, and report the Diarization Error Rate (DER) of different setups on various evaluation datasets. When computing DER, we tolerate a collar value of 250ms before and after each reference speaker segment boundary. For AMI, Callhome, Fisher, and ICSI, we convert their customized annotations into the Rich Transcription Time Marked (RTTM) format. DIHARD1 is already using the RTTM format and therefore no conversion is required. We then use the nonoverlapping union of the RTTM segments as the final Un-partitioned Evaluation Map (UEM), except for DIHARD1 which provides its own UEM files. To estimate the long-form efficiency, we report the total number of floating point operations (FLOPs) required to perform one individual clustering step for a specific value of N.

3.2. Datasets

The training data for the speaker turn detection model include Fisher [24] training subset, Callhome American English [25] training subset, AMI training subset, ICSI training subset ¹, 7500 hours of internal long-form videos, and 80 hours of internal simulated

| Table 2. DER (%) on short-form segmented versions of the evalu- |
|---|
| ation datasets for different setups of the fallback clusterer. L is the |
| lower bound of the main clusterer, and $L = 0$ means there is no |
| fallback clusterer. |

| Datasets | Length | DER (%) | | | | | |
|----------|--------|---------|--------|--------|--|--|--|
| Datasets | Lengui | L = 0 | L = 25 | L = 50 | | | |
| AMI | | 13.25 | 6.73 | 6.64 | | | |
| Callhome | | 12.34 | 6.8 | 6.8 | | | |
| DIHARD1 | | 33.04 | 26.47 | 26.39 | | | |
| Fisher | 20.0 | 12.84 | 4.08 | 4.08 | | | |
| ICSI | 508 | 17.96 | 5.35 | 5.35 | | | |
| Inbound | | 13.8 | 5.36 | 4.96 | | | |
| Outbound | | 17.91 | 9.39 | 9.22 | | | |
| Average | | 17.31 | 9.17 | 9.06 | | | |
| AMI | | 16.81 | 8.48 | 6.95 | | | |
| Callhome | | 12.11 | 5.74 | 6.06 | | | |
| DIHARD1 | 60s | 35.85 | 26.9 | 27.03 | | | |
| Fisher | | 8.6 | 3.59 | 3.25 | | | |
| ICSI | | 20.99 | 7.24 | 6.16 | | | |
| Inbound | | 13.76 | 6.02 | 5.1 | | | |
| Outbound | | 14.48 | 9.38 | 8.66 | | | |
| Average | | 17.51 | 9.62 | 9.03 | | | |
| AMI | | 14.74 | 14.06 | 8.04 | | | |
| Callhome | 120s | 6.56 | 6.16 | 6.44 | | | |
| DIHARD1 | | 33.34 | 32.27 | 27.19 | | | |
| Fisher | | 2.43 | 2.41 | 2.54 | | | |
| ICSI | | 13.35 | 12.98 | 7.06 | | | |
| Inbound | | 10.02 | 9.22 | 5.49 | | | |
| Outbound | | 7.55 | 7.36 | 7.94 | | | |
| Average | | 12.57 | 12.07 | 9.24 | | | |

business meeting recordings. The training data for the speaker encoder model are the same as [26]. Our experiments abide by Google AI principles [27].

Our evaluation datasets are listed in Table 1. Some additional details are listed below:

- 1. For AMI [28], we use the official "Full-corpus-ASR partition"² test subset. The speaker label ground truth was obtained based on the word-level annotations in the v1.6.2 AMI manual annotation release.
- 2. For Callhome American English Speech [25], we only evaluate on the official evaluation subset, as the training subset is used for training the speaker turn detection model.
- 3. For DIHARD1 [29], we use the eval subsets from 9 sources, but remove all YouTube-based data. We use the original UEM files from the challenge. Since the original UEM include overlapping speech which is not handled by our system, we expect the DER numbers to be high on this dataset.
- 4. For Fisher [24], we use a test subset of 172 utterances.³
- 5. For ICSI [30], we use a test subset that is segmented to shorter utterances of less than 30 min⁴.
- 6. "Outbound" and "Inbound" are vendor-provided call center telephone conversations between call center attendants and customers, initiated by the call center and by customers, respectively. These had also been used in [5].

As discussed in Sec 1, short-form performance is also critical for on-device streaming applications. To measure the quality of shortform inputs, we created segmented versions of the above mentioned datasets, where each utterance is approximately only 30, 60 or 120 seconds.

https://github.com/kaldi-asr/kaldi/tree/master/egs/ icsi

²https://groups.inf.ed.ac.uk/ami/corpus/datasets.shtml

³https://github.com/google/speaker-id/blob/master/ publications/Multi-stage/evaluation/Fisher/eval_whitelist. txt

⁴https://github.com/google/speaker-id/tree/master/ publications/Multi-stage/evaluation/ICSI/eval_ segmentation.csv

Table 3. Speaker count errors and breakdown. We show the Mean Absolute Error (MAE) of speaker count for each dataset, along with the breakdown numbers in the parentheses: (percentage of utterances with correct number of speakers, percentage of utterances with overestimated number of speakers, percentage of utterances with underestimated number of speakers). L = 0 indicates we only use the main clusterer, while $L = \inf$ indicates only the fallback clusterer is used.

| Mean absolute error of speaker count (% of correct estimate, % of over estimate, % of under estimate) | | | | | | | | | | |
|---|------------------------------------|--------------------------------|----------------------------------|--------------------------------|----------------|------------------------------|---------------------------------|---------------------------------|--|--|
| System | AMI | Callhome | DIHARD1 | Fisher | ICSI | Inbound | Outbound | Average | | |
| $0 \leq L \leq 50$ $L = \inf$ | 0.94 (19,50,31) 12 19 (0 100 0) | 0.2(80,15,5) 0.85(30.60,10) | 1.43 (32,33,35) 3 94 (4 89 7) | 0.05 (95,5,0) 2.46 (3.97.0) | 2.38 (15,8,77) | 1.68(20,9,71) 2.22(8.875) | 0.34 (72,28,0) 3 37 (3 97 0) | 1.0 (48,21,31) 5.24 (7.90.3) | | |

Table 4. DER (%) on different evaluation datasets for different setups of multi-stage clustering. We also report FLOPs of performing one individual clustering step when N = 2000. For the main clusterer, L = inf indicates we do not use spectral clustering at all, but directly use AHC to produce final results; $U_1 = inf$ indicates we do not use AHC pre-clusterer.

| | System | | | | DER (%) | | | | | | | FLOPs |
|-----|------------|----------------|---------------|-------|----------|---------|--------|-------|---------|----------|---------|---------------------|
| Exp | Fallback | Main clusterer | Pre-clusterer | AMI | Callhome | DIHARD1 | Fisher | ICSI | Inbound | Outbound | Average | N = 2000 |
| 1 | $L = \inf$ | $U_1 = \inf$ | $U_2 = \inf$ | 6.09 | 6.8 | 29.22 | 2.54 | 7.18 | 5.76 | 9.26 | 9.55 | 2.6×10^{7} |
| 2 | L = 0 | $U_1 = \inf$ | $U_2 = \inf$ | 7.81 | 2.71 | 34.09 | 1.58 | 12.41 | 9.77 | 6.83 | 10.74 | $7.7 	imes 10^9$ |
| 3 | L = 50 | $U_1 = \inf$ | $U_2 = \inf$ | 7.8 | 2.71 | 34.33 | 1.58 | 11.98 | 9.19 | 6.98 | 10.65 | 7.7×10^9 |
| 4 | L = 50 | $U_1 = 300$ | $U_2 = \inf$ | 9.88 | 2.7 | 34.27 | 1.58 | 11.12 | 9.2 | 6.93 | 10.81 | 2.1×10^{8} |
| 5 | L = 50 | $U_1 = 100$ | $U_2 = \inf$ | 15.29 | 2.69 | 33.12 | 1.57 | 18.37 | 9.79 | 5.98 | 12.40 | 6.4×10^{7} |
| 6 | L = 50 | $U_1 = 300$ | $U_2 = 600$ | 17.55 | 2.7 | 34.24 | 1.58 | 13.1 | 9.13 | 6.89 | 12.17 | 1.8×10^{8} |
| 7 | L = 50 | $U_1 = 100$ | $U_2 = 600$ | 18.01 | 2.7 | 33.38 | 1.57 | 17.97 | 9.8 | 5.98 | 12.77 | 3.9×10^{7} |
| 8 | L = 50 | $U_1 = 100$ | $U_2 = 300$ | 24.94 | 2.7 | 33.24 | 1.57 | 30.79 | 9.59 | 6.22 | 15.58 | 3.5×10^{7} |

3.3. Experimental results

3.3.1. Short-form results

First, the DER results on short-form segmented versions of the evaluation datasets are shown in Table 2. The column of L = 0 indicates no fallback clusterer was used, and only the main clusterer was used. We can clearly see that the DER on all of the 30s, 60s, and 120s segmented datasets are pretty bad when L = 0. By introducing the AHC fallback clusterer, the DER is significantly reduced on these short-form datasets. Specifically, with a larger L, the fallback clusterer is capable to handle longer audio. This validates our hypothesis that spectral clustering does not work well given insufficient input data points.

On the other hand, we still prefer spectral clustering as our main clusterer. As shown in Table 3, with threshold tuning, the AHC clusterer can be configured to produce decent DER across our testsets, but inevitably has the tendency to overestimate the number of clusters. This gets much worse when the audio is longer (*e.g.* AMI and ICSI both have unacceptably big speaker count errors). As a resolution, we find L = 50 to be a sweet point between short-form and long-form quality, which uses AHC fallback clusterer long enough while yielding not-too-far-off number of speakers.

3.3.2. Long-form results

Table 4 shows the diarization evaluation results from different multistage clustering setups on various test datasets. For the system (1) with $L = \inf$, meaning no spectral clustering is used and AHC is directly used to produce final results, we find the performance is significantly worse than a system like (2) or (3) with L = 0 or L = 50on datasets with only 2 speakers (*i.e.* Callhome, Fisher and Outbound). This is because AHC tends to over-estimate the number of clusters, and spectral clustering is better at finding the correct number of clusters via the eigen-gap criterion. This echoes the observation from Sec 3.3.1 regarding overestimation.

With the introduction of pre-clustering and dynamic compression, experiments (3)vs(4)vs(5), (4)vs(6) and (7)vs(8) present expected degradation in diarization quality. Specifically, the degradation is more significant when we use a small value for U_2 , and more significant on AMI and ICSI datasets, as the utterances in these datasets are much longer in average than other datasets. As a tradeoff, the long-form computational cost is remarkably reduced when we set an finite number of U_1 and U_2 , according to the FLOPs of the clustering when N = 2000 (corresponding to ~ 2 hours of audio).

3.3.3. Discussions

From the above results, we can see that an optimal value of L can usually be found via evaluating the quality trade-off (both DER and speaker count errors) between short-form and long-form data using AHC and spectral clustering. However, for U_1 and U_2 , there is usually no optimal value. For offline systems which have unlimited computational resources and no latency requirements, we can set both U_1 and U_2 to infinity to achieve the best long-form quality. However, for a realistic on-device application, the system must work reliably with a very limited budget of resources including CPU, memory, and battery. Thus U_1 and U_2 need to be carefully tuned based on these requirements, for a balance between computational cost and quality.

In addition, we also experimented the idea of reducing the AHC pre-clusterer computational cost with the canopy approach [31]. However, this approach is very data-dependent due to the fact that it is built upon hashing, which does not guarantee an upper bound of the computational cost, thus is infeasible for on-device applications.

4. CONCLUSIONS

In this paper, we described a multi-stage clustering strategy for streaming on-device speaker diarization which consists of an AHC fallback clusterer, a main spectral clusterer, and an AHC preclusterer with dynamic compression. This strategy leverages the benefits of different unsupervised clustering algorithms. It helps us build a speaker diarization system that is capable of producing high quality results for inputs of variable lengths, with an upper bounded time and space complexity that is easy to deploy to on-device environments such as mobile phones. This system can also be easily configured to balance between computational cost and quality, in order to fit hardware constraints of different devices.

5. REFERENCES

- Daniel Garcia-Romero, David Snyder, Gregory Sell, Daniel Povey, and Alan McCree, "Speaker diarization using deep neural network embeddings," in *ICASSP*. IEEE, 2017, pp. 4930– 4934.
- [2] Dimitrios Dimitriadis and Petr Fousek, "Developing on-line speaker diarization system," in *Proc. Interspeech*, 2017, pp. 2739–2743.
- [3] Quan Wang, Carlton Downey, Li Wan, Philip Andrew Mansfield, and Ignacio Lopez Moreno, "Speaker diarization with LSTM," in *ICASSP*. IEEE, 2018, pp. 5239–5243.
- [4] Tae Jin Park, Kyu J Han, Manoj Kumar, and Shrikanth Narayanan, "Auto-tuning spectral clustering for speaker diarization using normalized maximum eigengap," *IEEE Signal Processing Letters*, vol. 27, pp. 381–385, 2019.
- [5] Wei Xia, Han Lu, Quan Wang, Anshuman Tripathi, Yiling Huang, Ignacio Lopez Moreno, and Hasim Sak, "Turn-to-Diarize: Online speaker diarization constrained by transformer transducer speaker turn detection," in *ICASSP*. IEEE, 2022, pp. 8077–8081.
- [6] Tae Jin Park, Manoj Kumar, and Shrikanth Narayanan, "Multiscale speaker diarization with neural affinity score fusion," in *ICASSP.* IEEE, 2021, pp. 7173–7177.
- [7] Aonan Zhang, Quan Wang, Zhenyao Zhu, John Paisley, and Chong Wang, "Fully supervised speaker diarization," in *ICASSP*. IEEE, 2019, pp. 6301–6305.
- [8] Qiujia Li, Florian L Kreyssig, Chao Zhang, and Philip C Woodland, "Discriminative neural clustering for speaker diarisation," in *Spoken Language Technology Workshop (SLT)*. IEEE, 2021.
- [9] Yusuke Fujita, Naoyuki Kanda, Shota Horiguchi, Kenji Nagamatsu, and Shinji Watanabe, "End-to-end neural speaker diarization with permutation-free objectives," in *Proc. Interspeech*, 2019, pp. 4300–4304.
- [10] Quan Wang, Yash Sheth, Ignacio Lopez Moreno, and Li Wan, "Speaker diarization using an end-to-end model," US Patent App. 16/617,219, 2020.
- [11] Ivan Medennikov et al., "Target-speaker voice activity detection: a novel approach for multi-speaker diarization in a dinner party scenario," in *Proc. Interspeech*, 2020.
- [12] Yushi Ueda, Soumi Maiti, Shinji Watanabe, Chunlei Zhang, Meng Yu, Shi-Xiong Zhang, and Yong Xu, "EEND-SS: Joint end-to-end neural speaker diarization and speech separation for flexible number of speakers," *arXiv preprint arXiv:2203.17068*, 2022.
- [13] Thilo von Neumann, Keisuke Kinoshita, Marc Delcroix, Shoko Araki, Tomohiro Nakatani, and Reinhold Haeb-Umbach, "Allneural online source separation, counting, and diarization for meeting analysis," in *ICASSP*. IEEE, 2019, pp. 91–95.
- [14] Shlomo E Chazan, Sharon Gannot, and Jacob Goldberger, "Attention-based neural network for joint diarization and speaker extraction," in 2018 16th International Workshop on Acoustic Signal Enhancement (IWAENC). IEEE, 2018, pp. 301–305.
- [15] Tae Jin Park, Naoyuki Kanda, Dimitrios Dimitriadis, Kyu J Han, Shinji Watanabe, and Shrikanth Narayanan, "A review of speaker diarization: Recent advances with deep learning," *Computer Speech & Language*, vol. 72, pp. 101317, 2022.

- [16] Chao Zhang and Quan Wang, "Speaker diarization: A journey from unsupervised to supervised approaches," Odyssey: The Speaker and Language Recognition Workshop, 2022, Tutorial session.
- [17] Qian Zhang, Han Lu, Hasim Sak, Anshuman Tripathi, Erik McDermott, Stephen Koo, and Shankar Kumar, "Transformer transducer: A streamable speech recognition model with transformer encoders and RNN-T loss," in *ICASSP*. IEEE, 2020, pp. 7829–7833.
- [18] Li Wan, Quan Wang, Alan Papir, and Ignacio Lopez Moreno, "Generalized end-to-end loss for speaker verification," in *ICASSP*. IEEE, 2018, pp. 4879–4883.
- [19] Jason Pelecanos, Quan Wang, and Ignacio Lopez Moreno, "Dr-Vectors: Decision residual networks and an improved loss for speaker recognition," in *Proc. Interspeech*, 2021.
- [20] Anmol Gulati et al., "Conformer: Convolution-augmented transformer for speech recognition," in *Proc. Interspeech*, 2020.
- [21] Quan Wang, Yang Yu, Jason Pelecanos, Yiling Huang, and Ignacio Lopez Moreno, "Attentive temporal pooling for conformer-based streaming language identification in longform speech," in Odyssey: The Speaker and Language Recognition Workshop, 2022.
- [22] Victor Y Pan and Zhao Q Chen, "The complexity of the matrix eigenproblem," in *Proceedings of the thirty-first annual ACM symposium on Theory of computing*, 1999, pp. 507–516.
- [23] Don Coppersmith and Shmuel Winograd, "Matrix multiplication via arithmetic progressions," in *Proceedings of the nineteenth annual ACM symposium on Theory of computing*, 1987, pp. 1–6.
- [24] Christopher Cieri, David Miller, and Kevin Walker, "The Fisher corpus: A resource for the next generations of speechto-text," in *LREC*, 2004, vol. 4, pp. 69–71.
- [25] A Canavan, D Graff, and G Zipperlen, "CALLHOME American English speech LDC97S42," LDC Catalog. Philadelphia: Linguistic Data Consortium, 1997.
- [26] Jason Pelecanos, Quan Wang, Yiling Huang, and Ignacio Lopez Moreno, "Parameter-free attentive scoring for speaker verification," in *Odyssey: The Speaker and Language Recognition Workshop*, 2022.
- [27] Google, "Artificial intelligence at Google: Our principles," https://ai.google/principles.
- [28] Jean Carletta et al., "The AMI meeting corpus: A preannouncement," in *International workshop on machine learning for multimodal interaction*. Springer, 2005, pp. 28–39.
- [29] Neville Ryant, Kenneth Church, Christopher Cieri, Alejandrina Cristia, Jun Du, Sriram Ganapathy, and Mark Liberman, "First DIHARD challenge evaluation plan," 2018, Tech. Rep., 2018.
- [30] Adam Janin et al., "The ICSI meeting corpus," in *ICASSP*. IEEE, 2003, vol. 1, pp. I–I.
- [31] Andrew McCallum, Kamal Nigam, and Lyle H Ungar, "Efficient clustering of high-dimensional data sets with application to reference matching," in *ICKDDM*. ACM, 2000, pp. 169– 178.

- [32] Rohit Prabhavalkar, Raziel Alvarez, Carolina Parada, Preetum Nakkiran, and Tara N Sainath, "Automatic gain control and multi-style training for robust small-footprint keyword spotting with deep neural networks," in *ICASSP*. IEEE, 2015, pp. 4704– 4708.
- [33] Rubén Zazo Candil, Tara N Sainath, Gabor Simko, and Carolina Parada, "Feature learning with raw-waveform CLDNNs for voice activity detection," in *Proc. Interspeech*, 2016.
- [34] Jeffrey Dean and Sanjay Ghemawat, "MapReduce: simplified data processing on large clusters," *Communications of the ACM*, vol. 51, no. 1, pp. 107–113, 2008.
- [35] Hervé Bredin, "pyannote.metrics: a toolkit for reproducible evaluation, diagnostic, and error analysis of speaker diarization systems," in *Proc. Interspeech*, 2017, pp. 3587– 3591.

Appendices

A. FEATURE FRONTEND

We used a shared feature frontend for the speaker turn detection model and the speaker encoder model mentioned in Section 2.1. This frontend first applies automatic gain control [32] to the input audio, then extracts 32ms-long Hanning-windowed frames with a step of 10ms. For each frame, 128-dimensional log Mel-filterbank energies (LFBE) are computed in the range between 125Hz and 7500Hz. These filterbank energies are then stacked by 4 frames and subsampled by 3 frames, resulting in final features of 512 dimensions with a frame rate of 30ms. These features are then filtered by a CLDNN based Voice Activity Detection (VAD) model [33] before fed into the speaker turn detection and the speaker encoder models.

B. ADDITIONAL DETAILS ON EVALUATION METRICS

Due to the scale of the evaluations, we use an internal MapReduce [34] based C++ implementation to calculate the Diarization Error Rate (DER) reported in Section 3.3. Thus the DER numbers reported in this paper may have some discrepancies with numbers computed with other libraries such as pyannote.metrics [35].

The FLOPs estimation in Table 4 is based on PyPAPI⁵ by counting PAPI_FP_OPS, using the AHC implementation from scikit-learn⁶ and Python spectral clustering from [3]⁷. Note that the FLOPs of the feature frontend and neural network models are excluded in Table 4 as they are constant.

The original script that we used to estimate FLOPs of multistage clustering and the FLOPs results for more values of N are open sourced on GitHub⁸.

C. ADDITIONAL DETAILS ON EVALUATION DATASETS

When preparing the datasets for evaluation, we notice that different data sources have different representation of speaker label annotations. For example, the AMI dataset annotation is almost on a word-level basis, where most of the RTTM segments are extremely short. As mentioned in Section 3.1, during the evaluation, we extrude a collar value of 250ms centered around each reference speaker segment boundary. This leads to potential excessive removal of the audio from the original UEM. In order to mitigate this issue, we include an additional step in our data processing pipeline which merges neighboring RTTM segments that are from the same speaker and are close to each other. For our experiments, we specifically consider any gap smaller than 0.01 second to be close enough for RTTM merging.

⁵https://flozz.github.io/pypapi

⁶https://scikit-learn.org/stable/modules/generated/ sklearn.cluster.AgglomerativeClustering.html

⁸https://github.com/google/speaker-id/tree/master/ publications/Multi-stage/flops