TIGHT INTEGRATION OF NEURAL- AND CLUSTERING-BASED DIARIZATION THROUGH DEEP UNFOLDING OF INFINITE GAUSSIAN MIXTURE MODEL

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ABSTRACT

Speaker diarization has been investigated extensively as an important central task for meeting analysis. Recent trend shows that integration of end-to-end neural (EEND)- and clustering-based diarization is a promising approach to handle realistic conversational data containing overlapped speech with an arbitrarily large number of speakers, and achieved state-of-the-art results on various tasks. However, the approaches proposed so far have not realized tight integration yet, because the clustering employed therein was not optimal in any sense for clustering the speaker embeddings estimated by the EEND module. To address this problem, this paper introduces a trainable clustering algorithm into the integration framework, by deep-unfolding a non-parametric Bayesian model called the infinite Gaussian mixture model (iGMM). Specifically, the speaker embeddings are optimized during training such that it better fits iGMM clustering, based on a novel clustering loss based on Adjusted Rand Index (ARI). Experimental results based on CALLHOME data show that the proposed approach outperforms the conventional approach in terms of diarization error rate (DER), especially by substantially reducing speaker confusion errors, that indeed reflects the effectiveness of the proposed iGMM integration.

Index Terms— Diarization, deep learning, infinite GMM

1. INTRODUCTION

Automatic meeting/conversation analysis is one of the essential technologies required for realizing futuristic speech applications such as communication agents that can follow, respond to, and facilitate our conversations. As an important central task for the meeting analysis, speaker diarization has been extensively studied [1–3].

Current competitive diarization approaches can be categorized into three types: speaker embedding clustering-based approaches [4–6], neural end-to-end diarization (EEND) approaches [7–9], and combination/integration of the former two approaches [10–13]. The speaker embedding clustering-based approaches first segment a recording into short homogeneous chunks and compute speaker embeddings such as x-vectors [4] for each chunk assuming that only one speaker is active in each chunk. Then, the speaker embeddings are clustered to regroup segments belonging to the same speakers and obtain the diarization results. While these methods can cope with very challenging scenarios [5–6] and work with an arbitrarily large number of speakers, there is a clear disadvantage that they cannot handle overlapped speech.

The second category of diarization approaches, EEND, was recently developed [7–9] to specifically address the overlapped speech problem. Similarly to the neural source separation [14–15], a Neural Network (NN) receives frame-level spectral features and directly outputs a frame-level speaker activity for each speaker, no matter whether the input signal contains overlapped speech or not. While the system is simple and has started outperforming the conventional clustering-based algorithms [6–9], it still has difficulty in generalizing to recordings containing a large number of speakers [9].

To this end, the third category of diarization approaches, integration of the EEND- and clustering-based approaches [10–13], referred to as EEND-vector clustering (EEND-VC) hereafter, has been recently proposed to cope with realistic recordings containing overlapped speech with an arbitrarily large number of speakers. It first splits the input recording into fixed-length chunks. Then, it applies a modified version of EEND to each chunk to obtain diarization results for speakers speaking in each chunk as well as speaker embeddings for them. Finally, to estimate which of the diarization results estimated in local chunks belongs to the same speaker, speaker clustering is performed across the chunks based on the speaker embeddings by using a constrained clustering algorithm. While this integrated approach is shown to achieve state-of-the-art results for real conversational data such as CALLHOME data [10–12], we argue that there is a large room for improvement because the integration is not tight enough. Although the estimation of diarization results and speaker embeddings is based on a single NN and thus are tightly coupled, the clustering stage is formulated as an independent process that is not guaranteed to be optimal in clustering the speaker embeddings, and thus the overall system could not be optimal.

To address this problem and tightly integrate EEND- and clustering-based diarization, this paper introduces a trainable clustering framework, unfolded infinite Gaussian mixture model (iGMM) [16], into the EEND-VC framework. Desired properties of a clustering algorithm for EEND-VC are (1) it should deal with arbitrary unbounded number of speakers, (2) it should estimate the number of speakers in an optimal sense, (3) it should handle non-sequential data (unlike [17]) because a set of the speaker embeddings in the EEND-VC framework has no specific order. As a typical clustering algorithm that fulfills these conditions, we propose to employ a non-parametric Bayesian model called iGMM, which is a GMM but with a theoretically infinite number of mixture components. The number of mixture components, corresponding to the number of speakers in diarization, can be optimized in a maximum marginal likelihood sense, given an observation. To jointly optimize this novel clustering step with speaker embedding estimation and diarization results estimation, we opt to unfold the parameter estimation process of iGMM and optimize directly the clustering results through a novel adjusted Rand index (ARI)-based loss [16]. Experiments based on CALLHOME data show the proposed approach can outperform the conventional EEND-VC in terms of diarization error rate (DER) especially by reducing speaker confusion errors, which indeed reflects the effectiveness of the proposed iGMM integration.

2. PROPOSED DIARIZATION FRAMEWORK

2.1. Overall framework

Figure 1 shows a schematic diagram of the proposed framework, EEND-vector clustering with iGMM (EEND-VC-iGMM), for an exemplary 2 chunks out of continuous 3-speaker meeting data.

It first passes a several-minute long input recording to NN (“Encoder NN” in Fig. 1), and obtain a set of D-dimensional frame fea-
In our experiments, the chunk size \( T \) and \( S_{\text{local}} \) are set at 5 s and 3, respectively.
2.3.1. Generative process of the speaker embeddings

First, let us explain the generative process assumed in the proposed iGMM. For the sake of convenience, let us introduce a variable \( N \) that corresponds to the total number of input speaker embeddings, i.e., \( N = I \times S_{\text{local}} \), and an index for the embeddings, \( n \), such as \( e_n \). Then, in this paper, we employ a spherical iGMM with the mixture generative process for the speaker embeddings, where the following generative process for the speaker embeddings, where the mixture generative process is constructed via a DP prior with concentration parameter \( \alpha \) by a stick-breaking process [20], as:

1. For each speaker cluster \( k = 1, \ldots, \infty \):
   a. Draw stick proportion \( \eta_k \sim \text{Beta}(1, \alpha) \)
   b. Set mixture weight \( \pi_k = \eta_k \prod_{k=1}^{k-1} (1 - \eta_v) \)
   c. Draw cluster mean \( \mu_k \sim N(0, I) \)
   d. Draw cluster precision \( \beta_k \sim \text{Gamma}(1, 1) \)

2. For each speaker embedding \( n = 1, \ldots, N \):
   a. Draw cluster assignment \( r_n \sim \text{Categorical}(\pi) \)
   b. Draw instance representation \( e_n \sim N(\mu_{r_n}, \beta_{r_n}^{-1}I) \)

Beta is the beta distribution, \( N(\mu, \Sigma) \) is the Gaussian distribution with mean \( \mu \) and covariance \( \Sigma \), Gamma is the gamma distribution, Categorical is the categorical distribution, and \( \pi = \{ \pi_k \}_{k=1}^{\infty} \).

The DP prior by a stick-breaking process (steps 1-(a) and 1-(b)) is a key to allow us to use the infinite number of mixture components.

2.3.2. Parameter estimation for iGMM

Following the above generative process, we can derive the following parameter estimation steps based on the VB expectation-maximization (EM) algorithm. Because of the space limitation, the derivation of the following equations is omitted, but it follows a straightforward procedure of maximizing an evidence lower bound derived from the iGMM likelihood as shown in [16]. The iGMM parameter estimation in the variational posterior distributions is achieved by alternately calculating the following VB M-step:

\[
\begin{align*}
\gamma_{k1} &= 1 + \sum_{n=1}^{N} r_{n,k}, \\
\gamma_{k2} &= \alpha + \sum_{n=1}^{N} \sum_{k' = k+1}^{K'} r_{n,k'}, \\
\theta_k &= \frac{b_k}{\sum_{n=1}^{N} r_{n,k}} \\
a_k &= 1 + C \sum_{n=1}^{N} r_{n,k}, \\
b_k &= 1 + \frac{1}{2} \sum_{n=1}^{N} r_{n,k} (\| e_n - \theta_k \|^2 + C),
\end{align*}
\]

and the following VB E-step to obtain a cluster assignment \( r_{n,k} \):

\[
\log r_{n,k} \propto \Psi(\gamma_{k1}) - \Psi(\gamma_{k1} + \gamma_{k2}) - \frac{C}{2} (\Psi(a_k) - \log(b_k)) - \frac{a_k}{2 b_k} (\| e_n - \theta_k \|^2 + C) + \sum_{k' = k+1}^{K'} (\Psi(\gamma_{k2}) - \Psi(\gamma_{k1} + \gamma_{k2})),
\]

where \( \Psi \) is the digamma function. For the computational efficiency, we truncate the number of clusters at \( K' \) as in [20]. Note that the truncated DP is shown to closely approximate a true DP for large enough \( K' \) relative to the number of samples [21].

Since [16] shows that, to help the VB EM steps converge faster to a better solution, it is beneficial to estimate an initial value of the posterior probability \( R \) with another small NN, we also employ such a small network, which corresponds to a block denoted as “Initial posterior prediction” in Fig. 2. Its details are summarized in [16].

2.3.3. Deep unfolding of iGMM parameter estimation process

The above VB EM steps are all clearly differentiable. Thus, by following an idea of general deep unfolding framework, e.g., [22], we unfold the EM iterations into a sequential processing as in the upper right part of Fig. 2 to incorporate iGMM-based clustering into the overall NN optimization framework.

2.4. Loss functions

Now, let us explain how we optimize the network. As it is shown in Fig. 2 the system can be optimized by the following multi-task loss:

\[
L = (1 - \lambda_1 - \lambda_2) L_{\text{Diar}} + \lambda_1 L_{\text{Cluster}} + \lambda_2 L_{\text{Spk}},
\]

where \( L_{\text{Diar}} \), \( L_{\text{Cluster}} \), \( L_{\text{Spk}} \) correspond to losses that control chunk-wise diarization accuracy, clustering accuracy, and a speaker embedding space to have small intra-speaker and large inter-speaker variability, respectively. \( W = \{ \lambda_1, \lambda_2 \} \) includes weights for the multi-task loss. In the following, we will detail \( L_{\text{Diar}} \) and \( L_{\text{Cluster}} \), while we ask readers to refer to [10] for details of \( L_{\text{Spk}} \).

2.4.1. Chunk-level diarization loss

As in [7], the diarization loss \( L_{\text{Diar}} \) in each chunk is formulated as:

\[
L_{\text{Diar},i} = \frac{1}{T S_{\text{local}}} \min_{\phi \in \text{perm}(S_{\text{local}})} \sum_{t=1}^{T} \text{BCE} \left( \hat{y}_{t,i}, y_{t,i}, \right),
\]

where \( \text{perm}(S_{\text{local}}) \) is the set of all the possible permutations of \( (1, \ldots, S_{\text{local}}) \), \( \hat{y}_{t,i} = [\hat{y}_{t,1}, \ldots, \hat{y}_{t,S_{\text{local}}} \in R^{S_{\text{local}}} \), \( y_{t,i} \) is the \( \phi \)-th permutation of the reference speaker labels, and \( \text{BCE}(\cdot, \cdot) \) is the binary cross-entropy function between the labels and the estimated diarization outputs.

2.4.2. Clustering loss: Adjusted Rand index loss

A common practice to evaluate clustering accuracy is to use the ARI [23-25], that directly measures similarity between a ground-truth clustering result and an estimated one, even when the estimated and true number of clusters does not agree. We here propose to use the (negative) ARI as a loss to directly improve the accuracy of the iGMM-based speaker embedding clustering, i.e., the accuracy of the posterior probability \( R \) obtained in 2.3.3.

Specifically, we use the following continuous approximation of ARI [16] (hereafter, cARI) that can handle soft cluster assignments, as opposed to the original non-differentiable ARI. Let us first define \( N_1 \) as the approximated number of pairs of instances (i.e., speaker embeddings) that are in different clusters in both the true and estimated assignments, \( N_2 \) as the approximated number of pairs that are in different clusters in the true assignments but not in the estimated assignments, \( N_3 \) as the approximated number of pairs that are in the same cluster in the true assignments but not in the estimated assignments, and \( N_4 \) as the approximated number of pairs that are in the same cluster in both the true and estimated assignments. Then, cARI is formulated as:

\[
c\text{ARI} = \frac{2(N_1 N_4 - N_2 N_3)}{(N_1 + N_2)(N_3 + N_4) + (N_1 + N_3)(N_2 + N_4)},
\]

where \( N_i (i = 1, \ldots, 4) \) is mathematically defined as:

\[
N_1 = \sum_{n=1}^{N} \sum_{n'=n+1}^{N} I(h_n \neq h_{n'}) d_{n,n'},
\]

\[
N_2 = \sum_{n=1}^{N} \sum_{n'=n+1}^{N} I(h_n \neq h_{n'})(1 - d_{n,n'}),
\]

2This index conversion is possible because the obtained speaker embeddings are non-sequential data.
As a loss function one with the speaker embedding loss identify labels, and one without it, by setting maximum number of speakers per chunk to be 3, i.e., \( S = 3 \). The only difference comes from the clustering model of EEND-based and clustering-based diarization approaches.

The training procedure is as follows. We first created the seed model using the 1-to-3-speaker training data and 30 seconds chunks for 100 epochs. We then re-trained the baseline EEND-VC and proposed EEND-VC-iGMM on the 2-to-7-speaker training data with 5-second chunks, i.e., \( T = 5 \) s. These chunks are taken from 100 s and 300 s consecutive recordings for EEND-VC and EEND-VC-iGMM, respectively. Finally, we performed adaption using the CALLHOME adaptation data. For adaptation, we cut the recordings to 100 s for the baseline and 600 s for the proposed method, which corresponds to the optimal setting for each. This setting allows EEND-VC-iGMM to have sufficient number of embedding samples for the iGMM clustering during training. For the iGMM, we set the number of EM iterations at 10, \( \alpha = 1 \), and 10, respectively. In both training and inference stages.

The performance was evaluated including overlapped speech frames in terms of DER with a collar tolerance of 0.25 s as in [1, 9, 19].

### 3.3. Results

Table 1 shows the DERs for the conventional EEND-VC and EEND-VC-iGMM with and without the speaker embedding loss \( L_{Spk} \). We can see that EEND-VC-iGMM outperforms EEND-VC in all but the 2-speaker condition. By looking at the breakdown of DERs, we observe that EEND-VC-iGMM greatly reduces speaker confusion errors in most cases. This clearly confirms the effectiveness of incorporating the trainable iGMM-based clustering and tightly coupling the embedding estimation and the clustering stages.

Looking at Avg. conditions, we can see that EEND-VC-iGMM with the speaker embedding loss \( L_{Spk} \) performed the best. Another variant of EEND-VC-iGMM that does not use \( L_{Spk} \) which is based on absolute speaker identity labels, achieves overall performance comparable to the baseline but with lower speaker confusion errors. Unlike the baseline, this proposed variant does not require absolute speaker identity labels and relies only on diarization labels. Considering that (1) the performance of EEND-VC is fairly good on this data in general and (2) there are many cases that the absolute speaker identity labels are not available, this is an encouraging result.

The numbers reported in Table 1 are slightly worse than those reported in [11, 19], because of the different chunk size (i.e., we use here a chunk size of 5 s, while the best performance in [11] was achieved with a chunk size of 30 s). Although the chunk size of 5 s may not be optimal for the CH data, it is arguably a much more practical setting in general as it allows us to cope with rapid speaker changes such as a meeting or casual conversations. In future work, we plan to investigate the proposed EEND-VC-iGMM in such challenging conditions.

### 4. Conclusion

This paper introduced a trainable clustering, i.e., deep unfolded iGMM, into the EEND-VC framework, that allows tighter integration of EEND-based and clustering-based diarization approaches. We confirmed experimentally that the proposed method could outperform the conventional EEND-VC with constrained AHC, by significantly reducing the speaker confusion errors.
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