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END-TO-END DIARIZATION FOR VARIABLE NUMBER OF SPEAKERS WITH LOCAL-GLOBAL NETWORKS AND DISCRIMINATIVE SPEAKER EMBEDDINGS

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ABSTRACT

We present an end-to-end deep network model that performs meeting diarization from single-channel audio recordings. End-to-end diarization models have the advantage of handling speaker overlap and enabling straightforward handling of discriminative training, unlike traditional clustering-based diarization methods. The proposed system is designed to handle meetings with unknown numbers of speakers, using variable-number permutation-invariant cross-entropy based loss functions. We introduce several components that appear to help with diarization performance, including a local convolutional network followed by a global self-attention module, multi-task transfer learning using a speaker identification component, and a sequential approach where the model is refined with a second stage. These are trained and validated on simulated meeting data based on LibriSpeech and LibriTTS datasets; final evaluations are done using LibriCSS, which consists of simulated meetings recorded using real acoustics via loudspeaker playback. The proposed model performs better than previously proposed end-to-end diarization models on these data.

Index Terms— Diarization, attention, deep learning

1. INTRODUCTION

Diarization is the task of predicting "who spoke when" given a recording of, e.g. a meeting or conversation [1, 2, 3], and is an important additional step for many speech applications like automatic speech recognition [4, 5, 6]. In this work, we focus on diarization for meeting audio, where there may be overlapping speech, from an unknown but bounded number of speakers. In addition, we focus on continuous speech diarization, where the aim is to diarize recordings without prior information about utterance boundaries. Handling overlapping speech is important: in the ICSI meeting corpus, for example, it has been observed that there are overlaps in speech up to 13% of the time [7]. This number may be larger for less formal meetings such as dinner conversations.

Traditionally, speaker diarization uses speaker embeddings and clustering. Speaker clustering diarization [8, 9, 10] is done in multiple steps: segment the audio, extract speaker embeddings, and perform clustering. Usually an i-vector [11], d-vector [12] or x-vector [13] is used as the speaker embedding. Such speaker verification embeddings assume one speaker at a time is active; hence such a model cannot handle speaker overlap.

In contrast, we follow an emerging trend in using an end-to-end neural network for diarization [14, 15] in a meeting scenario, where diarization is predicted at each frame. Such a network can be trained to predict diarization from meeting mixtures directly, and hence does not rely on external speaker embeddings. End-to-end diarization can therefore be trained from audio with speaker overlap.

We propose a two-stage end-to-end diarization model. First stage uses a time-dilated convolutional neural network (TDCN) to extract local features from speech and a self-attention neural network to focus on global speaker modeling. We also show that a learned speaker identification module further improves diarization performance.

We show significant improvement over previously proposed end-to-end diarization models on two simulated datasets, with 100K and dynamic mixing of meetings. Additionally, we find that using learned joint speaker embeddings with corresponding losses further improves overall diarization performance.

Contributions: Our proposed approach makes the following contributions: (1) an end-to-end system that handles a variable number of speakers in a single step, (2) an effective architecture consisting of local TDCN followed by a global self-attention network, (3) a speaker classification auxiliary task to improve the global discriminability of embeddings, (4) the use of linear-complexity self attention to improve performance, and (5) a sequential architecture, that uses a second stage to refine the initial estimates.

2. RELATED WORK

Traditionally, clustering-based methods are used for speaker diarization, using representations such as i-vectors [8, 9], x-vectors [16], or d-vectors [12, 17]. Such systems first detect small speech segments, then extract a speaker embedding for each segment, and finally cluster the embeddings. Such clustering based diarization methods are effective only when one speaker is present in each segment, but cannot handle overlapping speech. In recent years, some hybrid methods combining clustering and discriminative methods addressed overlap [6, 18] but they do not perform end-to-end diarization directly. TS-VAD [6] which uses speaker embeddings as conditioning inputs to a neural network was inspired from a speaker conditioned VAD approach [19].

In contrast, end-to-end diarization has been a recent trend motivated by the promise of discriminative training. Previous works [20, 14, 15, 21, 22, 23] have introduced a variety of architectures including BLSTM [14], self-attention [15] and their combination [24] that handle overlapping speech for a fixed numbers of speakers.

Whereas some approaches handle variable numbers of sources but not overlapping speech, [25, 26], some recent end-to-end approaches [21, 20, 22] handle both cases. The latter utilize recursive decoder-style models to estimate each speaker's activity, one at a time until all the speakers have been decoded. Theoretically recursive models could handle an unbounded number of speakers, but the recursion may introduce difficulty in training as well as run-time inefficiency. Our approach avoids these problems by directly diarizing all speakers at once, up to a known maximum number of speakers.

[*] The author performed the work while at Google.

3. METHODS

Given an input audio signal x, a speaker diarization model estimates a binary speaker activity image $\mathbf{y} \in \{0,1\}^{S\times T}$, with elements $y_{s,t} = 1$ if speaker s is present at segment t, and $y_{s,t} = 0$ otherwise. S is the maximum number of speakers. Note that in the case of overlap, $\sum_s y_{s,t} > 1$, and if a speaker s is not present in a meeting, then $y_{s,t} = 0 : \forall t$. We generate diarization labels at a fixed rate of 10 acoustic frames per second. End-to-end diarization aims to predict this binary image through diarization probabilities $\hat{\mathbf{y}} \in [0,1]^{S\times T}$ within a permutation of speakers.

3.1. Proposed method: end-to-end diarization network

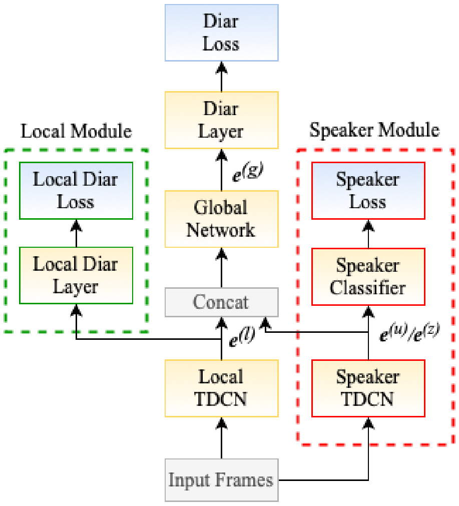


Fig. 1. Proposed local-global diarization model, with optional local and speaker losses; the global network can be LSTM or SA.

The proposed diarization model consists of two subnetworks: TDCN (local) and SA (global). Inspired by recent advances using residual convolutional networks in separation [27], we use a stacked TDCN as the first diarization submodule with M dilation layers and 4 repeats with a total of $4M$ blocks. The local submodule maps input audio x into local embeddings $\mathbf{e}_t^{(l)} \in \mathbb{R}^D$ for each frame.

Since convolutional networks have a limited receptive field, we use a self-attention module to model global context. Self-attention (SA) blocks used are similar to transformer encoder layers [28]. Each self-attention block consists of multi-head attention layer with H heads. The output is then fed to two linear layers, where the first layer expands the model dimension (D) by a factor of 4 with a ReLU activation, and the second layer projects back to the model dimension. Residual connections are used around this block, and layer normalization is applied to the output. Multiple such self-attention blocks are stacked. The global layers map local features $\mathbf{e}_t^{(l)}$ to global features $\mathbf{e}_t^{(g)} \in \mathbb{R}^D$. A linear output layer with a sigmoid activation, called diarization layer in Figure 1, produces all diarization probabilities $\hat{y}_{s,t} \in [0,1]$ which are thresholded and post-processed to obtain predicted binary diarization labels.

For typical meetings, the sequence length T can be prohibitively high for self-attention models because their memory and computation complexity have a quadratic dependence on T. The quadratic complexity of the self-attention module arises from the softmax attention computation. For linear approximation, we can replace the softmax attention with a linear dot product of kernel feature map (ϕ) of query Q and key K. Given query Q, key K and value V, where $Q, K, V \in \mathbb{R}^{T\times D}$ the output of the self-attention module can be computed as

$$O = \text{softmax}\left(\frac{QK^T}{\sqrt{D}}\right)V. \tag{1}$$

Inspired by [29], to avoid such complexity we use a linear approximation of full-attention:

$$O = \phi(Q)(\phi(K)^T V). \tag{2}$$

We use the feature map proposed in [29], $\phi(x) = \text{elu}(x) + 1$, where the exponential linear unit $\text{elu}(x) = x$ if $x > 0$, and $\alpha(e^x - 1)$ if $x \leq 0$ [30]. Such approximation allows us to use a large self-attention model with simpler memory requirements.

3.2. Permutation Invariant Loss

To allow our end-to-end diarization network to handle permutations between its predictions and the reference labels, as shown in Figure 1, we use a diarization loss which is a permutation-invariant cross entropy loss:

$$\begin{aligned} L_{\text{diar}}(\hat{\mathbf{y}}, \mathbf{y}) &= \min_{\pi\in\Pi} \sum_{s=1}^{S} \sum_{t} \text{BCE}(\hat{y}_{\pi(s),t}, y_{s,t}), && (3) \\ \text{BCE}(\hat{y}, y) &= -\left[y \log(\hat{y}) + (1-y)\log(1-\hat{y})\right], && (4) \end{aligned}$$

where $\pi(s)$ is the permuted index, and Π is the set of permutations of S items. For some models, we use a *local diarization loss* on top of the embeddings $\mathbf{e}^{(l)}$ obtained from an initial convolutional network. This local loss has the same form as the final diarization loss (3), where the only difference is that it uses local embeddings $\mathbf{e}^{(l)}$ as input, which are processed by a separate diarization layer to obtain a locally estimated diarization probability image.

3.3. Speaker module

Though speaker identification is not required for the task of diarization, the neural network has to discriminate between speakers in the meeting. The network at training time sees a limited amount of meeting audio and so the embeddings may only be trained to contrast with speakers in the local region. Adding a speaker identification loss may encourage embeddings to be globally discriminable. To this end, we propose to train an auxiliary speaker module jointly with the diarization network. The speaker loss minimizes frame-wise speaker identification from a global set of speakers in the training set. We propose two alternative versions of the speaker module, one producing a joint speaker embedding and another producing multiple individual speaker embeddings per frame.

In the joint speaker embedding, for each frame we identify active speakers in that frame. The speaker module predicts a speaker label vector, $\mathbf{u}_t \in \mathbb{R}^C$, where C is the number of speakers in the training set, and $u_{i,t} = 1$ if speaker i is active in frame t and $u_{i,t} = 0$ otherwise. Note that, speaker overlap is indicated by multiple 1's in the joint speaker label vector at a frame. The speaker network probability output $\hat{u}_{i,t}$ is generated by passing speaker embedding $\mathbf{e}_t^{(u)} \in \mathbb{R}^D$ through a speaker classifier layer as shown in Figure 1. The speaker classifier consists of a linear layer with a sigmoid activation, and is trained with binary cross-entropy as:

$$L_{\text{jointspk}} = \sum_t \sum_i \text{BCE}(\hat{u}_{i,t}, u_{i,t}). \tag{5}$$

For individual speaker embeddings, we assign a label to each individual speaker at each frame. The speaker label is $\mathbf{z}_t \in [C+1]^S$, where S is the maximum possible number of speakers in a meeting and $[C+1]$ indicates the set of all integers from 0 to C. We assign each speaker in a meeting a speaker slot from S such slots. At frame t, for each speaker i with allotted slot s, if speaker i is speaking at frame t, i is assigned and if the speaker is not speaking at t, a dummy speaker id (zero) is assigned. Each label vector is formed as $z_{s,t} = i$ if output slot s is active and assigned to i at frame t and $z_{s,t} = 0$ otherwise.

This model outputs S small embeddings $\mathbf{e}_{s,t}^{(z)} \in R^{\frac{D}{S}}$ for each frame t from which we derive output probabilities $\hat{z}_{i,s,t} \in [0,1]$ through S different linear mappings and softmax operations (speaker classifier layer), where i is a training speaker index. l_2 normalization is applied on $\mathbf{e}_{s,t}^{(z)}$. We let the model decide on the order of speakers predicted and train with a permutation-invariant softmax cross entropy speaker identification loss:

$$L_{\text{indspk}} = \min_{\pi \in \Pi} \sum_{s,t,i} \delta(z_{s,t}, i) \log(\hat{z}_{i,\pi(s),t}). \tag{6}$$

The speaker module takes the same input as the diarization network. We use a TDCN network to generate embedding $\mathbf{e}^{(z)}$ or $\mathbf{e}^{(u)}$, concatenate with local network embedding $\mathbf{e}^{(l)}$, and feed the result to the self-attention module. For individual speaker embeddings, we concatenate S embeddings $\mathbf{e}_s^{(z)}$ into $\mathbf{e}^{(z)}$ before l_2-normalization. For individual speaker embeddings, we make sure the model generates same speaker permutation for diarization and speaker losses. We also experiment with directly applying the joint speaker loss on local embedding $\mathbf{e}^{(l)}$ instead of extracting speaker embeddings.

3.4. Sequential model

We also experimented with a sequential diarization model, where we feed the outputs from a first diarization model into a second one along with the input signal. Diarization probabilities from a first round of output are concatenated with the features calculated from the input signal and used in the second network. This enables the second network to focus on parts where the first network does not get right. We use all the losses in the first and second networks. This sequential application of networks is shown to improve the results.

4. EXPERIMENTS

4.1. Simulated meeting data

We train end-to-end diarization models with simulated meeting-style audio mixtures. We prepare two separate training and test sets with varying overlap. LibriMeet-100K uses utterances from LibriSpeech dataset to create 100,000 120 second meetings with maximum 8 speakers and an overlap ratio between 20% and 50%. LibriMeet-Dyn uses utterances from LibriTTS and forms on-the-fly meetings of length 90 seconds involving maximum 8 speakers and with overlaps between 0% and 40%. LibriMeet-Dyn has infinite training data and uses on-the-fly mixing which makes it more powerful. Meeting dynamics to generate the meetings are borrowed from LibriCSS [5] where we draw a random overlap target for each meeting but there are constraints such as no overlapping utterances from the same speaker, and at a given time instant, there can at most be two active speakers.

Input features are 64-dimensional log-mel spectrograms with 40 ms window and 10 ms hop. We concatenate 21 neighboring feature vectors and downsample the result result to a rate of 10 Hz (hop size of 100 ms), which are the input features to the model.

Table 1. Simulated meeting experiments.

	DER(%)	
Model	LibriMeet-100K	LibriMeet-Dyn
BLSTM	39.3	40.0
TDCN-BLSTM	27.8	22.1
SA	24.9	29.8
TDCN	22.1	12.5
TDCN-SA	21.4	11.5
TDCN-SA + local loss	16.3	9.4

4.2. Simulated meeting experiments

We train two baseline end-to-end diarization models, BLSTM and SA. BLSTM was configured with 2 layers and 512 units in each layer. For SA, we use $H = 8, D = 512$ and 6 such layers. We train a local TDCN model, with 32 layers and $M = 8$. Our local-global model, has TDCN followed by SA with same architecture as baseline. We also train a TDCN-BLSTM model, where BLSTM is used as global model to compare effectiveness of SA with BLSTM. All models are trained with Adam optimizer with learning rate of 10.0^{-4} and with batch size 3. For sequential model, we use smaller network TDCN and SA, TDCN-small has 24 layers and $M = 6, D = 256$, SA-small has 4 layers and $H = 8$. We also use a large SA model, SA-Large with $H = 8, D = 512$ and 10 layers. We train our models with meetings where each one is about $90 - 120$ seconds long. All models were trained with same input and same computation time. All models except BLSTM were trained for 800K iterations, since BLSTM training speed is slower it was trained for $200K$. We evaluate the systems with diarization error rate (DER) [31].

Results are reported in Table 1. For LibriMeet-100K trained models, we observe SA has lower DER than BLSTM. This is a similar finding as previous papers [15]. We also observe that TDCN only model achieves lower DER than SA. Moreover TDCN-SA model achieves lower DER than TDCN, especially adding diarization loss on both TDCN and SA embeddings, we observe lower DER. We also observe that BLSTM as a global model with TDCN is worse than TDCN. This is probably because the the TDCN-BLSTM model training speed was slower due to BLSTM and the TDCN model may have been under-trained due to slower speed.

When training with LibriMeet-Dyn, we observe that dynamically mixed meetings achieves lower DER. We observe a similar pattern to LibriMeet-100K training, where TDCN-SA with local loss performs best and achieves a DER of 9. Note that the test sets here are not the same, each training set comes with its own test set, so the DER numbers are not directly comparable between two columns, but the model performances are similar across two training/test setups.

4.3. Experiments with speaker loss

Next we add a separate speaker loss module and train it jointly with the diarization network for the best performing model, TDCN-SA+local, from Table 1. We test using the individual speaker loss, and joint speaker loss on eval sets of LibriMeet-100K and LibriMeet-Dyn. Results are in Table 2. Using the speaker loss directly on local embeddings (second row of Table 2) slightly improves DER for LibriMeet-Dyn, but worsens DER for LibriMeet-100K. Individual speaker loss improves DER by 2.2%, and joint speaker loss improves DER by 2.5%. DER on LibriMeet-Dyn improves by about 1.3% for both loss types.

Table 2. Adding speaker losses to TDCN-SA model + local loss.

Speaker Embedding	Loss	DER LibriMeet-100K	DER LibriMeet-Dyn
–	–	16.3	9.4
Local ($\mathbf{e}^{(l)}$)	L_{jointspk} (5)	18.1	9.3
Joint ($\mathbf{e}^{(u)}$)	L_{jointspk} (5)	13.8	8.1
Indiv. ($\mathbf{e}^{(z)}$)	L_{indspk} (6)	14.1	8.1

Table 3. Full vs linear attention. TDCN-SA use local + speaker loss.

Model	Attention	DER LibriMeet-100K	DER LibriMeet-Dyn
SA	Full	25.3	30.0
SA	Linear	25.4	29.6
SA-Large	Linear	23.8	27.6
TDCN-SA	Full	13.8	8.1
TDCN-SA-Large	Linear	11.7	6.2

4.4. Linear attention and sequential model experiments

Since we train using longer audio clips, (few minutes of audio), we often observe limitation in using a large self-attention model. Using linear approximation of self-attention allows us to use a larger SA model with similar memory requirements of a smaller full-attention SA model. We report results of linear vs full attention using SA and TDCN-SA models in Table 3. We observe, SA-Full and SA-Linear achieves similar DER given enough training time, for LibriMeet-100K about 25% and LibriMeet-Dyn around 30%. SA-Large-linear attention achieves lower DER than SA. When using TDCN and SA together, we observe TDCN-SA-Large-Linear achieves lowest DER in both datasets, about 6% in LibriMeet-Dyn and 12% in LibriMeet-100K. This denotes that using larger self-attention model helps in diarization and for training a long context diarization model, linear approximation of self-attention is useful. The decomposition of DER in terms of missed speech, false acceptance and speaker confusion is as follows. The TDCN-SA-Large+local+speaker model yields 1.6, 1.8, and 8.3 when trained on LibriMeet-100K, and 1.3, 1.7, and 3.2 when trained on LibriMeet-Dyn.

Table 4 shows results with a sequential model versus a single step model. The sequential model improves DER by $\approx 1\%$ absolute.

4.5. Experiments on LibriCSS

LibriCSS is a dataset of meeting-like data recorded in a conference room with far-field microphones where speech utterances are played from loudspeakers placed in the room [5]. The order of utterances and overlap amounts are decided using a meeting simulation tool similar to the one we used for our training data. The meetings in this test set are 10 minutes long and always contain 8 speakers. We also have access to the clean sources that were played from the loudspeakers, so in addition to the LibriCSS re-recorded data, we also consider anechoic and artificially reverberated versions, and evaluate the performance of our diarization models on them. The results are presented in Table 5.

We report the results with the best performing model, a sequential two step model with TDCN-SA-Large and linear attention trained with LibriMeet-Dyn data. We used a threshold of 0.7 and a median filter of length 31 frames to post-process the output diarization probabilities to obtain the diarization labels. This setup was better than using a threshold of 0.5 and no median filter.

The best result is obtained on artificially reverberated version which shows that the diarization model relies considerably on the reverb structure to determine the diarization output. Since we use single channel data, the information coming from the reverb is the consistent RIR filter used for a speaker over the duration of the meeting which seems important to get better results. We conjecture that due to this reliance as well as due to mismatch with the training data which is always reverberated, the dry/anechoic mixture gets the worst performance among the three conditions. The performance was not significantly varying with overlap ratio as long as the training data included examples covering the range of overlap ratios appearing in the test set.

Table 4. Comparison of sequential model vs single-step model.

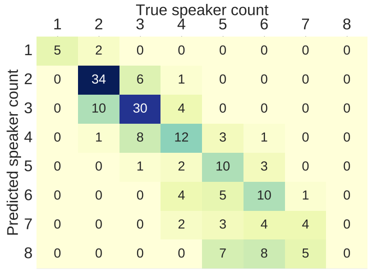
Model	Dataset	DER
TDCN-SA	LibriMeet-100K	11.7
TDCN-SA(Sequential)	LibriMeet-100K	11.0
TDCN-SA	LibriMeet-Dyn	6.2
TDCN-SA(Sequential)	LibriMeet-Dyn	5.3

Table 5. DER on various forms of LibriCSS test data.

Test data	Training data	0L	0S	10	20	30	40	avg
anechoic	LibriMeet-Dyn	16.4	12.5	15.8	17.1	16.8	20.0	16.4
reverberated	LibriMeet-Dyn	8.4	11.9	10.3	12.4	11.5	10.8	10.9
re-recorded	LibriMeet-Dyn	12.4	15.9	9.6	11.8	17.1	14.0	13.5

4.6. Variable number of speakers

To test the diarization model's performance for a variable number of speakers, we trained the TDCN-SA+local+speaker model on 100K, 90 second meetings with 1 to 8 speakers. The 1-8 speaker test set uses LibriSpeech test data, and the observed DER on this test set is 19%. Figure 2 shows a confusion matrix for estimated speaker count from the diarization prediction. Note that, for lower numbers of speakers (< 5), the model predicts speaker count more accurately.



	1	2	3	4	5	6	7	8
1	5	2	0	0	0	0	0	0
2	0	34	6	1	0	0	0	0
3	0	10	30	4	0	0	0	0
4	0	1	8	12	3	1	0	0
5	0	0	1	2	10	3	0	0
6	0	0	0	4	5	10	1	0
7	0	0	0	2	3	4	4	0
8	0	0	0	0	7	8	5	0

Fig. 2. Confusion matrix with variable number of speakers.

5. CONCLUSION

We introduced an end-to-end diarization model that performs meeting diarization in a single inference step and improves upon previous proposals by incorporating a local loss and a speaker detection module, a local-global network, and using a sequential iteration. The model is shown to work well on simulated meeting data as well as the LibriCSS dataset which contains real acoustic mixing. Future work involves improving the robustness and generalization of the model and testing on more realistic meeting data.

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