This paper presents Transcribe-to-Diarize, a new approach for neural
speaker diarization that uses an end-to-end (E2E) speaker-attributed
diary (E2E) is a joint model that was recently proposed for speaker counting, multi-talker
speech recognition, and speaker identification from monaural audio
speech activity of each speaker while it has the advantages of (i) handling
unlimited number of speakers, (ii) leveraging linguistic information
for speaker diarization, and (iii) simultaneously generating
speaker-attributed transcriptions. Experimental results on the LibriCSS and
AMI corpora show that the proposed method achieves significantly
better diarization error rate than various existing speaker diarization
methods when the number of speakers is unknown, and achieves a
comparsable performance to TS-VAD when the number of speakers
is given in advance. The proposed method simultaneously generates
speaker-attributed transcription with state-of-the-art accuracy.

Index Terms— Speaker diarization, rich transcription, speech
recognition, speaker counting

1. INTRODUCTION

Speaker diarization is a task of recognizing “who spoke when” from
audio recordings [1]. A conventional approach is based on speaker
embedding extraction for short segmented audio, followed by clus-
tering of the embeddings (sometimes with some constraint regard-
ing the speaker transitions) to attribute the speaker identity to each
short segment. Many variants of this approach have been investi-
gated such as the methods using agglomerate hierarchical clustering
(AHC) [2], spectral clustering (SC) [3], and variational Bayesian in-
ference [4, 5]. While these approaches showed a good performance
for difficult test conditions [6], they cannot handle overlapping speech
[7]. Several extensions were also proposed to handle overlapping
speech, such as using overlapping detection [8] and speech separa-
tion [9]. However, such extensions typically end up with a combina-
tion of multiple heuristic rules, which is difficult to optimize.

A neural network-based approach provides more consistent
ways to handle the overlapping speech problem by representing the
speaker diarization process with a single model. End-to-end neural
speaker diarization (EEND) learns a neural network that directly
maps an input acoustic feature sequence into a speaker diarization
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result with permutation-free loss functions [10, 11]. Various ex-
tensions of EEND were later proposed to cope with an unknown
number of speakers [12, 13]. Region proposal network (RPN)-based
speaker diarization [14] uses a neural network that simultaneously
performs speech activity detection, speaker embedding extraction, and
the resegmentation of detected speech regions. Target-speaker
voice activity detection (TS-VAD) [15] is another approach where
the neural network is trained to estimate speech activities of all the
speakers specified by a set of pre-estimated speaker embeddings. Of
these speaker diarization methods, TS-VAD achieved the state-of-
the-art (SOTA) results in several diarization tasks [7, 15] including
recent international competitions [16, 17]. On the other hand, TS-
VAD has a limitation that the number of recognizable speakers is
bounded by the number of output nodes of the model.

Speaker diarization performance can also be improved by lever-
gaging the linguistic information. For example, the transcription
of the input audio provides a strong clue to estimate the utterance
boundaries. Several works were proposed to combine the automatic
speech recognition (ASR) with speaker diarization, such as using
the word boundary information from ASR [18, 19] or improving the
speaker segmentation and clustering based on the information from
ASR [20, 21]. While these works showed promising results, the
ASR and speaker diarization models were separately trained. Such
a combination may not fully utilize the inherent inter-dependency
between the speaker diarization and ASR.

With these backgrounds, in this paper, we present Transcribe-to-
Diarize, a new speaker diarization approach that uses an end-to-end
(E2E) speaker-attributed automatic speech recognition (SA-ASR)
[22] as the backbone. The E2E SA-ASR was originally proposed to
recognize “who spoke what” by jointly performing speaker count-
ing, multi-talker ASR, and speaker identification from monaural
audio that possibly contains overlapping speech. Although the orig-
inal E2E SA-ASR model does not estimate any information about
“when”, in this study, we show that the start and end times of each
word can be estimated based on the decoder network of the E2E
SA-ASR, making the model to recognize “who spoke when and
what”. A rule based method for estimating the time information
from the attention weights was investigated in our previous work
[23]. Here we substantially improve the diarization accuracy by
introducing a learning based framework. In our experiment using
the LibriCSS [24] and AMI [25] corpora, we show that the proposed
method achieves the SOTA performance in both diarization error
rate (DER) and the concatenated minimum-permutation word error
rate (cpWER) [26] for the speaker-attributed transcription task.

2. E2E SA-ASR: REVIEW

2.1. Overview

The E2E SA-ASR model [22] uses acoustic feature sequence \( X \in \mathbb{R}^{f' \times t'} \) and a set of speaker profiles \( D = \{ d_k \in \mathbb{R}^{f'} | k = 1, ..., K \} \) as input. Here, \( f' \) and \( t' \) are the feature dimension and length of

\[ R^k = \{ d_k \} \]

\[ \mathbb{R}^{f'} \]
the feature sequence, respectively. Variable \( K \) is the total number of profiles, \( d_k \) is the speaker embedding (e.g., d-vector [27]) of the \( k \)-th speaker, and \( f^j \) is the dimension of the speaker embedding. We assume \( D \) includes the profiles of all the speakers present in the observed audio. \( K \) can be greater than the actual number of the speakers in the observed audio.

Given \( X \) and \( D \), the E2E SA-ASR model estimates a multi-talker transcription, i.e., word sequence \( Y = \{y_n \in \{1, \ldots, |V|\} | n = 1, \ldots, N\} \) accompanied by the speaker identity of each token \( S = \{s_n \in \{1, \ldots, K\} | n = 1, \ldots, N\} \). Here, \( |V| \) is the size of the vocabulary, \( y_n \) is the word index for the \( n \)-th token, and \( s_n \) is the speaker index for the \( n \)-th token. Following the serial-ized output training (SOT) framework [28], a multi-talker transcription is represented as a single sequence \( Y \) by concatenating the word sequences of the individual speakers with a special “speaker change” symbol (\( \langle \cdot \rangle \)). For example, the reference token sequence to \( Y \) for the three-speaker case is given as \( R = \{r^1_1, \ldots, r^1_{N_1}, \langle \cdot \rangle, r^2_1, \ldots, r^2_{N_2}, \langle \cdot \rangle, r^3_1, \ldots, r^3_{N_3}, \langle \cdot \rangle\} \), where \( r^i_n \) represents the \( i \)-th token of the \( j \)-th speaker. A special symbol (\( \langle \cdot \rangle \)) is inserted at the end of all transcriptions to determine the termination of inference. Note that this representation can be used for overlapping speech of any number of speakers.

2.2. Model architecture

The E2E SA-ASR model consists of two attention-based encoder-decoders (AEDs), i.e., an AED for ASR and an AED for speaker identification. The two AEDs depend on each other, and jointly estimate \( Y \) and \( S \) from \( X \) and \( D \).

The AED for ASR is represented as,

\[
H_{\text{asr}} = \text{AsrEncoder}(X),
\]

\[
o_n = \text{AsrDecoder}(y_{[1:n-1]}, H_{\text{asr}}, \bar{d}_n). \tag{2}
\]

The AsrEncoder module converts the acoustic feature \( X \) into a sequence of hidden embeddings \( H_{\text{asr}} \in \mathbb{R}^{f_{\text{asr}} \times l_{\text{asr}}} \) for ASR (Eq. (1)), where \( f_{\text{asr}} \) and \( l_{\text{asr}} \) are the embedding dimension and the length of the embedding sequence, respectively. The AsrDecoder module then iteratively estimates the output distribution \( o_n \in \mathbb{R}^{|V|} \) for \( n = 1, \ldots, N \) given previous token estimates \( y_{[1:n-1]}, H_{\text{asr}} \), and the weighted speaker profile \( \bar{d}_n \) (Eq. (2)). Here, \( \bar{d}_n \) is calculated in the AED for speaker identification, which will be explained later. The posterior probability of token \( i \) (i.e., the \( i \)-th token in \( Y \)) at the \( n \)-th decoder step is represented as

\[
Pr(y_n = i | y_{[1:n-1]}, s_{[1:n]}, X, D) = o_{n,i}, \tag{3}
\]

where \( o_{n,i} \) represents the \( i \)-th element of \( o_n \).

The AED for speaker identification is represented as

\[
H^{\text{spk}} = \text{SpeakerEncoder}(X), \tag{4}
\]

\[
q_n = \text{SpeakerDecoder}(y_{[1:n-1]}, H^{\text{spk}}, H_{\text{asr}}), \tag{5}
\]

\[
\beta_{n,k} = \frac{\exp(\cos(q_n, d_k))}{\sum_{k=1}^{K} \exp(\cos(q_n, d_k))}, \tag{6}
\]

\[
\bar{d}_n = \sum_{k=1}^{K} \beta_{n,k} d_k. \tag{7}
\]

The SpeakerEncoder module converts \( X \) into a speaker embedding sequence \( H^{\text{spk}} \in \mathbb{R}^{f_{\text{spk}} \times l_{\text{spk}}} \) that represents the speaker characteristic of \( X \) (Eq. (4)). The SpeakerDecoder module then iteratively estimates speaker query \( q_n \in \mathbb{R}^{f_{\text{spk}}} \) for \( n = 1, \ldots, N \) given \( y_{[1:n-1]}, \bar{d}_n \).

\( H^{\text{spk}} \) and \( H_{\text{asr}} \) (Eq. (5)). A cosine similarity-based attention weight \( \beta_{n,k} \in \mathbb{R} \) is then calculated for all profiles \( d_k \) in \( D \) given the speaker query \( q_n \) (Eq. (6)). A posterior probability of person \( k \) speaking the \( n \)-th token is represented by \( \beta_{n,k} \) as

\[
Pr(s_n = k | y_{[1:n-1]}, s_{[1:n-1]}, X, D) = \beta_{n,k}. \tag{8}
\]

Finally, a weighted average of the speaker profiles is calculated as \( \bar{d}_n \in \mathbb{R}^{f_{\text{spk}}} \) (Eq. (7)) to be fed into the AED for ASR (Eq. (2)).

The joint posterior probability \( Pr(Y, S | X, D) \) can be represented based on Eqs. (3) and (8) (see [22]). The model parameters are optimized by maximizing \( \log Pr(Y, S | X, D) \) over training data.

2.3. E2E SA-ASR based on Transformer

Following [29], a transformer-based network architecture is used for the AsrEncoder, AsrDecoder, and SpeakerDecoder modules. The SpeakerEncoder module is based on Res2Net [30]. Here, we describe only the AsrDecoder because it is necessary to explain the proposed method. Refer to [29] for the details of the other modules.

Our AsrDecoder is almost the same as a conventional transformer-based decoder [31] except for the addition of the weighted speaker profile \( \bar{d}_n \) at the first layer. The AsrDecoder is represented as

\[
z_{\text{asr}}^{[n-1],:0} = \text{PosEnc}(\text{Embed}(y_{[1:n-1]})), \tag{9}
\]

\[
z_{\text{asr}}^{n-1,l} = z_{\text{asr}}^{n-1,l-1} + \text{MHA}_{\text{asr-self}}(z_{\text{asr}}^{n-1,l-1}, z_{\text{asr}}^{[1:n-1],l-1}, H_{\text{asr}}, H_{\text{asr}}), \tag{10}
\]

\[
z_{\text{asr}}^{n-1,l} = z_{\text{asr}}^{n-1,l} + \text{MHA}_{\text{asr}}(z_{\text{asr}}^{n-1,l}, H_{\text{asr}}, H_{\text{asr}}), \tag{11}
\]

\[
z_{\text{asr}}^{n-1,l} = \left( z_{\text{asr}}^{n-1,l} + \text{FFN}_{\text{asr}}(z_{\text{asr}}^{n-1,l}) \right) (l = 1) \tag{12}
\]

\[
o_n = \text{SoftMax}(W^o \cdot z_{\text{asr}}^{1:n-1,l} + b^o). \tag{13}
\]

Here, \( \text{Embed}() \) and \( \text{PosEnc}() \) are the embedding function and absolute positional encoding function [31], respectively. \( \text{MHA}_{\text{asr}}(Q, K, V) \) represents the multi-head attention of the \( l \)-th layer [31] with query \( Q \), key \( K \), and value \( V \) matrices. \( \text{FFN}^\text{asr} \) is a position-wise feed forward network in the \( l \)-th layer.

A token sequence \( y_{[1:n-1]} \) is first converted into a sequence of embedding \( z_{\text{asr}}^{[1:n-1],:0} \in \mathbb{R}^{f_{\text{asr}} \times (n-1)} \) (Eq. (9)). For each layer \( l \), the self-attention operation (Eq. (10)) and source-target attention operation (Eq. (11)) are applied. Finally, the position-wise feed forward layer is applied to calculate the input to the next layer \( z_{\text{asr}}^{[n-1],l} \) (Eq. (12)). Here, \( \bar{d}_n \) is added after being multiplied by the weight \( W^{spk} \in \mathbb{R}^{f_{\text{spk}} \times f_{\text{spk}}} \) in the first layer. Finally, \( o_n \) is calculated by applying SoftMax function on the final \( L \)-th layer’s output with weight \( W^o \in \mathbb{R}^{|V| \times f_{\text{asr}}} \) and bias \( b^o \in \mathbb{R}^{|V|} \) application (Eq. (13)).

3. SPEAKER DIARIZATION USING E2E SA-ASR

3.1. Procedure overview

The overview of the proposed procedure is shown in Fig. 1. VAD is first applied to the long-form audio to detect silence regions. Then,
speaker embeddings are extracted from uniformly segmented audio with a sliding window. A conventional clustering algorithm (in our experiment, spectral clustering) is then applied to obtain the cluster centroids. Finally, the E2E SA-ASR is applied to each VAD-segmented audio with the cluster centroids as the speaker profiles. In this work, the E2E SA-ASR model is extended to generate not only a speaker-attributed transcription but also the start and end times of each token, which can be directly translated to the speaker diarization result. In the evaluation, detected regions for temporally close tokens (i.e., tokens apart from each other with less than $M$ sec) with the same speaker identities are merged to form a single speaker activity region. We also exclude abnormal estimations where (i) end_time - start_time $\geq N$ sec or (ii) end_time $< start_time$ for a single token. We set $M = 2$ and $N = 2$ in our experiment according to the preliminary results.

3.2. Estimating start and end times from Transformer decoder

In this study, we propose to estimate start and end times of $n$-th estimated token from the query $\bar{z}_{n-1}^{asr}$ and key $H_{asr}$, which are used in the source-target attention (Eq. (11)), with a small number of learnable parameters. Note that, although there are several prior works that conducted the analysis on the source-target attention, we are not aware of any prior works that directly estimate the start and end times of each token with learnable parameters. It should also be noted that we can not rely on a conventional force-alignment tool (e.g. [32]) because the input audio may be including overlapping speech.

With the proposed method, the probability distribution of start time frame of the $n$-th token over the length of $H_{asr}$ is estimated as

$$
\alpha_{n}^{start} = \text{Softmax}\left(\sum_{l} \left(\frac{W_{1-l}^{n-q} z_{n-1,l}^{asr}}{\alpha_{l}^{end}} \right)^{T} W_{l}^{n,k} H_{asr}^{l}\right). \quad (14)
$$

Here, $f^{w}$ is the dimension of the subspace to estimate the start time frame of each token. The terms $W_{1-l}^{n-q} \in \mathbb{R}^{f^{w} \times f^{h}}$ and $W_{l}^{n,k} \in \mathbb{R}^{f^{w} \times f^{h}}$ are the affine transforms to map the query and key to the subspace, respectively. The resultant $\alpha_{n}^{start} \in \mathbb{R}^{f^{w}}$ is the scaled dot-product attention accumulated for all layers, and it can be regarded as the probability distribution of the start time frame of $n$-th token over the length of embeddings $H_{asr}$. Similarly, the probability distribution of the end time frame of the $n$-th token, represented by $\alpha_{n}^{end} \in \mathbb{R}^{f^{w}}$, is estimated by replacing $W_{l}^{n,q}$ and $W_{l}^{n,k}$ of Eq (14) with $W_{l}^{n,q} \in \mathbb{R}^{f^{w} \times f^{h}}$ and $W_{l}^{n,k} \in \mathbb{R}^{f^{w} \times f^{h}}$, respectively.

The parameters $W_{l}^{n,q}$, $W_{l}^{n,k}$, $W_{l}^{n,q}$, and $W_{l}^{n,k}$ are learned from training data that includes the reference start and end time indices on the embedding length of $H_{asr}$. In this paper, we apply a cross entropy (CE) objective function on the estimation of $\alpha_{n}^{start}$ and $\alpha_{n}^{end}$ on every token except special tokens $\langle sc \rangle$ and $\langle eos \rangle$. We perform the multi-task training with the objective function of the original E2E SA-ASR model and the objective function of the start-end time estimation with an equal weight to each objective function. In the inference, frames with the maximum value on $\alpha_{n}^{start}$ and $\alpha_{n}^{end}$ are selected as the start and end frames for the $n$-th token, respectively.

4. EVALUATION RESULTS

We evaluated the proposed method with the LibriCSS corpus [24] and the AMI meeting corpus [25]. We used DER as the primary performance metric. We also used the cpWER [26] for the evaluation of speaker-attributed transcription.

4.1. Evaluation on the LibriCSS corpus

4.1.1. Experimental settings

The LibriCSS corpus [24] is a set of 8-speaker recordings made by playing back “test_clean” of LibriSpeech in a real meeting room. The recordings are 10 hours long in total, and they are categorized by the speaker overlap ratio from 0% to 40%. We used the first channel of the 7-ch microphone array recordings in this experiment.

We used the model architecture described in [33]. The AsrEncoder consisted of 2 convolution layers that subsamples the time frames by a factor of 4, followed by 18 Conformer [34] layers. The AsrDecoder consisted of 6 layers and 16k subwords were used as a recognition unit. The SpeakerEncoder was based on Res2Net [30] and designed to be the same with that of the speaker profile extractor. Finally, SpeakerDecoder consisted of 2 transformer layers. We used a 80-dim log mel filterbank extracted every 10 msec as the input feature, and the Res2Net-based d-vector extractor [9] trained by VoxCeleb corpora [35, 36] was used to extract a 128-dim speaker embedding. We set $f^{w} = 64$ for the start and end-time estimation. See [33] for more details of the model architecture.

We used a similar multi-speaker training data set to the one used in [23] except that we newly introduced a small amount of training samples with no overlap between the speaker activities. The training data were generated by mixing 1 to 5 utterances of 1 to 5 speakers from LibriSpeech with random delays being applied to each utterance, where 90% of the delay was designed to have speaker overlaps while 10% of the delay was designed to have no speaker overlaps.
with 0 to 1 sec of intermediate silence. Randomly generated room impulse responses and noise were also added to simulate the reverberant recordings. We used the word alignment information on the original LibriSpeech utterances (i.e. the ones before mixing) generated with the Montreal Forced Aligner [32]. If one word consists of multiple subwords, we divided the duration of such a word by the number of subwords to determine the start and end times of each subword. We initialized the ASR block by the model trained with the original LibriSpeech utterances (i.e. the ones before mixing) generated with the Montreal Forced Aligner [32].

In the evaluation, we first applied the WebRTC VAD\(^1\) with the least aggressive setting, and extracted the d-vector from speech region based on the 1.5 sec of sliding window with 0.75 sec of window shift. Then, we applied the speaker counting and clustering based on the normalized maximum eigengap-based spectral clustering (NME-SC) [3]. Then, we cut the audio into a short segment at the middle of silence region detected by WebRTC VAD. We split the audio when the duration of the audio was longer than the 20 sec. We then ran the E2E SA-ASR for each segmented audio with the average speaker embeddings from the speaker cluster generated by the NME-SC.

### 4.2. Evaluation on the AMI corpus

#### 4.2.1. Experimental settings

We also evaluated the proposed method with the AMI meeting corpus [25], which is a set of real meeting recordings of four participants. For the evaluation, we used single distant microphone (SDM) recordings or the mixture of independent headset microphones, called IHM-MIX. We used scripts of the Kaldi toolkit [37] to partition the recordings into training, development, and evaluation sets. The total durations of the three sets were 80.2 hours, 9.7 hours, and 9.1 hours, respectively.

We initialized the model with a well-trained E2E Conformer-based ASR pre-trained by 75K data and fine-tuned by AMI [33] used on top of the speaker diarization result.

#### 4.2.2. Evaluation Results

The evaluation results are shown in Table 2. The proposed method achieved significantly better DERs for both SDM and IHM-MIX conditions. Especially, we observed significant improvements in the miss error rate, which indicates the effectiveness of the proposed method in the speaker overlapping regions. The proposed model, pre-trained on a large-scale data [33, 38], simultaneously achieved the SOTA cpWER on the AMI dataset among fully automated monaural SA-ASR systems.

### 5. Conclusion

This paper presented the new approach for speaker diarization using the E2E SA-ASR model. In the experiment with the LibriCSS corpus and the AMI meeting corpus, the proposed method achieved significantly better DER over various speaker diarization methods under the condition of the speaker number being unknown while achieving almost the same DER as TS-VAD when the oracle speaker number is available.

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1. https://github.com/wiseman/py-webrtcvad

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| Audio                | System               | VAD       | dev          | eval          |
|---------------------|----------------------|-----------|--------------|--------------|
| IHM-MIX             | AHC [5]              | oracle\(^1\)| 6.16 / 13.45 / 0.00 / 19.61 | -            |
| IHM-MIX             | VBx [5]              | oracle\(^1\)| 2.88 / 13.45 / 0.00 / 16.33 | -            |
| IHM-MIX             | SC                   | automatic | 3.37 / 14.89 / 9.67 / 27.93 | 23.1\(^\d\) |
| IHM-MIX             | Transcribe-to-Diarize| automatic | 3.05 / 11.46 / 9.00 / 23.51 | 15.9         |
| IHM-MIX             | Transcribe-to-Diarize| oracle\(^1\)| 2.83 / 9.69 / 3.46 / 15.98 | 16.3         |
| SDM                 | SC                   | automatic | 3.50 / 21.93 / 4.54 / 29.97 | 28.6\(^\d\) |
| SDM                 | Transcribe-to-Diarize| automatic | 3.48 / 15.93 / 7.17 / 26.58 | 22.6         |
| SDM                 | Transcribe-to-Diarize| oracle\(^1\)| 3.38 / 10.62 / 3.28 / 17.27 | 21.5         |

\(^\d\) Reference boundary information was used to segment the audio at each silence region.

\(^\d\) Single-talker Conformer-based ASR pre-trained by 75K data and fine-tuned by AMI [33] was used on top of the speaker diarization result.
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