Speaker diarization assisted ASR for multi-speaker conversations

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Abstract

In this paper, we propose a novel approach for the transcription of speech conversations with natural speaker overlap, from single channel recordings. We propose a combination of a speaker diarization system and a hybrid automatic speech recognition (ASR) system with speaker activity assisted acoustic model (AM). An end-to-end neural network system is used for speaker diarization. Two architectures, (i) input conditioned AM, and (ii) gated features AM, are explored to incorporate the speaker activity information. The models output speaker specific senones. The experiments on Switchboard telephone conversations show the advantage of incorporating speaker activity information in the ASR system for recordings with overlapped speech. In particular, an absolute improvement of 11% in word error rate (WER) is seen for the proposed approach on natural conversation speech with automatic diarization.

Index Terms: Automatic speech recognition, speaker diarization, end-to-end diarization, multi-speaker ASR.

1. Introduction

The transcription of long-form conversations between multiple speakers is challenging, due to the speaker variability, unknown segment end-points and the conversational language. Further, the speakers may speak simultaneously, leading to overlapped speech in single channel recordings. A “rich transcription” is often desired for downstream applications in speech analytics, recording archival, audio indexing, etc. Speaker diarization (SD) and the automatic speech recognition (ASR) are the two important components of a rich transcription system. In this paper, we consider the transcription of long-form telephone speech conversations between two speakers from single channel recordings.

Most of the ASR research has focused on the single talker speech in controlled settings or on multi-talker speech with reference speaker activity. On the other hand, overlapped speech recognition has focused on artificial overlap of single talker speech. However, natural multi-talker conversations are rich in speaker overlaps, back channels and turn-taking. The recent CHiME-6 evaluations \cite{11} are a step in this direction. Several approaches to multi-talker ASR, based on source separation, sequence transduction and end-to-end architectures are investigated recently \cite{2,3,4,5}. A single architecture for two-talker speech recognition is proposed in \cite{2}, which is trained with a permutation invariant objective. In source separation based approaches \cite{4,5}, individual source signals/features are first obtained using a neural network \cite{6,7}, followed by a single channel ASR. The separation and ASR neural networks are either trained individually, or jointly as a single system. A sequence transduction approach is proposed in \cite{8} for joint speech recognition and speaker diarization. However, in \cite{8}, the authors assume a non-overlapping speech scenario with speakers taking turns. The multi-speaker ASR in the End-To-End framework is first proposed in \cite{9}, and extended recently using serialized output training \cite{9,10}.

The traditional speaker diarization systems are based on the clustering of speaker-sensitive speech representations, such as i-vectors or x-vectors, extracted from different segments of a long speech recording. These systems do not consider the overlapped speaker regions. The end-to-end (EEND) neural speaker diarization approaches overcome this limitation using multi-output prediction at each frame and permutation-free training \cite{11,12}. A bidirectional-LSTM (BLSTM) based model was first proposed in \cite{12} and later extended using self-attentive (SA) transformer encoder layers in \cite{11}. The approach is further extended to account for an unknown number of speakers using LSTM-based encoder-decoder attractor (EDA) model, referred to as self-attentive EEND model with EDA (SA-EEND-EDA), in \cite{13}. The neural networks are trained to predict the speaker activity, including the overlap speech regions.

In this paper, we consider the transcription of multi-speaker speech conversations from a single-channel recording. The proposed system consists of an end-to-end neural diarization system to predict the frame-level speaker activity and a speaker activity assisted ASR system for the transcription. We use the SA-EEND-EDA model \cite{13} for the diarization system. The ASR system uses the hybrid HMM-DNN (hidden Markov model - deep neural network) system \cite{14} approach with a neural acoustic model (AM) and a trigram language model. The speaker activity, predicted by the diarization system, is given as an additional input to the AM. We explore two variants (i) input conditioning and (ii) feature gating approach to combine the speaker activity information with the input features. The diarization and AM neural networks can be trained separately, as two independent models, or jointly in a single end-to-end system. This approach unifies the supervised speaker diarization, and speaker conditioned ASR in a single joint task. The method does not rely on explicit source separation as in \cite{4,5}. Also, the information about the participating speakers is not required, as in \cite{10}, and the model also applies to overlapping speaker scenarios.

2. Proposed approach

Let $X$ denote the speech input corresponding to a conversation, with $S$ number of speakers and possible overlap between speaker utterances. Let $W_s$ be the set of sentences uttered by $s^{th}$ speaker, and $L_s$ be the indicator of speech activity along time of speaker $s$. We pose the task of rich transcription of spoken conversations as the problem of computing the spoken utterances $\{W_1, \ldots, W_S\}$ along with the activity along time $\{L_1, \ldots, L_S\}$ of all speakers speech in the conversation. We decompose the task into two sub-tasks, (i) speaker activity prediction (speaker diarization) and (ii) speaker activity assisted ASR. A block diagram description of the proposed scheme is shown in Fig. 1. The same input $X$ is given to both the speaker
2.1. Speaker diarization

We consider the end-to-end neural speaker diarization approach to predict the frame-level speaker activity. In particular, we use the self-attention transformer encoder architecture with encoder-decoder attractor calculation, proposed in [13] for the diarization system. The network is trained to predict the speech activity $L_s$ for each speaker $s$, including the overlap speech regions.

2.2. Automatic speech recognition

We consider the hybrid system approach for ASR, in which a neural-network, referred to as the acoustic model (AM), is trained to predict senones (hidden states of a tri-phone HMM) for each speaker at each time frame. The network predictions are then used in conjunction with a finite state transducer (FST) decoder and a language model to generate the transcription. The speaker activity, predicted by the diarization module, is given as an additional input to the AM neural-network to generate speaker specific senones. In the present work, we explore two architectures for speaker activity conditioned AM.

2.2.1. Input conditioned AM architecture

The architecture of the input conditioned acoustic model (ICAM) is shown in Fig. 2. The 40-dimensional Mel-frequency cepstral coefficients (MFCCs) with a context of ±2 frames ($X$) are input to a linear layer, and two time-delay neural network (TDNN) layers of output size 512. The total context for the TDNN stack including the input is ±8 frames. The TDNN layer output is averaged over the given speaker’s active time-frames to generate a pooled representation. The pooling layer output is further passed through a linear layer to project into a 100-dimensional embedding space. The generated embedding $c$ is concatenated with the input features $X$ and fed to a stack of two BLSTM layers with 512 units in each direction. The final BLSTM layer output is projected into the senone space using a linear layer.

2.2.2. Gated features AM architecture

The architecture of the gated features acoustic model (GFAM) is shown in Fig. 3. A 100-dimensional embedding $c$ is first derived using the input MFCC features $X$ and the given speaker activity $L$, similar to the ICAM architecture in Fig. 2. The MFCC features $X$ are also input to a stack of two BLSTM layers to generate hidden representations $H$. The embedding $c$ is concatenated with the representations $H$ and passed through a linear layer with sigmoid activation function to generate a mask $M$. The features $H$ are multiplied with the mask $M$ and fed to a stack of 4 BLSTM layers followed by a linear layer to generate senone outputs.

3. Experimental setup

3.1. Evaluation dataset

We consider evaluation on the HUB5 English evaluation speech [15]. The dataset consists of 20 telephone conversations from the Switchboard corpus and 20 conversations from the CALL-HOME American English speech corpus [16]. We convert the two channel recordings into a single channel using “sox” tool, prior to evaluation.

3.2. Speaker diarization

The end-to-end speaker diarization model is trained on 100,000 two-speaker mixtures, simulated using audio from Switchboard-2 [17,18,19], Switchboard Cellular [20,21] and NIST-SRE (2004-08) datasets. The model is trained for 100 epochs using binary cross-entropy loss with utterance-level
permutation-invariant training (PIT), with default configuration from the reference implementation.\footnote{https://github.com/hitachi-speech/EEND} The model is further fine-tuned on the Switchboard-1 phase III dataset\footnote{https://github.com/kaldi-asr/kaldi/tree/master/egs/swbd/s5c}, for 100 epochs. The two-channel audio in the dataset is mixed to form a single channel prior to model adaptation.

For comparison, we studied diarization using an x-vector based system, which comprises of a x-vector extractor (trained\footnote{https://github.com/kaldi-asr/kaldi/tree/master/egs/swbd/s5c} on the NIST SRE datasets), followed by probabilistic linear discriminant analysis (PLDA) based similarity scoring\footnote{https://github.com/kaldi-asr/kaldi/tree/master/egs/swbd/s5c}, and agglomerative hierarchical clustering (AHC)\footnote{https://github.com/kaldi-asr/kaldi/tree/master/egs/swbd/s5c}.

We evaluate the diarization systems using the miss rate, false-alarm (FA) rate, speaker error (SE), and the diarization error rate (DER) metrics. The metrics are computed using the NIST DER evaluation script, with a collar interval of 250 ms. Tab. 1 shows the performance measures, computed with and without considering overlap speaker regions for evaluation. The miss rate is less for the SA-EEND-EDA system than the x-vector system. Overall, the DER for the SA-EEND-EDA system is better by an absolute $8\%$ compared to the x-vector diarization system.

| System       | Miss % | FA %  | SE %  | DER % |
|--------------|--------|-------|-------|-------|
| x-vector     |        |       |       |       |
| W overlap    | 13.3   | 2.4   | 1.7   | 17.42 |
| W/o overlap  | 1.7    | 3.2   | 2.3   | 7.12  |
| SA-EEND-EDA  |        |       |       |       |
| W overlap    | 5.5    | 3.2   | 0.4   | 9.16  |
| W/o overlap  | 0.4    | 4.3   | 0.5   | 5.23  |

Table 1: Speaker diarization performance. The two rows show the results with and without considering overlap speech for the evaluation.

![Figure 4: Segment formation and augmentation for mixed-channel speech. Type-A,B segments contain speech without speaker overlap. Type-C segments contain speech with speaker overlap. Segments of type-C are augmented by artificially overlapping segments of type-A and type-B.](image)

We evaluate the ASR system performance using the word error rate (WER) metric. The dataset has transcription for the ground-truth segmentation. The segments obtained from speaker diarization often do not coincide with the ground-truth. To overcome this, we evaluate the system using longer segments. The silence regions common to the reference transcripts and the diarization system output are first obtained to define a chunk for scoring. If a common silence is not detected, then the scoring is performed for the recording. The transcripts for the long chunks are obtained by concatenating the segment level reference transcripts. Since the ASR system uses speaker diarization output, the permutation with respect to the ground truth speaker labels is resolved by maximum correlation prior to scoring. The WER scores are computed separately for each speaker. We use the lattice scoring scheme available in Kaldi for scoring\footnote{https://github.com/kaldi-asr/kaldi/tree/master/egs/swbd/s5c}.

![Figure 6: An illustration of the ICAM output. The ground truth speaker activity for the entire duration of 5 s is given as input to the neural network. The plot shows the senone index with maximum posterior probability at each frame.](image)
see that, during the overlap speech region, the network predicts different senones for the two speaker channels, indicating implicit source filtering. The transcription obtained using ICAM output is given in Table 2. We see that the ICAM transcription is accurate with two insertions for the first speaker channel and one deletion during the speech overlap region for the second channel. Table 2 also shows the transcription obtained using the BLSTM-mix system (the baseline system). The system makes errors during the speaker overlap region, for example, the word “that” from the first speaker is also transcribed for the second speaker.

Fig. 5 shows a scatter-plot of the two-dimensional Student’s-t stochastic neighbourhood embedding (tSNE) projection of the embedding vector $e$ computed in the ICAM model for all segments of an example conversation in the test data. We see that the embeddings are approximately separable in the projected space, indicating speaker discriminability in the learnt embeddings. For the example illustrated in Fig. 2 the normalized cross-correlation coefficient for the embeddings $e$ of two speaker channels is found to be less than 0.1. The pooling layer in Fig. 2 performs the average over the desired speaker active regions, irrespective of the other speaker activity. We have observed that the presence of overlap regions increases the correlation between the embeddings and affects the performance of ASR.

Table 2: Example transcripts for the segment illustrated in Fig. 5. The blue and red colors correspond to the two speakers. The ground truth transcript is shown in Fig. 6.

| Architecture | GTS | SA-EEND-EDA |
|--------------|-----|--------------|
| BLSTM-iso    | 38.3| 37.7         |
| BLSTM-mix    | 40.7| 40.9         |
| ICAM         | 25.8| 26.5         |
| GFAM         | 27.4| 27.1         |

Table 3: WER comparison between the baseline BLSTM systems and the speaker conditioned AM based systems.

As seen in Tab. 3 the proposed approach leads to significant improvements in the ASR word-error-rates (WER) compared to the baseline system. The speaker activity conditioning in the proposed models helps alleviating the problem of separating speakers in the overlapping regions. Among the two approaches considered, the early combination in the ICAM model is found to be better compared to the feature gating in the GFAM model. The proposed approach yields an absolute improvement of 11.2% in WER over the baseline system with automatic diarization (relative improvement of 30%) over the baseline system.

4. Summary

A system for the transcription of natural conversations with two speakers is proposed in this paper. The speaker activity, predicted using a neural speaker diarization system, is used as additional input to the acoustic model, to predict speaker specific senones in a DNN-HMM hybrid ASR system. Implicit source separation and speaker signal extraction is observed in the network output. The speaker diarization and the acoustic model neural networks are trained separately in the present work. Experiments show the effectiveness of the proposed framework on natural two speaker conversations in terms of significant improvements in the word error rates.

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6. References

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