Bi-LSTM Scoring Based Similarity Measurement with Agglomerative Hierarchical Clustering (AHC) for Speaker Diarization

Recognition Technologies, Inc.
Technical Report: RTI-20220519-02

DOI: 10.13140/RG.2.2.13977.29288

Siddharth S. Nijhawan[1] *and Homayoon Beigi*[1,2]

[1]Electrical Engineering Dept., Columbia University
[2]Recognition Technologies, Inc. and Columbia University
[1]sn2951@columbia.edu, [2]beigi@recotechnologies.com

Abstract

Majority of speech signals across different scenarios are never available with well-defined audio segments containing only a single speaker. A typical conversation between two speakers consists of segments where their voices overlap, interrupt each other or halt their speech in between multiple sentences. For a variety of applications such as transcription, it is really important to identify multiple speakers in a conversation, for instance, generating captions for a discussion or a meeting. Thus, it becomes important for us to effectively perform speaker diarization in speech signals containing conversations among two or more speakers. Recent advancements in diarization technology leverage neural network-based approaches to improvise multiple subsystems of speaker diarization system comprising of extracting segment-wise embedding features and detecting changes in the speaker during conversation. However, to identify speaker through clustering, models depend on methodologies like PLDA to generate similarity measure between two extracted segments from a given conversational audio. Since these algorithms ignore the temporal structure of conversations, they tend to achieve a higher Diarization Error Rate (DER), thus leading to misdetections both in terms of speaker and change identification. Therefore, to compare similarity of two speech segments both independently and sequentially, we propose a Bi-directional Long Short-term Memory network for estimating the elements present in the similarity matrix. Once the similarity matrix is generated, Agglomerative Hierarchical Clustering (AHC) is applied to further identify speaker segments based on thresholding. To evaluate the performance, Diarization Error Rate (DER %) metric is used. The proposed model achieves a low DER of 34.80% on a test set of audio samples derived from ICSI Meeting Corpus as compared to traditional PLDA based similarity measurement mechanism which achieved a DER of 39.90%.

***Index Terms*—** Voice Activity Detection, Speaker Diarization, x-vector, Bi-LSTM, AHC

1. Introduction

The process involving identification of the speaker of a particular audio segment in a given audio file is called Speaker Diarization [1]. In layman's terms, speaker diarization determines who spoke when.

Over the years, speaker diarization systems have lacked the full utilization of advancements in deep learning techniques as compared to speaker verification or recognition systems. Since the diarization labels are confusing, for example, both '12223' and '31112' present equally apt sequences of speaker labels throughout the audio file, and diarization is treated as an unsupervised learning problem, there is a need for devising a fully-supervised learning model for this problem statement. Taking this into account, there have been recent advancements in the use of Convolutional Neural Networks [2] and Recurrent-Neural Networks [3] for improvising the performance of speaker diarization.

In state-of-the-art methods, PLDA is applied to estimate the similarity metric between two speech segments, however, since PLDA is a hypothesis testing-based method [1], comparisons are only performed in pairs therefore completely dismissing the time-related organization of similarity computation. The sequential-order of speech segments is completely disregarded due to their probabilistic nature. Since people always converse in a structured manner and not randomly over time, using PLDA for similarity scoring leads to a high diarization error rate. This problem can be tackled by using a bi-directional LSTM to compute the elements of the similarity matrix (backward as well as forward) of audio signal. Therefore, the use of Bi-LSTM over PLDA is proposed to compare the similarity of 2 segments both independently and sequentially and achieve a lower diarization error rate.

In summary, the proposed work achieved the following: an end-to-end diarization pipeline is designed using the ICSI Meeting Corpus dataset [4] consisting of around 70 hours of meeting recordings of multiple speakers. The Time-delayed Neural Network used to extract x-vector embeddings is trained from scratch on a portion of ICSI Meeting Corpus dataset and the Bi-LSTM is also trained on a portion of the dataset through k-fold cross validation. To further boost the performance efficiency of training Bi-LSTM and reduce the consumption of memory, batch processing is employed which breaks down the similarity chunks into small matrices and feeds them into the memory sequentially. The computed DER % based on the similarity matrix generated from Bi-LSTM and clustering is compared with the traditional scoring algorithm of PLDA across various parameters like x-vector embeddings dimension, window length, AHC threshold, etc. to showcase the low error rate of the proposed algorithm. Finally, we also compared the performance of AHC clustering with the traditional graph-based algorithm of Spectral Clustering (SC) for Bi-LSTM scoring.

The remaining paper is categorized as follows: Section 2 talks about the various state-of-the-art diarization techniques along with their implications. Section 3 formulates the problem statement through a theoretical description of the techniques used followed by a detailed system overview of the proposed diarization pipeline and the pseudo code executed to achieve the results through Kaldi in Section 4. Experimental techniques and the quantitative results obtained are detailed in the 5th Section and finally, we draw conclusions along with scope for future work in this domain in the last section.

2. State of the art

Typically, a lot of sub-systems are coupled together to develop a holistic speaker diarization system. Starting with separating the speaker audio from background noise, Voice Activity Detection (VAD) [5, 1] is performed which is usually based on energy thresholds. Once we segregate these speech regions from original audio, uniform segmentation [6] is applied to further split them into segments containing speaker-homogenous contents. In typical scenarios, this process can also be achieved using a Speech Change Detector (SCD) [7, 8], which splits these speech regions into multiple same-speaker segments. To extract features out of these homogenous segments, a mapping to a fixed dimensional space is applied through speaker embedding systems such as x-vector [9, 10] or i-vector [11]. Over the years, i-vectors have been extensively used in the form of low-dimensional vector embeddings computed over MFCC features [1] for automatic speech recognition. However, while using i-vectors for speaker diarization, a clustering layer is required as these embeddings represent both channel as well as speaker features. Since the process of clustering is extremely correlated with the total size of speech segments analyzed by the system, there is a high risk of poor performance in mapping these segments to speakers if the embeddings process short segments of speech containing less information [12]. Due to this risk associated with using i-vectors, anchor modelling techniques were introduced in [13] to output a similarity score for utterance anchors which represent the speech utterances from a set of pre-trained speak models. Several diarization algorithms also employ speaker verification methods [14, 15] to generate these feature embeddings from the outputs present in the penultimate layer. [16] performed speaker classification by training a 3-layer neural network which was then applied to a Gaussian Mixture Universal Background model. As a scoring mechanism, various similarity measurement techniques like Probabilistic Linear Discriminant Analysis (PLDA) [17] or Cosine Similarity are used to identify similarity metric between a pair of these segments to generate a similarity matrix. To obtain diarization results, similarity matrix is passed on as an input to various clustering algorithms like Spectral Clustering [6], Agglomerative Hierarchical Clustering (AHC) [18], etc.

3. Problem Formulation

A typical speaker diarization system is tasked with the objective of identifying the set of labels depicting when each speaker talks by analyzing a given set of speech signals. In terms of computational learning paradigm, we can formulate this problem as a typical supervised learning-based classification task provided we know the identities of speakers in some form of the data input to the system. However, this is an extremely ideal case, and does not occur in real world. So, to approach the problem of speaker diarization, we can split it into two stages.

Firstly, we classify each of the speakers by training a time-delayed neural network which can extract time-dependent speaker characteristics or speaker embeddings called x-vectors [9]. Generally, the activations generated from the penultimate layer of the neural network are used as x-vectors. These x-vectors are obtained by aggregating the outputs after sigmoid layer in a class-by-class manner followed by normalizing these values over the entire audio signal.

Once we have extracted all the speaker dependent information, we analyze these embeddings as a function of time so that the computational algorithm can detect when the speaker changes. The speakers which are new to the system are then compared with the existing database of previous speakers' feature embeddings through a similarity measurement methodology. In layman's terms, if similarity measure between two embeddings is below a particular user-defined threshold, the speaker is considered as new, otherwise it is mapped with the closest speaker embedding. This process can also be implemented using a learning algorithm (Bi-LSTM in our case) where the primary objective of the neural network is to predict elements of similarity matrix between each of the speaker embeddings. For this supervised learning task, we input the speaker embeddings as the features and the ground truth labels based on speaker identity information. Equation 1 denotes the Binary Cross Entropy (BCE) loss function which the neural network aims to optimize for N training samples and n classes (dimension of similarity matrix).

$$L(y, \bar{y}) = -\sum_{a=1}^{N}\sum_{b=1}^{N} y_a^b log(\bar{y}_a^b) \quad (1)$$

The predicted similarity measure is denoted by $\bar{y}_a$ for a_{th} data point and $\bar{y}_a$ denotes the ground truth for the same data point.

3.1. x-vector embeddings

x-vector is a type of feature embeddings extracted using deep neural network which was originally used in speaker verification systems as features. These x-vectors are obtained through supervised learning of a time-delayed neural network where MFCCs extracted from the speech data are used as input features. The various frame-level features are transformed into a single segment-level embedding through time-pooling modules of time-delay neural network. x-vector is the output of the second last layer in the neural network.

For the given problem statement of speaker diarization, Table 1 provides a holistic view of neural network architecture which is trained as an x-vector extractor.

Name	Layer Type	Input Size	Output Size
tdnn1	relu-batchnorm-layer	13	512
tdnn2	relu-batchnorm-layer	1536	512
tdnn3	relu-batchnorm-layer	1536	512
tdnn4	relu-batchnorm-layer	512	512
tdnn5	relu-batchnorm-layer	512	1500
stats	stats-layer (pooling)	1500T	3000
tdnn6	relu-batchnorm-layer	3000	512 or 128
tdnn7	relu-batchnorm-layer	512 or 128	512
output	output-layer	512	N

Table 1: *Architecture design for x-vector extractor*

Here, T is the number of frames present in the input and N represents the number of speakers in the training set. Layers tdnn1-5 correspond to feature-level layers in the speech containing a small context centered around the frame currently in processing. 'stats' layer or statistics pooling layer computes the mean and standard deviation after adding all the T frame-level outputs from previous layer tdnn5. The output of stats layer contains a 1500-dimensional vector for each input segment T. Further, segment level layers comprising of tdnn6 and tdnn7 aggregate the computed mean and standard deviation to the output layer containing a SoftMax operation with the number of identifiable speakers as the output size (class size). The size of penultimate layer tdnn6 (or the affine component of tdnn6) determines the dimension of x-vector embeddings which is 512 or 128 depending on the experiments performed in the later sections.

3.2. PLDA based Similarity Measurement

Probabilistic Linear Discriminant Analysis or PLDA is a state-of-the-art algorithm used for computing similarity scores between any two segments of speech (or any other form of data). Once a PLDA system is trained on a given set of features (x-vector embeddings in our case), hypothesis testing is used to compute similarity between 2 segments, say, a and b as described in equation Equation 2.

$$S_{ab} = F_{plda}(x_a, x_b) \quad (2)$$

Here, S_{ab} is the similarity measurement between x_a and x_b. PLDA originally outputs a score between [-1, 1] which is not ideal for clustering. Therefore, we normalize the output score using a logistic function to bound the similarity measure between [0, 1]. The logistic function l(x) is defined in Equation 3.

$$l(x) = \frac{1}{1 + e^{-5x}} \quad (3)$$

Therefore, now S_{ab} is bounded between [0, 1] where 1 denotes that segments a and b originate from a single speaker and 0 denotes otherwise.

3.3. Bi-LSTM based Similarity Measurement

An ideal similarity matrix contains Boolean elements where 0 denotes no similarity and 1 denotes that the two elements are from the same speaker. Moreover, content of the matrix does not change with the change in speaker index. To treat this problem as a supervised learning problem, the entire speaker embedding sequence x is used with matrix S as the class label. This is how we formulate the objective for Bi-LSTM model optimization. Therefore, we use binary cross entropy loss during the training of Bi-LSTM model to predict each row of S.

First step is to concatenate 2 x-vectors x_a and x_b which generates a 2D input for LSTM in the form $[x_a^T, x_b^T]^T$ having the output as S_{ab}. Equations 4 and 5 depicts the formulation of learning problem for Bi-LSTM in sequential manner.

$$S_a = [S_{a1}, S_{a2}, ..., S_{an}] \quad (4)$$

$$[S_{a1}, S_{a2}, ..., S_{an}] = F_{bilstm}(\begin{bmatrix} x_a \\ x_1 \end{bmatrix}, \begin{bmatrix} x_a \\ x_2 \end{bmatrix}, ..., \begin{bmatrix} x_a \\ x_n \end{bmatrix}) \quad (5)$$

Here, S_a also depicts the output of a^{th} sequence in a batch containing a total of n sequences. Therefore, to form the similarity matrix S, each of the n outputs are stacked row-wise. Figure 1 shows the high-level architectural working of Bi-LSTM based similarity measurement.

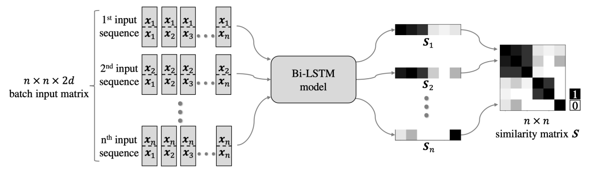


Figure 1: *Bi-LSTM System Design [19]*

For audio signals, the value of n is usually large leading to the size of matrix S being extremely large. For instance, if n equals 10,000 and d equals 512, the total size of batch input matrix will be 10,000 x 10,000 x (2 x 512), i.e., 1024 x 10^8. If each data point is stored as a floating-point datatype (requiring 4 bytes of memory), the matrix will require around 190.73 GB of RAM to perform computations on the entire matrix at once. Apart from this, LSTMs usually have poor generalization performance when given very long sequences as an input. The challenge of memory requirement can be solved by using the technique of sliding window, however, the similarity matrix generated will be of the form of a diagonal block. This will lead to the system being unable to identify the different or same speakers among different windows.

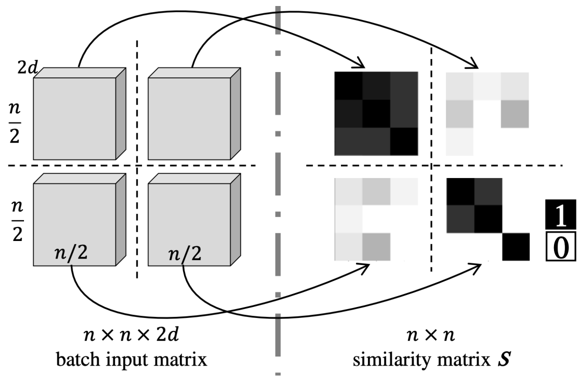

$2d$
$\frac{n}{2}$
$\frac{n}{2}$
$n/2$
$n/2$
1
0
$n \times n \times 2d$ batch input matrix
$n \times n$ similarity matrix S

Figure 2: *Batch-processing technique [19]*

In the proposed work, we suggest the technique of batch processing to tackle the above-mentioned shortcomings. Similarity matrix S is divided into several small chunks of matrices with size dependent on a max length threshold and process these batches sequentially through the Bi-LSTM model. Figure 2 denotes the breakage of a single $n \times n$ matrix into 4 sub-matrices of size $\frac{n}{2} \times \frac{n}{2}$ which is then passed onto the Bi-LSTM network sequentially.

In terms of neural network architecture, the model consists of 2 Bi-LSTM layers having 512 outputs each. Since the LSTM is bidirectional, 256 outputs are in forward direction and 256 are in backwards direction. This is followed by a fully connected layer having 64 dimensions and ReLU activation layer. The final layer is a single dimensional layer connected to a Sigmoid operation. The Sigmoid function is responsible for generating the similarity measurement between 0 and 1.

3.4. Spectral Clustering (SC)

Spectral Clustering (SC) is a clustering algorithm which is based on graphs [20]. To compute values of a similarity matrix S, SC generates an undirected graph with the number of nodes equal to the number of rows or columns in S. All the nodes are connected with edges having weights equal to S_{ab} (for edge between a and b). SC then removes edges with weights less than a threshold value and hence, forms multiple sub graphs from the existing graph.

As a first step in SC, every single diagonal element is set as 0 because it denotes self-similarity. Then Laplacian matrix L is formulated using the difference between diagonal matrix D defined as $D_a = \sum_{b=1}^{n} S_{ab}$ and similarity matrix S (as shown in Equation 6).

$$L = D - S \tag{6}$$

Here, the norm of Laplacian matrix is computed in equation 7.

$$L_{norm} = D^{-1} L \tag{7}$$

After computing eigenvalues and eigenvectors of L_{norm}. SC then takes k smallest eigenvalues and their corresponding eigenvectors to construct a matrix P containing each column as the set of k smallest eigenvectors. Finally, each row of P is clustered using k-means to generate the similarity matrix.

3.5. Agglomerative Hierarchical Clustering (AHC)

Agglomerative Hierarchical Clustering (AHC) is a form of hierarchical clustering methodology where the objective of the algorithm is to perform consecutive unification operations [21]. Unification or merging occurs when two particular data points are assigned the same cluster based on a similarity measure. These similar clusters are then further used for clustering. AHC algorithm starts by initializing clusters equal to the total number of datapoints, n in our case (number of rows or columns of similarity matrix S_{ab}). As the next step, algorithm looks for the pair having highest similarity, unifies them, and subtracts 1 from the total number of available clusters. This process is recursively repeated with the stopping condition that the similarity measure between any 2 clusters falls below a particular value designated by the user.

4. Proposed Methodology

Figure 3 describes a high-level flow of the proposed diarization model. From a given set of audio signals (obtained from ICSI Corpus) containing both voice and background noise, we first prepare the data for processing by splitting it into train and eval directories (93% & 4% respectively) followed by splitting each speaker's data into 30-second chunks. This step ensures a baseline form of diarization which will assist in the further process of actual diarization. From these 30s chunks, we extract MFCCs and perform Voice Activity Detection to generate speech separated audio signals. Finally, to generate input features for time-delayed neural network, cepstral mean and variance normalization is performed to generate set of 13-dimensional audio features for both train and eval sets.

For developing the x-vector extractor, a time-delay neural network is trained on the train set of the prepared data to generate feature embeddings in the form of x-vector $[x_1, x_2, ...x_n]$. As mentioned in the previous section, 2 different sets of neural networks are trained: one to generate 512-dimensional x-vectors and another to generate 128-dimensional x-vectors. Once the training is complete, a set of x-vectors are extracted for both train and eval sets using varying window size and time period.

A bi-directional LSTM model is used to predict similarity score S_a of every embedding vector pair (x_a, x_b) to generate similarity matrix S using the binary cross entropy loss function. To compare the performance of our model with state-of-the-art diarization techniques, a PLDA model is also trained on the train set x-vectors after reducing the dimensions through LDA (150-dim and 100-dim for experimentation). These reduced set of x-vector features are then scored on eval set features to generate similarity matrix.

For the task of supervised diarization learning, we leverage the entire matrix S as the class for the given speaker embedding sequence. Once similarity matrix is generated, Agglomerative Hierarchical Clustering is applied which initializes each segment as a singleton cluster. Since AHC algorithm is represented as a binary-tree building process, it works from bottom to top by considering each cluster as a leaf. During learning iterations, we merge clusters having a large similarity value and stop when the score is below a particular threshold hyperparameter value. This process is repeated for similarity matrix generated by PLDA as well. Again, we also apply Spectral Clustering algorithm for both Bi-LSTM and PLDA based similarity matrices. The final Diarization Error Rate (DER%) are generated by using Statistical Language Modelling Toolkit (SCTK) which compares the generated segment labels with ground truth present in respective utt2spk files.

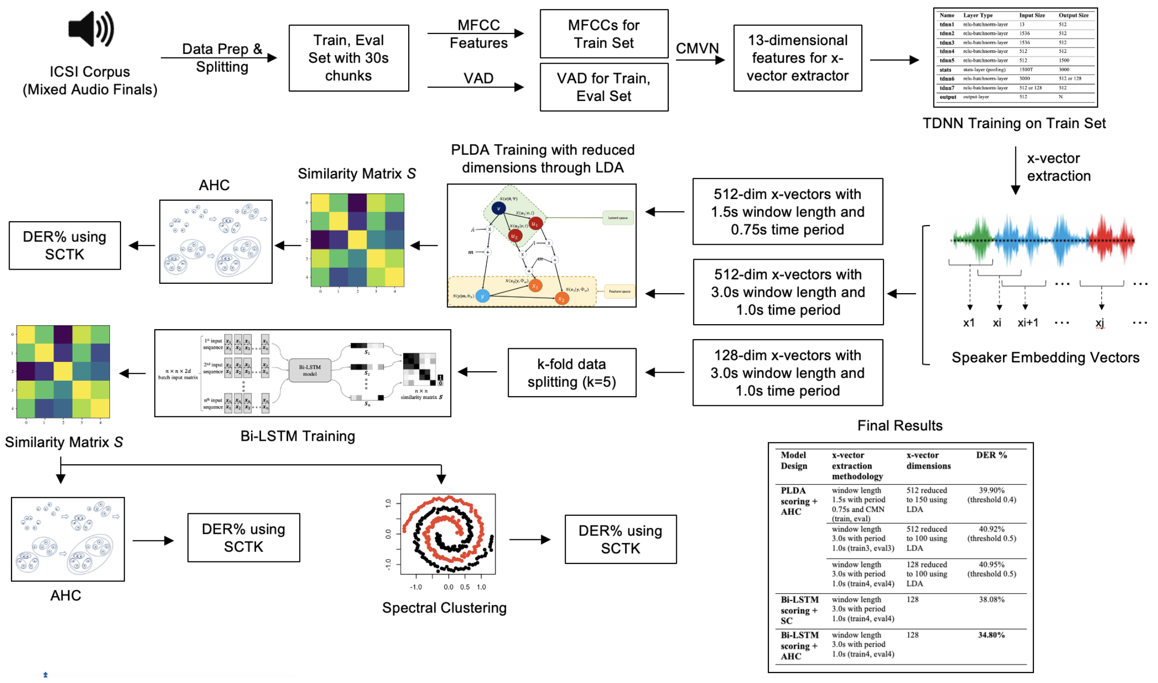
Kaldi speech recognition toolkit [22] is used to create the end-to-end diarization pipeline. The pseudo code for the entire process is depicted by Algorithm 1.

Algorithm 1: Diarization Pipeline in Kaldi

```
Input: ICSI Corpus Dataset (individual headset mix) + Transcriptions

run_prepare_shared.sh
-prepare dictionary ./icsi_prepare_dict.sh
-prepare language resources ./prepare_lang.sh
-convert transcriptions from MRT format to annotations ./icsi_text_prep.sh
-generate language model ./icsi_train_lms.sh

run.sh
-split data directories: dev, train, eval
-for data in train dev eval... do:
./modify_speaker_info.sh 30 (split 30s chunks)
-mfcc extraction for train set ./make_mfcc.sh
-for data in train dev eval... do:
./compute_vad_decision.sh
-for data in train dev eval... do:
./prepare_feats.sh
-for d = 512 and 128... train x-vector extractor
./run_xvector_1a.sh
-for d = 512 and 128... extract x-vectors ./extract_xvectors.sh
-for d = 512 and 128... train and score using plda
ivector-compute-plda
-for d = 512 and 128... predict DER using AHC
./cluster.sh

-for d = 128... 5-fold split ./ kfold.py
-for each split... train bi-lstm ./train.py
-for each split... predict similarity matrix ./predict.py
-for each split... compute DER using AHC and SC
./cluster.py

Output: DER logs per experiment for eval set
```

4.1. Dataset

The proposed work utilizes ICSI Corpus [11] for training various methodologies in the pipeline as well as evaluation. ICSI Corpus is a dataset which is based on multi-channel audio samples extracted from a set of 75 meetings entirely based in English language. These meetings have been collected between the time period 2000-2002 which occurred at International Computer Science Institute, Berkeley. The minimum length of a meeting is 17 minutes whereas meetings as long as 103 minutes are present in the dataset as well. In total, around 72 hours of audio data is present in the form of meeting room speech. The dataset also contains transcriptions for each of these meetings along with specific annotations of non-speech as well as speech segments within the data. This information is present in the MRT extension. In terms of demographical information, each meeting contains around 3 to 10 participants, with a total of 53 unique speakers in the entire dataset. To add to the variation, dataset also contains a good amount of non-native English speakers having different levels of fluency. For our pipeline, the speech segments are divided into 3 sets of training (67.5 hours), development (2.2 hours) and evaluation (2.8 hours) which ensures that there is a minimum overlap of same speakers across these sets. Dataset was originally recorded in 3 different types: individual headset mic recording, distant multiple mics recording and distant single mic recording. For our purpose, we used individual headset recordings. The information regarding the speaker mapping to the headset is present in the


ICSI Corpus (Mixed Audio Finals)
Data Prep & Splitting
Train, Eval Set with 30s chunks
MFCC Features
VAD
MFCCs for Train Set
VAD for Train, Eval Set
CMVN
13-dimensional features for x-vector extractor
TDNN Training on Train Set
x-vector extraction
Speaker Embedding Vectors
x1
xi
xi+1
xj
512-dim x-vectors with 1.5s window length and 0.75s time period
512-dim x-vectors with 3.0s window length and 1.0s time period
128-dim x-vectors with 3.0s window length and 1.0s time period
PLDA Training with reduced dimensions through LDA
Similarity Matrix S
AHC
DER% using SCTK
k-fold data splitting (k=5)
Bi-LSTM Training
Similarity Matrix S
AHC
DER% using SCTK
Spectral Clustering
DER% using SCTK
Final Results

Model Design	x-vector extraction methodology	x-vector dimensions	DER %
PLDA scoring + AHC	window length 1.5s with period 0.75s and CMN (train, eval)	512 reduced to 150 using LDA	39.90% (threshold 0.4)
	window length 3.0s with period 1.0s (train3, eval3)	512 reduced to 100 using LDA	40.92% (threshold 0.5)
	window length 3.0s with period 1.0s (train4, eval4)	128 reduced to 100 using LDA	40.95% (threshold 0.5)
Bi-LSTM scoring + SC	window length 3.0s with period 1.0s (train4, eval4)	128	38.08%
Bi-LSTM scoring + AHC	window length 3.0s with period 1.0s (train4, eval4)	128	**34.80%**

Figure 3: *System Architecture*

MRT transcription files which is decoded through Kaldi.

4.2. Implementation Details

As the entire pipeline is designed using Kaldi, there exists a recipe to prepare the ICSI Corpus for individual headset mic recording type. First, we execute the script run_prepare_shared.sh available in Kaldi's ICSI Corpus recipe for ASR to generate dictionary, language resources, language model and annotations. Post this step, everything is implemented in the script titled run.sh which is designed from scratch and suited to ICSI Corpus dataset.

In the initial stages, we do some data-preprocessing: splitting data into dev, test, and train sets, and making 30s chunks of speaker speech segments. Kaldi's pre-designed bash scripts are used for these stages. Once the data is ready, MFCCs are extracted, followed by VAD and then generating final set of 13-dimensional features post CMVN. For our experiments involving PLDA, we train an x-vector extractor from the scripts present in SRE16 recipes of Kaldi. run_xvector_1a.sh script is executed which generates examples for training the TDNN and finally, trains the TDNN. For this script, we hardcode min-frames-per-chunk as 16 and max-frames-per-chunk as 50. With these examples, we train 2 TDNN's (512 and 128-dimensional x-vector extractors). For our experiments involving PLDA, we use Kaldi's in-built scripts ivector-compute-lda, ivector-compute-plda, score_plda.sh to generate PLDA-based scores for window length and time period as discussed in the experiments section. Next, AHC is applied using cluster.sh script included with Kaldi where we search for the optimum threshold between -0.3 and 0.5. To evaluate the DER, we use SCTK's md-eval.pl script to generate diarization report for each of these experiments.

Bi-LSTM network is trained using a readily available library for Kaldi [19] which contains script to train a custom Bi-LSTM network, split the data to perform k-fold validation, and clustering (AHC and SC). We train the Bi-LSTM for a total of 10 epochs due to constraints in time and resources. For splitting the data into batches, we used a threshold of 200, i.e., if sequence length is above 200, it will be broken down into batches dependent on the size of sequence. Learning rate is set as 0.01 initially in the training process. Once, the network is trained, we perform AHC and SC clustering with varying thresholds between 0 and 1.0 to find the best optimum value for each fold. These results per fold are then combined to generate predictions using predict.py script. Finally, cluster.py script uses SCTK's md-eval.pl to generate DER results for best possible threshold value.

5. Results and discussion

5.1. Evaluation Metric: Diarization Error Rate (DER%)

DER is a metric used for quantitatively evaluating speaker diarization modules. The following errors are included in computing the DER: errors from voice activity detection, segmentation error, and classification error. DER % can be computed with the expression depicted in Equation 8.

$$DER\% = \frac{err_{spk} + err_{fas} + err_{miss}}{T} \times 100 \quad (8)$$

The numerator is an absolute sum of total time incorrectly identified as voice (err_{spk}), total timestamps assigned to incorrect speakers (err_{fas}), and the amount of speech missed due to faulty voice activity detection (err_{miss}). Here, T denotes the total time of the audio sequence. Since the annotation of speech data is performed manually, there is always a chance for human error. DER computation also takes into account the possibility of human error by providing an acceptance margin of 250ms.

5.2. Quantitative Evaluation

Quantitative evaluation is performed by carrying out experiments to determine DER% for two different scoring algorithms: PLDA and Bi-LSTM. For PLDA based scoring, to demonstrate the trade-off between memory consumption and accuracy, we use 2 different sets of x-vector models having 512 and 128 dimensions respectively. Also, 2 different types of window lengths and time periods are used to generate separate sets of x-vectors which, however, did not have a noticeable impact on the accuracy of model. Finally, to test the efficacy of our proposed pipeline using Bi-LSTM scoring and AHC clustering, we also tested the model by using Spectral Clustering to generate DER for eval set. 128-dimensional x-vector extractor was used for both of the experiments involving Bi-LSTM with a window length of 3.0s having time period 1.0s during extraction. Apart from the first experiment containing 512-dimensional x-vectors on PLDA + AHC pipeline, the sliding window cepstral mean normalization was not applied.

Table 2 contains the resulting DER % on the eval set of ICSI Corpus for different model designs and experiments. As evident from the table, the proposed algorithm which uses Bi-LSTM network for scoring and AHC for clustering achieved the least DER of 34.80% which is a noticeable improvement in comparison to the DER of range 39.9% - 43.51% achieved by state-of-the-art PLDA scoring and AHC based system. Since LSTMs have the capability to learn the sequential patterns in the data, our proposed work performed better in the classification task of identifying speakers for each of the audio segments. PLDA does not take into account the sequential information of conversation, i.e., how speakers take turns in talking and perform a highly structured conversation. Therefore, as evident from our analysis, Bi-LSTM is able to fully understand the statistical information in conversations with the help of its forward and backward layers.

For PLDA based similarity matrix generation pipeline, reducing the number of dimensions for x-vectors also increased the DER with a trade-off between memory consumption and accuracy of classification. As the dimensions are reduced from 150 to 100, the DER drops from 39.9% to 40.92%. However, there is a significant drop in the memory requirement as the total datapoints reduce from $n \times n \times (2 \times 150)$ to $n \times n \times (2 \times 100)$.

Model Design	**x-vector extraction methodology**	**x-vector dimensions**	**DER%**
PLDA scoring + AHC	window length 1.5s with period 0.75s and CMN	512 reduced to 150 using LDA	39.90% (threshold 0.4)
	window length 3.0s with period 1.0s and no CMN	512 reduced to 128 using LDA	43.51% (threshold 0.5)
	window length 3.0s with period 1.0s and no CMN	512 reduced to 100 using LDA	40.92% (threshold 0.5)
	window length 3.0s with period 1.0s and no CMN	128	43.26% (threshold 0.5)
	window length 3.0s with period 1.0s and no CMN	128 reduced to 100 using LDA	40.95% (threshold 0.5)
Bi-LSTM scoring + SC	window length 3.0s with period 1.0s and no CMN	128	38.08%
Bi-LSTM scoring + AHC	window length 3.0s with period 1.0s and no CMN	128	**34.80**%

Table 2: *DER % for different model designs*

In our experiments, AHC is proven to perform better than SC which achieved a DER of 38.08% for Bi-LSTM based similarity matrix as compared to 34.80% for AHC.

6. Conclusion and future scope

In conclusion, we proposed an alternative speaker diarization pipeline which leverages the sequential property of Bi-LSTM to predict similarity measures between two datapoints instead of state-of-the-art PLDA based scoring algorithm. The training as well as evaluation of the computational learning algorithms like TDNN, LSTM, PLDA, etc. was performed on ICSI Corpus which contains around 72 hours of human speech in the form of meeting conversations. We also demonstrated the trade-off between memory consumption and accuracy in terms of DER and proposed a batch-processing methodology to train the extremely deep Bi-LSTM. We performed experiments to choose the best clustering methodology for generating the final output and chose AHC over Spectral Clustering based on its improved performance. Our best performing model achieved a low DER of 34.08% on the evaluation set extracted from ICSI Corpus.

In future, we plan to expand this work by performing data augmentation on the dataset which adds noise, reverberation, babble noises, and music to the original audio files. This will make the system more robust and will feed the neural network more data, thus, boosting the accuracy of the system. Training the TDNN and Bi-LSTM for more than 200 epochs is also a target since the computational limitation and time constraints limited the total number of epochs to 10. Continuing the training process for longer can further optimize the BCE objective function leading to a better generalization capability of the system on unseen data. We also plan to include more largescale datasets like VoxCeleb [4] to further enhance the system.

7. References

[1] H. Beigi, *Fundamentals of Speaker Recognition*. New York: Springer, 2011, ISBN: 978-0-387-77591-3, http://www.fundamentalsofspeakerrecognition.org.

[2] Y. X. Lukic, C. Vogt, O. Dürr, and T. Stadelmann, "Speaker identification and clustering using convolutional neural networks," in *IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP)*, Sep. 13-16 2016.

[3] A. Zhang, Q. Wang, Z. Zhu, J. Paisley, and C. Wang, "Fully supervised diarization," May 12-17 2019.

[4] A. Janin, D. Baron, J. Edwards, D. Ellis, D. Gelhart, N. Morgan, B. Peskin, T. Pfau, E. Shribberg, A. Stolcke, and C. Wooters, "The icsi meeting corpus," in *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Apr. 2003.

[5] J. Chen, D. Zhou, Y. Tang, Z. Yang, Y. Cao, and Q. Gu, "Closing the generalization gap of adaptive gradient methods in training deep neural networks," in *International Joint Conference on Artifical Intelligence (IJCAI)*, 2020.

[6] Q. Wang, C. Downey, L. Wan, P. A. Mansfield, and I. L. Moreno, "Speaker diarization with lstm," *arXiv preprint arXiv:1710.10468 [eess.AS]*, Jan. 23 2022.

[7] M. Hrúz and Z. Zajíc, "A convolutional neural network for speaker change detection in telephone speaker diarization system," 2017.

[8] R. Yin, H. Berdin, and C. Barras, "Speaker change detection in broadcast tv using bidirectional long short-term memory networks," in *InterSpeech*. Interspeech, Aug. 20-24 2017.

[9] D. Snyder, D. Garcia-Romero, G. Sell, D. Povey, and S. Khudanpur, "X-vectors: Robust dnn embeddings for speaker recognition," Apr. 15-20 2018.

[10] D. Garcia-Romero, D. Snyder, G. Sell, D. Povey, and A. McCree, "Speaker diarization using deep neural network embeddings," Mar 2017, pp. 4930–4934.

[11] G. Sell and D. Garcia-Romero, "Speaker diarization with plda i-vector soring and unsupervised calibration," in *Proceedings of the IEEE Spoken Language Technology Workshop (SLT)*, Dec. 7–10 2014.

[12] B. Vesnicer and J. Žganec Gros, "Incorporating duration information into i-vector-based speaker recognition systems," in *The Speaker and Language Recognition Workshop (Odyssey)*, Jun. 16–19 2014.

[13] Y. Mami and D. Charlet, "Speaker identification by location in an optimal space of anchor models," Sep. 16–20 2002.

[14] W. Cai, J. Chen, and M. Li, "Exploring the encoding layer and loss function in end-to-end speaker and language recognition system," in *The Speaker and Language Recognition Workshop (Odyssey)*, June 26–29 2018. [Online]. Available: https://arxiv.org/pdf/1804.05160.pdf

[15] ——, "Analysis of length normalization in end-to-end speaker verification system," in *InterSpeech*. Interspeech, Sep 2018.

[16] M. Rouvier, P.-M. Bousquet, and B. Favre, "Speaker diarization through speaker embeddings," in *European Signal Processing Conference (EUSIPCO*, Aug.–Sep. 2015.

[17] S. J. Prince and J. H. Elder, "Probabilistic linear discriminant analysis for inference about identity," in *IEEE International Conference on Computer Vision (ICCV)*, Oct. 2007, pp. 1–8.

[18] S. Meignier and T. Merlin, "Lium spkrdiarization: An open source toolkit for diarization," in *CMU SPUD Workshop*, 2010.

[19] Q. Lin, R. Yin, M. Li, H. Bredin, and C. Barras, "Lstm based similarity measurement with spectral clustering for speaker diarization," in *InterSpeech*. Interspeech, Sep. 15-19 2019, source code available at https://github.com/cvqluu/nn-similarity-diarization.

[20] U. von Luxbrug, "A tutorial on spectrial clustering," *Statistics and Computing*, vol. 17, no. 4, 2007.

[21] "Agglomorative clustering using the concept of mutual nearest neighbourhood," *Pattern Recognition*, vol. 10, pp. 105–112, 1978.

[22] D. Povey, A. Ghoshal, G. Boulianne, L. Burget, O. Glembek, N. Goel, M. Hannemann, P. Motlíček, Y. Qian, P. Schwarz, J. Silovský, G. Stemmer, and K. Veselý, "The kaldi speech recognition toolkit," in *IEEE Workshop on Automatic Speech Recognition and Understanding*, 2011.