COMPOSITIONAL EMBEDDING MODELS FOR SPEAKER IDENTIFICATION AND DIARIZATION WITH SIMULTANEOUS SPEECH FROM 2+ SPEAKERS

Zeqian Li and Jacob Whitehill
Worcester Polytechnic Institute (WPI), Massachusetts, USA

ABSTRACT
We propose a new method for speaker diarization that can handle overlapping speech with 2+ people. Our method is based on compositional embeddings [1]: Like standard speaker embedding methods such as x-vector [2], compositional embedding models contain a function \( f \) that separates speech from different speakers. In addition, they include a composition function \( g \) to compute set-union operations in the embedding space so as to infer the set of speakers within the input audio. In an experiment on multi-person speaker identification using synthesized LibriSpeech data, the proposed method outperforms traditional embedding methods that are only trained to separate single speakers (not speaker sets). In a speaker diarization experiment on the AMI Headset Mix corpus, we achieve state-of-the-art accuracy (DER=22.93%), slightly higher than the previous best result (23.82% from [3]).

Index Terms— speaker identification, speaker diarization, one-shot learning, embeddings

1. INTRODUCTION
Real-world speech often includes moments with simultaneous speech from multiple speakers, and an important task in automated speech analysis is to identify not just the single speaker, but rather the entire set of speakers, who is speaking at each moment in time. This gives rise to the computational problems of (a) multi-person speaker identification and (b) speaker diarization with simultaneous speech. For single-speaker identification and diarization — i.e., where at most one person is speaking at a time — the state-of-the-art approach is based on deep speaker embedding models such as x-vector [2] and d-vector [6]. The latter can be trained to minimize a cross-entropy loss over a fixed set of training classes [2], or to minimize an embedding loss (e.g., triplet [7], generalized end-to-end [8]) in a one-shot learning setting.

Compositional embeddings: The computer vision community has recently explored compositional embeddings for object recognition problems in which each image can contain multiple objects. Li et al. [1] and Alfassy et al. [4] both proposed models containing separate embedding and set union functions, similar to our approach in this paper. In contrast to [1], our paper uses a different normalization method that we found generally gives higher accuracy (see Section 3.3).

Multi-person speaker diarization: The most common approach to speaker diarization with simultaneous speech is to use an overlapping speech detector; for those segments that contain overlap, the set of speakers can be estimated [3, 9, 10, 11, 12]. For the latter step, one approach is to select the top \( k \) closest speakers in the embedding space. In contrast, compositional embedding models can jointly predict both the number of speakers and their identities.

Contributions: (1) We propose novel methods for multi-person speaker identification, and for speaker diarization with simultaneous speech, based on compositional embeddings. (2) We improve upon the original compositional embedding model of Li et al. [1] by modifying its normalization method. (3) We show that the proposed diarization method achieves state-of-the-art accuracy, slightly outperforming the previous best result [3] on the AMI Headset Mix corpus.

2. RELATED WORK
Single-speaker identification and diarization: The state-of-the-art for these problems is based on embedding models, which can either be probabilistic subspace models such as i-vector [5], or deep neural network-based models such as x-vector [2] and d-vector [6]. The latter can be trained to minimize a cross-entropy loss over a fixed set of training classes [2], or to minimize an embedding loss (e.g., triplet [7], generalized end-to-end [8]) in a one-shot learning setting.

This material is based on work supported by the National Science Foundation under grants #1822768 and #2019805.
3. COMPOSITIONAL EMBEDDINGS FOR SPEAKER IDENTIFICATION & DIARIZATION

3.1. Single-Speaker Identification and Diarization

For the setting when at most one person is speaking at a time, the state-of-the-art approach to speaker identification and diarization is based on speaker embedding models. The set of speakers at test time is generally not known during training. For speaker identification, one enrollment example of each speaker in isolation is given to the model. The goal is to infer, in any given input audio, the single person who is speaking. For speaker diarization, there are no explicit enrollment examples; however, the process of computing distances for clustering is similar to comparing test examples with enrollment examples in identification.

Let \( S \) be the set of all possible speakers who may be speaking in a given audio. Let \( x \in \mathbb{R}^n \) be the input audio (or a feature representation such as MFCC), and let \( y(x) \in S \) be the single speaker contained in \( x \). We assume that, for each \( s \in S \), we have one enrollment example \( \bar{x}_s \) of person \( s \) speaking in isolation. Let \( d \) be a distance metric such as Euclidean distance, negative cosine similarity, etc. We wish to train an embedding function \( f : \mathbb{R}^n \rightarrow \mathbb{R}^m \) (where \( m \) is the dimension of the embedding space) with the property that \( d(f(x_a), f(x_b)) \) is small if \( y(x_a) = y(x_b) \) and is large if \( y(x_a) \neq y(x_b) \). Commonly used loss functions include the triplet loss \([7]\) and generalized end-to-end loss \([8]\).

**Inference:** Given a trained \( f \), we can determine the speaker \( s \) in a test example \( x \) by comparing \( f(x) \) with the embedded enrollment examples. First, define \( \hat{e}_s = f(\bar{x}_s) \). Then \( \hat{y}(x) = \arg\min_{s \in S} d(f(x), \hat{e}_s) \). Although we focus on one-shot learning, this formulation can be extended to the case with multiple enrollment examples per speaker \( s \) (few-shot learning) by computing the distance of \( f(x) \) to the centroid of the embedded enrollments for each speaker \( s \).

3.2. Multi-Speaker Identification and Diarization

Here we describe the compositional embedding approach that we use for speaker identification and diarization with simultaneous speech from 2+ speakers. Our model is based on work by [1], who originally proposed the method for multi-object image recognition. In contrast to the single-speaker setting, here the assumption is that, at any moment in time, a subset \( T \subseteq S \) may be speaking simultaneously. Hence, we redefine \( y \) to output the set of people speaking, i.e., \( y(x) \subseteq S \). As with single-speaker embedding models, we train \( f \) so that \( d(f(x_a), f(x_b)) \) is small if \( y(x_a) = y(x_b) \) and is large if \( y(x_a) \neq y(x_b) \). However, in contrast to the single-person setting, both individual speakers and any combination thereof must all reside at distinct locations within the embedding space. In addition, we also train a composition function \( g : \mathbb{R}^m \times \mathbb{R}^m \rightarrow \mathbb{R}^m \) that consumes two embedding vectors (each corresponding to a particular subset of speakers) and outputs the vector in the same embedding space corresponding to the union of the speaker sets in its two inputs. In other words, for any \( x_a, x_b, x_{ab} \) such that \( y(x_{ab}) = y(x_a) \cup y(x_b) \), we want \( g(f(x_a), f(x_b)) \approx f(x_{ab}) \) (see Figure 1). Note that \( g \) can be called recursively many times, e.g., \( g(f(x_c), g(f(x_a), f(x_b))) \approx x_{abc} \), where \( x_{abc} = x_a \cup x_b \cup x_c \). We train \( f \) and \( g \) jointly so as to encourage \( f \) to produce embeddings that can be composed with each other using \( g \).

**Inference:** Given trained \( f \) and \( g \), we can estimate the set \( T \) of speakers contained in any input \( x \): We first compute the pseudo-enrollments of each subset \( T \subseteq S \). Pseudo-enrollment \( \hat{e}_T \) denotes the location in the embedding space corresponding to the union of the speaker sets in its two inputs. In other words, we find the speaker set \( T \) whose enrollment (or pseudo-enrollment) example \( \hat{e}_T \) is closest to the embedding of the audio input \( x \). In the worst case, we must search over \( 2^{|S|} \) possible subsets. However, in practical diarization settings, the set of possible speakers, as well as maximum the number of overlapping speakers (e.g., \( |T| \leq 3 \), is typically small enough so that this iteration is very tractable.

![Figure 1: Compositional embedding model with embedding function \( f \) and composition function \( g \): given one example each of speakers 1, 2, and 3, the location in the embedding space of any set of speakers can be estimated with \( g \).](image-url)
3.3. Normalizing the Embedding Vectors

The original model by Li et al. [1] employed an $L_2$ normalization layer as the last layer of the neural networks of $f$ and $g$. This forces the output to lie on a sphere, which is a common embedding technique [13] and helps to prevent the embedding vectors from exploding in magnitude. However, given that $g$ may be called multiple times when computing the pseudo-enrollment examples, normalizing the output can slow training due to dampened gradients, and reduce the representational capacity of the model. In our work, we revise the model to omit the normalization layer from the last layers of $f$ and $g$. Instead we normalize just before inference; hence, to infer the speaker set, we find $\hat{g}(x) = \arg\min_{T \subseteq S} d(z(f(x)), z(\bar{e}_T))$ where $z(\cdot)$ normalizes its input to length 1.

4. EXPERIMENT 1: MULTI-PERSON SPEAKER IDENTIFICATION (LIBRISPEECH)

Here we assess the accuracy of compositional embeddings to identify the set of speakers in fixed-length (2sec) audios.

**Dataset:** For training and testing, we synthesize audio with simultaneous speech from 1-3 speakers by combining clips from LibriSpeech [4]. The LibriSpeech training sets (train-clean-100, train-clean-360, and train-other-500), validation set (dev-clean), and test sets (test-clean and test-other) contain a total of 2338, 40, and 73 speakers, respectively. We generate 2-second audios by randomly picking utterances from 1-3 speakers, adding their individual waveforms component-wise, and then normalizing for volume. From each synthesized clip, we extract MFCC features (32 coefficients, 0.025s window size, 0.01s step size) to yield the input $x$.

**Models:** We compared the following different models:

1. **CmpEmL2:** Compositional embeddings where the last layers of $f$ and $g$ perform $L_2$ normalization (like in [1]). For $f$, we used a 2-layer LSTM with 256 hidden units following by a 256-to-32 dense layer, and then normalized to length 1. Composition network $g$ was defined as $g(x_a, x_b) = z(W_1 x_a + W_1 x_b + W_2 (x_a \odot x_b))$, where $W_1, W_2$ are learned weight matrices.

2. **CmpEm:** Same as #1 above, except we use the normalization method described in Section 3.3.

3. **SingleEm:** Single-speaker embedding models have no inherent mechanism to represent simultaneous speech. Nonetheless, we can estimate the speaker set in a given audio $x$ by finding $\arg\min_{T \subseteq S} d\left(f(x), \frac{1}{|T|} \sum_{s \in T} \bar{e}_s\right)$. For example, to test whether $x$ contains speaker $a$, speaker $b$, or speakers $a \& b$, we compare $f(x)$ to $\bar{e}_a, \bar{e}_b, \bar{e}_{ab}$ and output the set that minimizes the distance. Alternatively, if $|T| = k$ is already known, we can pick the $k$ speakers whose enrollments $\bar{e}_s$ are closest to $f(x)$; this is the method used in [3] during overlapping speech.

4. **Guess:** Baseline for guessing.

**Training:** **CmpEm, CmpEmL2:** To train $f$ and $g$, we use episodic training, where each episode has 5 different speakers (i.e., $|S| = 5$) with at most 3 people speaking at once (i.e., $|T| \leq 3$). Since $\binom{3}{1} + \binom{3}{2} = 20$, there are 20 pseudo-enrollment + 5 enrollment examples for each episode. We generate 100,000 episodes for training set, 1,000 episodes for the validation set and 10,000 episodes for test set. Training is performed using Adam (lr = 0.003) to maximize the validation accuracy. We use triplet loss with $\epsilon = 0.1$. Functions $f$ and $g$ are trained jointly, with gradients backpropagated through $g$ to $f$. **SingleEm:** We trained a single-speaker embedding $f$ with the same architecture as in CmpEm; it achieved a test accuracy on identifying the single speaker (from a set of 5) of 95.3%.

**Evaluation:** The test set contains examples from speakers not seen during training; they are uniformly distributed across the 25 speaker sets (5 singletons, 10 2-sets, and 10 3-sets). We assessed test accuracy in 4 ways:

1. **Accuracy** (%-correct), over all examples, of inferring $T$.
2. **Accuracy** over examples for which $|T| = k$ ($k \in \{1,2,3\}$), of inferring $T$, when $|T|$ is *not given* to the model and must thus be inferred.
3. **Accuracy** over all examples, in determining just the number of classes in the set, i.e., $|T|$. In particular, if $|T| > 1$, then overlapping speech is detected.
4. **Accuracy** over examples for which $|T| = k$, when $|T|$ is *given* to the model by an oracle.

**Results:** $|T|$ is unknown: Results are given in Table 1. For inferring $T$, since there are 25 different possible speaker sets, the baseline for guessing is 4%. While SingleEm is much better than chance, it is worse than both compositional embedding methods (37.5% vs. 74.9% and 72.1%). This underlines the fact that single-speaker embeddings have no inherent ability to identify the size or identity of sets of speakers. Between the two compositional embedding methods, CmpEm generally does better. For inferring $|T|$, the guess rate is higher since there are only three possibilities (1,2,3), but the trend among methods is the same (Guess < SingleEm < CmpEm).

$|T|$ is given: The SingleEm slightly outperforms CmpEm when $|T| = 1$, which is expected since it focuses exclusively on modeling individual speakers. However, it performs much worse than CmpEm on simultaneous speech ($|T| \geq 2$).

5. EXPERIMENT 2: SPEAKER DIARIZATION (AMI)

Here we apply compositional embeddings to speaker diarization with simultaneous speech from multiple speakers.
### Experiment 1: Multi-Person Spkr ID on LibriSpeech

| #spkrs | CmpEmL2 | CmpEm | SingleEm | Guess |
|--------|---------|-------|----------|-------|
| ≤ 3    | 72.1    | 74.9  | 37.5     | 4.0   |
| 1      | 92.6    | 93.5  | 77.6     | 4.0   |
| 2      | 75.9    | 64.8  | 34.4     | 4.0   |
| 3      | 57.9    | 4.0   | 20.6     | 4.0   |

### Speaker Set Identification When |T| is Unknown

| ≤ 3    | 92.5    | 94.3  | 56.5     | 36.0 |

Table 1: Experiment 1 (LibriSpeech): Mean accuracy (%) correct in inferring the speaker set |T| in each audio, as well as the number of speakers |T|.

**Dataset:** We use AMI Headset Mix [15], one of the largest diarization datasets. In the test set, 81% of the speech is non-overlapping, and 19% is overlapping [3].

**Models:** In all models, the embedding function f has the same architecture (but different learned weights): From each audio input x (2sec long, step size of 0.5sec), SincNet features [16] are extracted and passed to an x-vector network [2], followed by a 512-dim embedding layer. Also, all models begin with a Voice Activity Detector (VAD) and then a Speaker Change (SCD) Detector to find speaker turns. We compare the following approaches, some of which operate on speaker turns and some on 1sec audio segments:

1. **SingleEm (turn):** Long (> 3.3sec) turns are diarized by computing the mean embedding of each and then clustering the mean embeddings using affinity propagation [17]: this yields the centroids for all the speakers. Each short (< 3.3sec) turn is diarized by averaging its embeddings and then assigning it to the speaker centroid with highest cosine similarity. Note that this model always predicts a single speaker. This approach is from [17].

2. **SingleEm (segment) with overlap detector:** After SCD, run the overlapping speech detector to find segments with multiple speakers. Instead of assigning whole turns to speakers, divide them into 1sec segments. Assign each non-overlapping segment to closest single speaker, and assign each overlapping segment to the 2 closest speaker centroids. This approach is very similar to and achieves equal accuracy as [3].

3. **CmpEm (segment):** Similar to #1, long turns are diarized by clustering their average embeddings into speakers. The centroid embedding for each speaker becomes its enrollment \( \bar{e}_s \), and enrollments are composed using g to compute pseudo-enrollments. Then, all turns are divided into 1sec segments, and each segment is assigned to a speaker set by maximizing cosine similarity of its embedding to |T| \( \in \{ \bar{e}_T : |T| \leq 2 \} \). Hence, this method can infer the set of speakers without a dedicated overlap detector.

### Experiment 2: Spkr Diarization on AMI Headset Mix

| Method | DER% |
|--------|------|
| SingleEm (turn) [17] | 30.12 |
| SingleEm (segment) with overlap detector [3] | 23.82 |
| CmpEm (segment) | 25.97 |
| CmpEm (segment) with overlap detector | 22.93 |

Table 2: Diarization Error Rate (DER%) of different speaker diarization methods on the AMI Headset Mix test set.

**Training:** We jointly train the f & g in the two CmpEm models above using VoxCeleb1 [18] and VoxCeleb2 [19] training sets augmented with MUSAN [20] background noise and music. The training procedure is the same as in Experiment 1. The f in the SingleEm models is from pyannote-audio [21] and pretrained using the same datasets. The VAD model, SCD, and overlap detector are all from pyannote-audio and pretrained using AMI training set.

**Evaluation:** We assess Diarization Error Rate (DER) – the fraction of the audio attributed to the wrong speaker(s).

**Results:** The CmpEm (segment) with the overlap detector gave the lowest diarization error (22.93%) and slightly outperformed the SingleEm (segment) with overlap detector method (23.82%, which matches the number reported in [3]). Without the use of an overlap detector, the CmpEm (segment) can jointly determine the size and identities in the speaker set for each segment: the DER is substantially better than the SingleEm approach without an overlap detector, though not as good as with the dedicated detector. Overall, the results suggest that compositional embedding models can increase accuracy for speaker diarization with overlapping speech.

6. **CONCLUSIONS**

We have shown promising results of compositional embeddings for speaker identification and diarization with simultaneous speech. Future work can examine how to cluster speaker embeddings and diarize them in a single pass, rather than the multi-stage approach we used in CmpEm (segment).
7. REFERENCES

[1] Zeqian Li, Mike Mozer, and Jacob Whitehill, “Compositional embeddings for multi-label one-shot learning,” arXiv preprint arXiv:2002.04193, 2020.

[2] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur, “X-vectors: Robust dnn embeddings for speaker recognition,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5329–5333.

[3] Latané Bullock, Hervé Bredin, and Leibny Paola García-Perera, “Overlap-aware diarization: Resegmentation using neural end-to-end overlapped speech detection,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 7114–7118.

[4] Amit Alfassy, Leonid Karlinsky, Amit Aides, Joseph Shtok, Sivan Harary, Rogerio Feris, Raja Giryes, and Alex M Bronstein, “Laso: Label-set operations networks for multi-label few-shot learning,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 6548–6557.

[5] Najim Dehak, Pedro A Torres-Carrasquillo, Douglas Reynolds, and Reda Dehak, “Language recognition via i-vectors and dimensionality reduction,” in Twelfth annual conference of the International Speech Communication Association, 2011.

[6] Ehsan Variani, Xin Lei, Erik McDermott, Ignacio Lopez Moreno, and Javier Gonzalez-Dominguez, “Deep neural networks for small footprint text-dependent speaker verification,” in 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2014, pp. 4052–4056.

[7] Kilian Q Weinberger and Lawrence K Saul, “Distance metric learning for large margin nearest neighbor classification,” Journal of Machine Learning Research, vol. 10, no. 2, 2009.

[8] Li Wan, Quan Wang, Alan Papir, and Ignacio Lopez Moreno, “Generalized end-to-end loss for speaker verification,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 4879–4883.

[9] Sree Harsha Yella and Hervé Boulard, “Overlapping speech detection using long-term conversational features for speaker diarization in meeting room conversations,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 22, no. 12, pp. 1688–1700, 2014.

[10] Martin Zelenák and Javier Hernando, “The detection of overlapping speech with prosodic features for speaker diarization,” in Twelfth Annual Conference of the International Speech Communication Association, 2011.

[11] Martin Zelenak, Carlos Segura, Jordi Luque, and Javier Hernando, “Simultaneous speech detection with spatial features for speaker diarization,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 20, no. 2, pp. 436–446, 2012.

[12] Yusuke Fujita, Naoyuki Kanda, Shota Horiguchi, Kenji Nagamatsu, and Shinji Watanabe, “End-to-end neural speaker diarization with permutation-free objectives,” arXiv preprint arXiv:1909.05952, 2019.

[13] Florian Schroff, Dmitry Kalenichenko, and James Philbin, “Facenet: A unified embedding for face recognition and clustering,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 815–823.

[14] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, “Librispeech: an asr corpus based on public domain audio books,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2015, pp. 5206–5210.

[15] Jean Carletta, “Unleashing the killer corpus: experiences in creating the multi-everything ami meeting corpus,” Language Resources and Evaluation, vol. 41, no. 2, pp. 181–190, 2007.

[16] Mirco Ravanelli and Yoshua Bengio, “Speaker recognition from raw waveform with sinnet,” in 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018, pp. 1021–1028.

[17] Ruiqing Yin, Hervé Bredin, and Claude Barras, “Neural speech turn segmentation and affinity propagation for speaker diarization,” 2018.

[18] Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Voxceleb: a large-scale speaker identification dataset,” arXiv preprint arXiv:1706.08612, 2017.

[19] Joon Son Chung, Arsha Nagrani, and Andrew Zisserman, “Voxceleb2: Deep speaker recognition,” arXiv preprint arXiv:1806.05622, 2018.

[20] David Snyder, Guoguo Chen, and Daniel Povey, “MU-SAN: A Music, Speech, and Noise Corpus,” 2015, arXiv:1510.08484v1.

[21] Hervé Bredin, Ruiqing Yin, Juan Manuel Coria, Gregory Gelly, Pavel Korshunov, Marvin Lavechin, Diego Fustes, Hadrien Titeux, Wassim Bouaziz, and Marie-Philippe Gill, “pyannote.audio: neural building blocks for speaker diarization,” in ICASSP 2020, 2020.