The goal of this work is to train robust speaker recognition models without speaker labels. Recent works on unsupervised speaker representations are based on contrastive learning in which they encourage within-utterance embeddings to be similar and across-utterance embeddings to be dissimilar. However, since the within-utterance segments share the same acoustic characteristics, it is difficult to separate the speaker information from the channel information. To this end, we propose augmentation adversarial training strategy that trains the network to be discriminative for the speaker information, while invariant to the augmentation applied. Since the augmentation simulates the acoustic characteristics, training the network to be invariant to augmentation also encourages the network to be invariant to the channel information in general. Extensive experiments on the VoxCeleb and VOiCES datasets show significant improvements over previous works using self-supervision, and the performance of our self-supervised models far exceed that of humans.

**Index Terms:** speaker recognition, unsupervised learning, self-supervised learning, adversarial training, data augmentation.

1. **INTRODUCTION**

Speaker recognition, the ability to identify or verify a speaker’s identity based on their voice, is an attractive skill, and very challenging for humans. It has gained popularity in biometric authentication due to its easy accessibility and non-invasive nature.

Although there is a large body of recent literature on speaker recognition using deep neural network models [1, 2, 3, 4, 5], the overwhelming majority of these are based on the supervised learning framework. The availability of new large-scale datasets [6, 7, 8] combined with powerful neural network models have facilitated fast progress on many popular tasks within speaker recognition, but there are many challenges to extending this strategy to every application. For instance, the cost of annotating a new dataset can be prohibitively expensive and the handling of sensitive biometric data can lead to privacy issues. The task of speaker verification is also very difficult for humans, resulting in inaccurate annotations in the absence of visual information.

On the other hand, there are many resources that can be used to learn representations, but have not been used due to the lack of annotations. For these reasons, unsupervised and self-supervised learning have recently received a growing amount of attention in order to leverage the abundant data available.

Existing literature on self-supervised learning of representations can be divided into two strands: generative or discriminative. Generative approaches learn representations by reconstructing the input data [9] or predicting withheld parts of the data, such as inpainting missing part of images [10] and colourising RGB images from only grey-scale images [11]. However, the element-wise generation is computationally expensive and is not necessary for representation learning.

Of relevance to our work is the second strand that learns discriminative representations directly, often using metric learning-based objectives. In particular, approaches based on contrastive learning in the latent space have shown to learn effective representations by taking within-class inputs from multiple views [12, 13, 14, 15] or modalities [16, 17, 18, 19, 20] of the same input data.

These strategies have been applied to speech signals in order to enable unsupervised learning of speaker representations. [21] samples two speech segments from the same utterance and trains the network to maximise the mutual information between them. A key difference between supervised metric learning and the proposed contrastive learning framework is that segments from a single utterance have the same noise and reverberation characteristics. This effect has been partially mitigated using data augmentation in [22], which mimics the strategy of [15] that has shown promising performance in vision tasks.

A key challenge in speaker recognition is to learn embeddings that are speaker-discriminative, but invariant to all other spurious variations. Inspired by the work on domain adaptation using adversarial training [23, 24], recent works have used this framework to improve generalisation between languages [25, 26, 27] and between datasets [26, 28]. In particular, [5] and [29] have proposed channel invariant training for speaker recognition by introducing a confusion loss between same speaker segments from across and within an utterance.

Within the contrastive learning framework, it is difficult to obtain same speaker segments from across different utterances, but one can simulate different environments using data augmentation. To this end, we propose Augmentation Adversarial Training (AAT) to explicitly train speaker discriminative and environment invariant embeddings without speaker labels. Since data augmentation simulates the channel environment, training the network to be invariant to augmentation also encourages the network to be invariant to the channel information in general. Our experiments using the contrastive learning framework demonstrate the effectiveness of the proposed strategy. The proposed model outperforms all existing
self-supervised methods on the VoxCeleb1 test set by a large margin, and we also show that the speaker verification performance of our model also far exceeds that of humans.

2. AUGMENTATION ADVERSARIAL TRAINING

This section describes the proposed unsupervised training strategy. First, we introduce the contrastive learning framework which samples two non-overlapping speech segments from each utterance and applies data augmentation. We then propose Augmentation Adversarial Training (AAT), which exploits an augmentation classifier in addition to speaker embedding extractor. Training is performed in turns to remove channel information from the speaker representation.

2.1. Contrastive training

Each mini-batch \( B \) contains randomly selected \( N \) clips \( x_1, x_2, \ldots, x_N \) out of training set. For each clip \( x_i \), we sample two non-overlapping speech segments, \( x_{i,1} \) and \( x_{i,2} \). Under the assumption that every utterance contains only one person’s speech, \( x_{i,1} \) and \( x_{i,2} \) are from same identity.

Since \( x_{i,1} \) and \( x_{i,2} \) are sampled from the same clip, the channel characteristics of the two segments are likely to be identical. As a result, using the standard metric learning methods, speaker network might learn the similarity of the environment between the two segments, not the speaker characteristics. Therefore, data augmentation such as additive noise or room impulse response (RIR) is added to simulate different channel characteristics.

Specifically, we sample a mini-batch \( B = \{ x_1, x_2, \ldots, x_N \} \) from the dataset. For \( 1 \leq i \leq N \), we take two non-overlapping segments \( x_{i,1} \) and \( x_{i,2} \) from \( x_i \). Then, the speaker embeddings \( e_{i,j,k} \) are computed as follows:

\[
e_{i,j,k} = f(x_{ij} \ast R_{ik} + N_{ik})
\]

where \( R_{ik} \) and \( N_{ik} \) are randomly selected from RIR filters and noise dataset. \( f(\cdot) \) is the speaker embedding extractor and is trained with speaker loss functions. \( \ast \) is the notation for convolution. Therefore, \( e_{i,j,k} \) refers to the embedding of \( j \)-th segment of \( i \)-th utterance, with augmentation type \( k \).

Prototypical loss. Prototypical network has been introduced for few-shot learning and has been shown to perform well in speaker verification [30, 31, 32]. In our case, \( e_{i,1,1} \) is a query and \( e_{i,2,2} \) is a prototype of size 1 support set. We compute the negative of the Euclidean distance as follows:

\[
S(e_i, e_j) = -\|e_i - e_j\|_2^2
\]

In the angular variant of the prototypical loss (AP) [32], the distance function is replaced by a cosine similarity combined with learnable weight and bias.

\[
S(e_i, e_j) = w \cdot \cos(e_i, e_j) + b
\]

Cross-entropy loss with a log-softmax function is used to minimise the distance between segments from same utterance and maximise the distance between different utterances.

\[
L_{spk} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{\exp(S(e_{i,1,1}, e_{i,2,2}))}{\sum_{k=1}^{N} \exp(S(e_{i,1,1}, e_{i,2,2}))}
\]

In contrast to supervised metric learning, it is not guaranteed that all \( x_i \) are from different speakers. If the batch size \( N \) is small relative to the total number of speakers, it can be expected that most of the utterances in a batch are from different speakers.

2.2. Augmentation Adversarial Training

Data augmentation methods help the learnt embeddings to be more robust to channel variance, however do not explicitly remove the information from the embeddings. Since the augmentation methods simulate different channel environments, training the embeddings to be invariant to the augmentation also encourages the embeddings to be channel-invariant. Here, we propose Augmentation Adversarial Training (AAT) that penalises the ability to predict the augmentation in order to prevent the speaker network from learning the channel information.

In addition to speaker representations \( e_{i,1,1} \) and \( e_{i,2,2} \), the third representation is extracted. The third representation \( e_{i,2,1} \) comes from the second segment \( x_{i,2} \). We apply same RIR filter \( R_{i,1} \) and additive noise \( N_{i,1} \) as the first.

\[
e_{i,j,k} = f(x_{ij} \ast R_{ik} + N_{ik}) \quad (j,k) \in \{(1,1),(2,1),(2,2)\}
\]

Discriminator training. In this step, we train the augmentation classifier \( g \). The assumption is that \( e_{i,1,1} \) and \( e_{i,2,1} \) share the same channel characteristic, while \( e_{i,1,1} \) and \( e_{i,2,2} \) have different characteristics. We generate two types of input, \( e_{i,1,1} + e_{i,2,1} \) and \( e_{i,1,1} + e_{i,2,2} \), where \( + \) indicates concatenation of vectors. The network is trained to classify whether two inputs are from the same channel by using cross entropy loss. In this step, the gradient does not flow to the speaker network.

Embedding training. In this step, we update the weights of the speaker embedding extractor \( f \). While training speaker network with \( e_{i,1,1} \) and \( e_{i,2,2} \) similar to Section 2.1, we also apply augmentation adversarial training loss to encourage speaker network to learn channel-invariant embedding. The weights of \( g \) are fixed during this step. Learning objective related to this strategy is described below.

AAT loss. The AAT loss is applied to remove the channel information from speaker embeddings. After training the augmentation classifier to distinguish channel similarities, we compute the cross entropy loss with a two-way softmax function. A gradient reversal layer is placed between embedding extractor and augmentation classifier, thereby penalising the ability to correctly predict whether the pair of segments share the same channel characteristics.

\[
L_{AAT} = -\frac{1}{2N} \sum_{j=1}^{N} \sum_{k=1}^{2} \log \frac{\exp(g_{j-1}(e_{j,1,1} + e_{j,2,2}))}{\sum_{l=1}^{2} \exp(g_{j-1}(e_{j,1,1} + e_{j,2,2}))}
\]
is activated in this phase. \( g_{-1}(x)_k \) indicates the \( k \)-th element of the network output.

The overall loss is summation of the speaker loss and the AAT loss with a weight \( \lambda \). \( L_{spk} \) can be either prototypical or angular prototypical loss function.

\[
L_{overall} = L_{spk} + \lambda L_{AAT}
\]

**Discussion.** We experiment with an additional variant of augmentation adversarial training. Instead of making augmentation classifier to output binary predictions, [5] proposes to train this network to produce environmental embeddings and utilises the triplet loss during training. We have observed that our method using the binary classifier performs marginally better than using the triplet loss.

### 3. EXPERIMENTS

#### 3.1. Input representations and model architecture

Since the utterances in VoxCeleb are always longer than 4 seconds, two 1.8-second segments are randomly sampled from each utterance during batch formation. The duration of the segments are slightly shorter than half of the shortest utterance in order to allow for small temporal perturbation. 40 dimensional log-mel spectrogram is extracted with window length 25 ms and hop length 10 ms. Instance normalisation [33] is performed as a mean variance normalisation to the input.

The network architecture of the speaker network closely follows the Fast ResNet-34 architecture in [32]. It is a lightweight version of original ResNet-34 with the same architecture but the channel sizes are reduced to a quarter. Self-attentive pooling is performed on the output of residual blocks along the time axis, followed by a fully connected layer. The dimension of the speaker embedding is 512.

The augmentation classifier consists of a gradient reversal layer followed by two fully connected layers with hidden size 512. ReLU activation and one-dimensional batch normalisation are performed between these layers. The size of last fully connected layer is 2 since the network is a binary classifier.

#### 3.2. Data augmentation

Data augmentation plays a crucial role in contrastive learning, as reported by previous literature in speaker recognition [22] and other domains [12, 13, 14, 15]. We exploit two popular augmentation methods in speech processing – additive noise and RIR simulation. For additive noise, we use the MUSAN corpus [34]; for room impulse responses, we use 1,000 pre-computed RIR filters. Both noise and RIR filters are randomly selected during training. The types of augmentation and the SNR range for each type is the same as those used by the original x-vector paper – see Section 3.3 of [35] for details.

In order to verify the effects of the different augmentation methods, we perform a number of experiments, (1) without any augmentation, (2) applying only noise addition, (3) applying either noise addition or reverberation and (4) applying both noise and reverberation. We also compare the results of only augmenting one of the speech segment (i.e. \( R_{i,1} = 1 \) and \( N_{i,1} = 0 \)) and augmenting both of the speech segments.

#### 3.3. Dataset

**VoxCeleb.** VoxCeleb is an audio-visual dataset consisting of short clips of human speech, extracted from celebrity interview videos uploaded to YouTube. The models are trained on the development set of VoxCeleb2 [7], and evaluated on the original test set of VoxCeleb1 [6] containing 40 speakers.

**VOiCES.** The Voices Obscured in Complex Environmental Settings (VOiCES) [36] corpus contains speech recorded by far-field microphones in noisy room conditions. Evaluation on this dataset is performed to provide out-of-domain trial for the models trained on the VoxCeleb2 dataset. In particular, we use the evaluation list provided in the development data for the 2019 VOiCES challenge.
which contains 4 million pairs from 15,904 utterances. Note that the speaker models are not trained or fine-tuned on this dataset, in order to verify that the models trained on the VoxCeleb dataset generalises to out-of-domain data.

3.4. Baselines

We compare the results of our methods with a range of baselines in Table 1.

Previous works using self-supervision. [19] and [20] use cross-modal self-supervision to learn the joint representation of face images and speech segments. [22] proposes audio-only self-supervised learning with data augmentation using additive noise and RIR filters, which is of closest relevance to our work since they use the same network inputs as well as the training and the test data.

I-vectors. I-vectors [37] have been used widely in speaker recognition before the emergence of deep learning. Although the i-vectors are often used in conjunction with PLDA back-end to improve performance [38, 39, 40], training of i-vectors and scoring with cosine similarity as proposed by the original paper [37] do not require any supervision. See Appendix B for our implementation.

Human benchmark. Humans do not learn how to recognise the speaker identity through supervised training. Therefore, it is interesting to compare the human performance on speaker verification as a self-supervised counterpart of our model. We conduct experiments with two groups of annotators—crowdworkers on Amazon Mechanical Turk and experts who have dealt with speaker recognition for several years. Details of these experiments are described in Appendix A.

3.5. Results

Evaluation protocol. We report two performance metrics: (i) the Equal Error Rate (EER) which is the rate at which both acceptance and rejection errors are equal; and (ii) the minimum detection cost of the function used by the NIST SRE [41] and the VoxSRC evaluations. For computing EER, we sample 10 speech segments for each utterance and compute the mean of 10×10=100 distances from all possible combinations per each pair. This protocol is in line with that used by [7]. The parameters $C_{mis} = 1$, $C_{fa} = 1$ and $P_{target} = 0.05$ are used for the cost function.

Discussion. Table 1 reports the experimental results. Data augmentation is a key to the performance of self-supervised speaker models. More aggressive augmentation schemes (e.g. noise and RIR) improve the performance of the models. AAT reduces the verification errors across a range of augmentation settings and objective functions. The best performing model training with angular prototypical loss and AAT achieves an equal error rate of 8.65%, outperforming all comparable works by a significant margin. Similar trend is observed in VOiCES dataset results, on which the models trained with AAT outperforms the counterparts without. This demonstrates that the models trained using AAT generalises better to unseen domains, as well as the dataset that the models have been trained on.

![Table 1: Speaker verification performance. All experiments are repeated three times and we report the mean and standard deviation. † uses the i-vector together with cosine similarity, as described in Section 3.4. ‡ computed on a subset of 2,000 pairs, see Appendix A for details. P: Prototypical, AP: Angular Prototypical, AAT: Augmentation Adversarial Training, N | R: Noise or RIR augmentation, N + R: Noise and RIR augmentation.](http://www.robots.ox.ac.uk/~vgg/data/voxceleb/competition2020.html)
A. APPENDIX: HUMAN BENCHMARK

This appendix provides detailed descriptions of the human experiments introduced in Section 3.4. The purpose of this task is to determine how well automated speaker recognition systems perform compared to human ability.

A.1. Experimental settings

Two groups of annotators – Amazon Mechanical Turk and experts – are asked to annotate random subsets of the VoxCeleb test set. The evaluation protocols for these experiments mimic the VoxCeleb evaluation for automatic speaker recognition – the annotators are given utterance pairs, and they are asked whether they believe that the two utterances are spoken by the same speaker.

The annotators are given a pair of utterances to listen to, and are asked to choose between one of the following options. The annotators are discouraged from using the score of 3 (borderline). They are given up to 30 seconds for the task.

- 1 - Definitely different,
- 2 - Probably different,
- 3 - Borderline,
- 4 - Probably the same,
- 5 - Definitely the same.

AMT. Amazon Mechanical Turk is a crowdsourcing marketplace to hire remotely located crowdworkers to perform discrete microtasks such as data annotation or surveys.

2,000 randomly sampled pairs from the VoxCeleb test set are given to the annotators through this platform, who are rewarded on a per-sample basis. The tasks are only made available to the most experienced and highly rated workers, however the annotators do not necessarily have previous experience in speaker recognition.

The annotators are told that the approximately half of the pairs are from the speaker, and are given some example pairs to listen to before working on the task.

Experts. The samples are also annotated by the authors of this paper, who have several years of experience in speaker recognition. The authors are very familiar with the VoxCeleb dataset, including the statistics of the test set.

The same 2,000 pairs used by the Mechanical Turk are divided into 4 subsets of 500, each of which is annotated by a different author. These subsets are referred to as Sets A, B, C and D in Table 2.

A.2. Evaluation

We report three metrics for the human benchmark – Equal Error Rates (EER), Area Under Receiver Operating Characteristic curve (AUROC), and binary classification accuracy. EER and AUROC are obtained by interpolating the ROC curve between the points for the 5 discrete scores. Binary classification accuracy is the most intuitive and fair metric for humans, since binary decision from each pair is exactly the same task that they have been asked to perform. The score of 3 (borderline) is assigned to the positive class for both AMT and experts, since this gives a better accuracy. In reality, the annotators only used the borderline option very few times. To compute the binary classification accuracy of our unsupervised automatic speaker verification model (ASV), we set the threshold tuned on the validation set that does not overlap with the test set in the table.

Table 2: Speaker verification performance of different methods on various subsets of the VoxCeleb1 test set. Exp.: Experts. ASV: Unsupervised Automatic Speaker Verification model trained using the AP + AAT loss.

| Set Pairs | Verif. EER (%) | AUROC (%) | Class. Acc. (%) |
|-----------|---------------|-----------|-----------------|
|           | AMT Exp. ASV  | AMT Exp. ASV | AMT Exp. ASV    |
| A 500     | 25.75 ± 16.53 | 8.10      | 76.80 ± 82.20   |
| B 500     | 25.63 ± 15.70 | 8.77      | 74.40 ± 86.00   |
| C 500     | 22.59 ± 17.78 | 9.01      | 75.40 ± 82.20   |
| D 500     | 25.91 ± 13.98 | 8.76      | 79.46 ± 89.28   |
| All 2,000 | 26.51 ± 15.77 | 8.50      | 74.10 ± 84.20   |

Table 3: The effect of the value of $\lambda$ on speaker verification performance, using Noise and RIR augmentation.