Robust Speech Representation Learning via Flow-based Embedding Regularization

Woo Hyun Kang, Jahangir Alam, Abderrahim Fathan
Computer Research Institute of Montreal
{woohyun.kang, jahangir.alam, abderrahim.fathan}@crim.ca

Abstract
Over the recent years, various deep learning-based methods were proposed for extracting a fixed-dimensional embedding vector from speech signals. Although the deep learning-based embedding extraction methods have shown good performance in numerous tasks including speaker verification, language identification and anti-spoofing, their performance is limited when it comes to mismatched conditions due to the variability within them unrelated to the main task. In order to alleviate this problem, we propose a novel training strategy that regularizes the embedding network to have minimum information about the nuisance attributes. To achieve this, our proposed method directly incorporates the information bottleneck scheme into the training process, where the mutual information is estimated using the main task classifier and an auxiliary normalizing flow network. The proposed method was evaluated on different speech processing tasks and showed improvement over the standard training strategy in all experimentation.

1 Introduction
In recent years, attributed to the wide deployment of smart devices, the interest in speech-based applications has been rapidly growing. One major sub-field that is gaining popularity is speech-based identity recognition task, which includes speaker verification, language identification, and voice spoof detection. Since the given speech signals are likely to have different durations, usually an utterance-level fixed-dimensional vector (i.e., embedding vector) is extracted and fed into a scoring or classification algorithm. To achieve this, various methods have been proposed utilizing deep learning architectures for extracting embedding vectors and have shown state-of-the-art performance when a large amount of training data is available [Variani et al., 2014], [Wan et al., 2018], [Snyder et al., 2018], [Snyder et al., 2017], [Xie et al., 2019], [Chung et al., 2020], [Heo et al., 2020]. However, despite their success in well-matched conditions, the deep learning-based embedding methods are vulnerable to the performance degradation caused by mismatched conditions [Meng et al., 2019a].

Recently, many attempts have been made to extract an embedding vectors robust to variability unrelated to the main task [Meng et al., 2019a], [Meng et al., 2019b], [Zhou et al., 2019], [Kang et al., 2020]. Especially in [Kang et al., 2020], a joint factor embedding (JFE) technique was proposed where the embedding network is trained to maximize the speaker-dependent information within the embedding while simultaneously maximizing the uncertainty on unwanted attributes (e.g., channel, emotion). Also in [Zhou et al., 2019], an adversarial training strategy is proposed, where the embedding network and a nuisance attribute discriminator network are trained in a competitive fashion. The authors of [Meng et al., 2019b] also adopted an adversarial strategy, but used a gradient reversal layer to force the embedding network to learn no information about the unwanted attributes. Although these methods were able to enhance the verification performance, they can only be used when a training set with nuisance labels is available due to their fully-supervised nature.

In this paper, we propose a novel approach to disentangle the unwanted information from the embedding vector without the need for any nuisance labels. Our proposed method exploits the information bottleneck framework, where the system is trained to produce a latent variable with maximum information on the main-task (e.g., speaker verification) while regularizing it to have minimum redundant information. In order to minimize the redundancy, we estimate the upper-bound of the mutual information between the input speech and the embedding using the contrastive log-ratio upper-bound (CLUB) scheme [Cheng et al., 2020]. Since CLUB requires a conditional likelihood estimator, we adopted a simple normalizing flow model which showed an outstanding performance in image generation and speech synthesis tasks. To maximize the speaker discriminability of the embedding while minimizing its information on unwanted variability within the input speech, we trained the embedding network and the flow-based conditional likelihood estimator in a competitive fashion, similar to the generative adversarial network (GAN) [Zhou et al., 2019]. Experimental results showed that the proposed regularization technique was able to enhance the speaker verification performance by suppressing the nuisance information within the embedding vector.

The contributions of this paper are as follows:
- We propose a new method to regularize the embedding network to have minimum redundancy, which can be
done without the need of any additional metadata (i.e., nuisance labels).
- We compared the proposed regularization method on various tasks including speaker verification, language identification and voice spoof detection.

2 Backgrounds

2.1 Deep Speech Embedding

In the past several years, various deep architectures for speech extraction have been proposed. In most of these frameworks, given a speech utterance X with T frames, a sequence of frame-level acoustic features \{x_1, ..., x_T\} extracted from X is fed into the frame-level network. Once the frame-level outputs \{h_1, ..., h_T\} are obtained, they are aggregated to obtain an utterance-level representation. One way of aggregating the frame-level outputs is the self-attentive pooling (SAP) [Zhu et al., 2018], which computes the weighted average as

\[ \omega = \sum_{t=1}^{T} \alpha_t h_t \]  

(1)

where \( \alpha_t \in [0, 1] \) is a normalized weight, which is computed by

\[ \alpha_t = \frac{\exp(e_t)}{\sum_{t=1}^{T} \exp(e_t)} , \]

(2)

In (2), the frame-level score (i.e. attention) \( e_t \) is computed as follows:

\[ e_t = \mathbf{v}_t^\top \text{tanh} (\mathbf{W}_t h_t + \mathbf{b}_t) \]

(3)

where \( \mathbf{v}_t \), \( \mathbf{W}_t \), and \( \mathbf{b}_t \) are trainable parameters and superscript \( \top \) indicates transpose operation. By using different weight for each frame, speech frames with relatively higher target-relevancy can contribute more to the embedding vector.

The embedding network is trained to maximize the target discriminability. Depending on the main task, different types of objective functions are used to achieve this. For binary classification tasks, such as anti-spoofing, the system is often trained via one-class softmax objective function, which can be formulated as [Zhang and others, 2021]:

\[ L_{OCUS} = -\frac{1}{N} \sum_{i=1}^{N} \log (1 + e^{k(m_{yi}_{i} - \hat{W}_0 \omega_i)(-1)^{yi}_{i}}) \]

(4)

where \( k \) is the scale factor, \( \omega_i \in \mathbb{R}^D \) and \( y_i \in \{0, 1\} \) are the D-dimensional embedding vector and label of the \( i \)-th sample respectively. \( N \) is the mini-batch size and \( m_{yi} \) defines the compactness margin for class label \( y_i \). The larger is the margin, the more compact the embeddings will be. \( \hat{W}_0 \) is the weight vector of our target class embeddings. Both \( \hat{W}_0 \) and \( \omega_i \) are normalizations of \( W_0 \) and \( \omega_0 \) respectively.

On the other hand, for multi-class classification tasks, one of the most popular softmax variant objectives is the additive angular margin softmax (AAMSsoftmax) [Deng et al., 2021]. The AAMSsoftmax objective is formulated as follows:

\[ L_{AAMSsoftmax} = -\frac{1}{N} \sum_{i=1}^{N} \log \left( \frac{e^{s \cos(\theta_{yi}_{i} + m)}}{K_1} \right), \]

(5)

where \( K_1 = e^{s \cos(\theta_{yi}_{i} + m)} + \sum_{j=1, j \neq i}^{c} e^{s \cos \theta_{j,i}} \) is the batch size, \( c \) is the number of classes, \( y_i \) corresponds to label index, \( \theta_{j,i} \) represents the angle between the column vector of weight matrix \( W_j \) and the \( i \)-th embedding \( \omega_i \), where both \( W_j \) and \( \omega_i \) are normalized. The scale factor \( s \) is used to make sure the gradient is not too small during the training and \( m \) is a hyperparameter that encourages the similarity of correct classes to be greater than that of incorrect classes by a margin \( m \).

2.2 Information Bottleneck

The information bottleneck is a theoretical method for learning a latent representation with minimum redundant information. Given an input data \( X \) and its corresponding target label \( y \), the information bottleneck aims to learn an encoder that produces a latent variable (embedding) \( \omega \) with high information on \( y \) and low relevance with the source \( X \). To achieve this, the objective for information bottleneck can be written as:

\[ L_{IB} = -I(y; \omega) + \beta I(X; \omega) \]

(6)

where hyperparameter \( \beta \) is a positive scalar coefficient.

Maximizing \( I(y; \omega) \) can be easily accomplished by using a typical discriminative objective function including softmax or contrastive losses. This is mainly attributed to the fact that the softmax and contrastive objective functions can be interpreted as a lower-bound of the mutual information. Moreover, one could use neural estimation methods such as mutual information neural estimation (MINE) [Belghazi et al., 2018] or InfoNCE [van den Oord et al., 2019], which also estimates the lower bound of the mutual information.

On the other hand, minimizing \( I(X; \omega) \) can be difficult due to the complex distribution of \( X \). In order to alleviate this problem, most previous approaches regularized the latent distribution to be Gaussian. However, using such simple distribution for the embedding may hinder its representational ability. Therefore various attempts have been made to exploit the neural mutual information estimation scheme (e.g., MINE, InfoNCE). Although these neural estimation methods do not assume the embedding to follow a certain distribution, minimizing these estimations showed minimum improvement since they estimate the lower-bound mutual information. Thus in order to effectively minimize \( I(X; \omega) \), one should estimate the upper-bound mutual information.

Contrastive Log-ratio Upper-Bound Mutual Information

CLUB [Cheng et al., 2020] is a mutual information estimation method that is trained via contrastive learning. Given
the conditional distribution \( p(X|\omega) \), the mutual information CLUB is defined as:
\[
I_{\text{CLUB}}(X; \omega) = E_{p(X,\omega)}[\log p(X|\omega)] - E_{p(X)p(\omega)}[\log p(X|\omega)].
\]  
(7)

Unlike the mutual information estimated via MINE or InfoNCE, \( I_{\text{CLUB}}(X; \omega) \) is the upperbound of the true mutual information \( I(X; \omega) \).

### 2.3 Normalizing Flow

Normalizing flow is a generative model which consists of a stack of invertible functions which map the samples from a simple distribution \( p_s(z) \) to a complex distribution \( p_X(x) \). Let \( f_i \) be a mapping from \( z^{i-1} \) to \( z^i \), \( z^0 = x \) and \( z^n = z \). Then \( x \) is transformed into \( z \) through a chain of invertible mappings:
\[
z = f_n \circ f_{n-1} \circ \ldots \circ f_1(x).
\]  
(8)

By the change of variables theorem, the log-likelihood of \( x \) can be computed as follows:
\[
\log p_X(x) = \log p_Z(z) + \sum_{i=1}^n \log |\det \frac{\partial f_i}{\partial z^{i-1}}|.
\]  
(9)

Usually, the latent distribution \( p_Z \) is set to be a standard normal distribution \( N(0, I) \). Since the second term \( \sum_{i=1}^n \log |\det \frac{\partial f_i}{\partial z^{i-1}}| \) can be computationally expensive to obtain, \( f_i \) is required to have a tractable Jacobian. One way to achieve this is to use an affine coupling layer which is defined as follows:
\[
z_a^1 = z_a^{i-1},
\]  
(10)
\[
z_b^i = z_b^{i-1} \circ \exp(\sigma(z_a^{i-1}) + \mu(z_a^{i-1})),
\]  
(11)
where \( z_a^1 \) is the first half, \( z_b^1 \) is the second half of \( z^i \), and \( \circ \) is the channel-wise product. The Jacobian matrix of the affine coupling layer is a lower triangular matrix, which allows efficient computation for \( \log |\det \frac{\partial f_i}{\partial z^{i-1}}| \):
\[
\log |\det \frac{\partial f_i}{\partial z^{i-1}}| = \sum_{j=1}^{D/2} \sigma(z_a^{i-1})_j,
\]  
(12)
where \( \sigma(z_a^{i-1})_j \) is the \( j \)th element of \( \sigma(z_a^{i-1}) \).

### 3 Flow-ER: Flow-based embedding regularization

In our proposed method, we aim to extract an embedding \( \omega \) from the input speech \( X \) with maximum target information while suppressing redundant information latent within \( X \) (e.g., channel, noise). To achieve this, we train the embedding network according to the information bottleneck scheme described in Equation 6.

#### 3.1 Mutual information interpretation of the cross-entropy loss

In order to maximize \( I(y; \omega) \), our system adopts cross-entropy-based objective functions, such as softmax-based losses. The cross-entropy-based loss functions can be interpreted as the lower bound of the mutual information as in the MINE framework [Belghazi et al., 2018].
Once the MelFlow model is trained, we can estimate the mutual information upperbound as follows:

\[ L_{\text{redundancy}} = E_p(X, \omega)[\log p_X(X|\omega)] - E_p(X)p(\omega)[\log p_X(X|\omega)], \]

(15)

where \( \log p_X(X|\omega) \) is the conditional log-likelihood estimated using the MelFlow.

### 3.3 Training strategy

In the proposed Flow-ER framework, the embedding network is trained according to the information bottleneck scheme, where the mutual information between the embedding \( \omega \) and the label \( y \) is maximized while the mutual information between \( \omega \) and the input representation \( X \) is minimized. To accomplish this, we optimize the network with the following objective function, which incorporates Eq. 3.1 and 15:

\[ L_{IB} = -L_{\text{xent}} + \beta L_{\text{redundancy}}, \]

(16)

where \( \beta \) is a predefined coefficient.

However, whenever the network parameters are updated, the distribution of the embedding vectors will change as well. Therefore, in order to compute \( L_{\text{redundancy}} \), the MelFlow should be updated with the new embedding vectors. Thus, as depicted in Figure 4 and Algorithm 1, we propose to train the embedding network and the MelFlow network in a competitive fashion, similar to the GAN training strategy. The Flow-ER training is done in a 2-stage process: embedding network update and MelFlow update. In the embedding network update phase, we freeze the MelFlow parameters and estimate the conditional likelihoods to compute \( L_{\text{redundancy}} \). Then the embedding network and classification network parameters are updated through \( L_{IB} = -L_{\text{xent}} + \beta L_{\text{redundancy}} \). In the MelFlow update phase, the embedding network parameters are frozen and the embeddings are extracted. Given the training data and their corresponding embeddings, the MelFlow is updated via likelihood maximization.

### 4 Experiments

To validate the impact of the proposed Flow-ER strategy in speech representation learning, we have conducted experiments in several speech processing tasks: speaker verification, voice anti-spoofing, and language identification. In all three tasks, it is essential to maximize the discriminability in terms of the target class, while minimizing the information on the nuisance attributes.

#### 4.1 Experimental Setup

**Speaker verification experimental setup**

In our speaker verification experiments, we have used the development subset of the VoxCeleb2 dataset [Chung et al., 2018], consisting of 1,092,009 utterances collected from 5,994 speakers. The evaluation was performed according to the original VoxCeleb1 trial list [Nagrani et al., 2017], which consists of 4,874 utterances spoken by 40 speakers.

The acoustic features used in the experiments were 40-dimensional MFCCs extracted at every 10 ms, using a 25 ms Hamming window via Kaldi toolkit [Povey et al., 2011].

We have experimented with the ECAPA-TDNN [Desplanques et al., 2020], an architecture that achieved state-of-the-art performance in text-independent speaker recognition. The ECAPA-TDNN uses squeeze-and-excitation as in the SE-ResNet, but also employs channel- and context-dependent statistics pooling and multi-layer aggregation.

The embedding networks are trained with segments consisting of 180 frames, using the ADAM optimization technique [Kingma and Ba, 2015]. The AAMSoftmax objective was used for training the embedding networks, and the experimented networks were implemented via PyTorch [Paszke et al., 2019], based on the voxceleb-trainer open-source project [Chung et al., 2020]1. The networks were trained with initial learning rate 0.001 decayed with ratio 0.95 for 150 epochs, and the models from the best performing checkpoint were selected. The batch size for training was set to be 200. Cosine

1https://github.com/joonson/voxceleb_trainer
Algorithm 1: Training steps for the Flow-ER framework

**Input:** Training set $X$, target label $Y$, embedding network with parameters $\Theta$, MelFlow network with parameters $\Phi$, information bottleneck coefficient $\beta$ and maximum epoch number $\text{epoch}^{\text{max}}$.

Initialize $\Phi$ and $\Theta$;

while $\text{epoch} < \text{epoch}^{\text{max}}$ do

if $\text{epoch} = 0$ then

$L_{\text{xent}} \leftarrow$ compute discriminative loss with $(X, Y, \Theta)$;

Optimize $\Theta$ with $L_{\text{xent}}$;

else

$\Omega \leftarrow$ extract embeddings with $(X, \Theta)$;

$log p_X \leftarrow$ compute log-likelihood loss with $(X, \Omega, \Phi)$;

Optimize $\Phi$ with $\log p_X$;

$L_{\text{xent}} \leftarrow$ compute discriminative loss with $(X, Y, \Theta)$;

$L_{\text{redundancy}} \leftarrow$ compute redundancy loss with $(X, \Omega, \Phi)$;

Optimize $\Theta$ with

$$L_{\text{IB}} = -L_{\text{xent}} + \beta L_{\text{redundancy}}$$;

end

end

similarity was used for computing the verification scores in the experiments.

Voice anti-spoofing experimental setup

In our anti-spoofing experiments, we have used the training subset the ASVspoof 2019 challenge dataset was used for optimizing the systems, which provides a common framework with a standard corpus for conducting spoofing detection research on logical access (LA) attacks. The LA dataset includes bonafide and spoof speech signals generated using various state-of-the-art voice conversion and speech synthesis algorithms. The evaluation was performed on the evaluation subset, which consists seen and unseen test sets in terms of spoofing attacks. For more details about the corpora, the interested readers are referred to [consortium, 2019 accessed May 13 2020].

The acoustic feature used in the experiments was 60-dimensional (including the delta and double delta coefficients) linear frequency cepstral coefficients (LFCC) extracted using 25ms analysis window over a frame shift of 10ms.

We have experimented with the SE-ResNet-18, a variant of the ResNet-18, where a squeeze-and-excitation (SE) block [Hu et al., 2018] is applied at the end of each non-identity branch of residual block to significantly decrease the computational cost of the system.

For training the experimented systems, the OCSoftmax objective function and balanced mini-batches of size 64 samples were used. The ADAM optimizer was used with initial learning rate of 0.0003 and exponential learning rate decay with rate of 0.5 was applied [Monteiro and others, 2020].

**Figure 5:** Normalized T-SNE plot of the speaker embeddings extracted from systems trained with and without Flow-ER. Different colors indicate distinct speakers.

(a) System trained with no regularization.

(b) System trained with Flow-ER.

**Language identification experimental setup**

In our language identification experiments, we have used the training subset of the OLR2021 Challenge dataset [Wang et al., 2021], which consists of recordings from 13 languages. The evaluation was performed on the progress set of the OLR2021 Challenge dataset, where the evaluation metric was $C_{\text{avg}}$ and EER.

The acoustic features used in the experiments were 40-dimensional MFCCs and 3-dimensional pitch extracted at every 10 ms, using a 25 ms Hamming window via Kaldi toolkit [Povey et al., 2011].

We have experimented with the ECAPA-TDNN [Desplanques et al., 2020] architecture as in the speaker verification experiment. The embedding networks are trained with segments consisting of 180 frames, using the ADAM optimization technique [Kingma and Ba, 2015]. Analogous to the speaker verification experiments, the AAMSoftmax objective function was used for training the embedding systems.

**Figure 6:** T-SNE plot of the language embeddings extracted from systems trained with and without Flow-ER. Different colors indicate distinct languages.

(a) System trained with no regularization.

(b) System trained with Flow-ER.

4.2 Results

**Analysis of the embeddings on the embedding space**

Figure 5 depicts the normalized T-SNE plot of the speaker embeddings extracted from systems trained with and without the proposed Flow-ER. From the embeddings extracted from the system trained without embedding regularization, we could observe numerous overlaps between samples from different speaker identities, which may be caused by the non-speaker attributes. Meanwhile from the T-SNE plot of the
Flow-ER embeddings, the overlapping is significantly alleviated.

Moreover, Figure 6 shows the T-SNE plot of the language embeddings extracted from systems trained with and without the proposed Flow-ER. From the embeddings extracted using the conventional method, it could be seen that some clusters are far away from each other even if they have the same class identity. Such variability may be attributed to the nuisance attributes, such as gender or speaker of the utterance. On the other hand, in the embeddings trained with the proposed Flow-ER, the clusters with the same class identity are relatively much closer to each other, and the general distribution of the embeddings is more spread out than the conventional embeddings. From these observations, we could assume that the proposed Flow-ER can help the embeddings to have better discriminability by disentangling the nuisance attributes from them.

Performance of Flow-ER in different down-stream tasks
The experimental results of the systems trained only with discriminative loss and ones trained with the proposed Flow-ER strategy are depicted in Table 1. As shown in the results, it could be observed that the proposed Flow-ER can improve the performance in all three tasks. Especially in anti-spoofing, the Flow-ER system outperformed the baseline with a relative improvement of 13.79% in terms of min t-DCF. These results tell us that the proposed Flow-ER is able to effectively improve the performance of various down-stream tasks.

5 Conclusion
In this paper, we proposed a novel approach, which we call Flow-ER, to disentangle the nuisance information from the speech embedding vector. The proposed method exploits the information bottleneck framework, where the embedding network is trained to have maximum information on the main-task, while suppressing the information of the unwanted attributes. To incorporate the information bottleneck scheme into the embedding network training process, the mutual information is estimated using the main task classifier and an auxiliary normalizing flow network.

In order to evaluate the proposed Flow-ER strategy, we have conducted several experiments on different down-stream tasks, including speaker verification, anti-spoofing, and language identification. Our results showed that the Flow-ER can improve the performance in all the experimented tasks, which may be attributed to its capability in disentangling the nuisance information from the embeddings. Especially in anti-spoofing, the Flow-ER system outperformed the baseline with a relative improvement of 13.79% in terms of min t-DCF.

In our future study, we will be investigating the potential of the Flow-ER strategy furthermore by applying it to more diverse tasks, including image classification and anomaly detection. Moreover, as the sensitivity of the mutual information estimation in the proposed Flow-ER will highly vary depending on the accuracy of the estimated conditional likelihood, the choice of the conditional likelihood estimator may be crucial for the disentanglement performance. Therefore we will also focus our research on finding the optimal normalizing flow model for the conditional likelihood estimator.

References

[Belghazi et al., 2018] Mohamed Ishmael Belghazi, Aristide Baratin, Sai Rajeshwar, Sherijl Ozair, Yoshua Bengio, Aaron Courville, and Devon Hjelm. Mutual information neural estimation. In Jennifer Dy and Andreas Krause, editors, Proceedings of the 35th International Conference on Machine Learning, volume 80 of Proceedings of Machine Learning Research, pages 531–540. PMLR, 10–15 Jul 2018.

[Cheng et al., 2020] Pengyu Cheng, Weituo Hao, Shuyang Dai, Jiachang Liu, Zhe Gan, and Lawrence Carin. Club: A contrastive log-ratio upper bound of mutual information. arXiv preprint arXiv:2006.12013, 2020.

[Chung et al., 2018] J. S. Chung, A. Nagrani, and A. Zisserman. Voxceleb2: Deep speaker recognition. In INTERSPEECH, 2018.

[Chung et al., 2020] Joon Son Chung, Jaesung Huh, Seongkyu Mun, Minjae Lee, Hee Soo Heo, Soyeon Choe, Chiheon Ham, Sunghwan Jung, Bong-Jin Lee, and Icksang Han. In defence of metric learning for speaker recognition. In Interspeech, 2020.

[consortium, 2019 accessed May 13 2020] ASVspoof consortium. ASVspoof 2019:Automatic Speaker Verification Spoofing and Countermeasures Challenge Evaluation Plan, 2019 (accessed May 13, 2020).

[Deng et al., 2021] Jiankang Deng, Jia Guo, Jing Yang, Niannan Xue, Irene Cotsia, and Stefanos P Zafeiriou. Arcface: Additive angular margin loss for deep face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, pages 1–1, 2021.

[Desplanques et al., 2020] Brecht Desplanques, Jenthe Thienpondt, and Kris Demuynck. ECAPA-TDNN: emphasized channel attention, propagation and aggregation in TDNN based speaker verification. In Helen Meng, Bo Xu, and Thomas Fang Zheng, editors, Interspeech 2020, pages 3830–3834. ISCA, 2020.

|                        | Speaker verification | Anti-spoofing | Language identification |
|------------------------|----------------------|---------------|-------------------------|
|                        | EER [%]              | EER [%]       | min t-DCF               | EER [%] | min Cavg |
| No regularization      | 1.8240               | 3.0589        | 0.0718                  | 8.0940  | 0.0671   |
| Flow-ER ($\beta = 0.001$) | 1.7391               | 2.8029        | 0.0619                  | 7.4370  | 0.0639   |
[Heo et al., 2020] Hee Soo Heo, Bong-Jin Lee, Jaesung Huh, and Joon Son Chung. Clova baseline system for the VoxCeleb speaker recognition challenge 2020. arXiv preprint arXiv:2009.14153, 2020.

[Ha et al., 2018] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7132–7141, 2018.

[Kang et al., 2020] W. H. Kang, S. H. Mun, M. H. Han, and N. S. Kim. Disentangled speaker and nuisance attribute embedding for robust speaker verification. IEEE Access, 8:141838–141849, 2020.

[Kim et al., 2020] Hyeongju Kim, Hyeonseung Lee, Woo Hyun Kang, Hyung Yong Kim, and Nam Soo Kim. Robust front-end for multi-channel ASR using flow-based density estimation. CoRR, abs/2007.12903, 2020.

[Kingma and Ba, 2015] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua Bengio and Yann LeCun, editors, 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.

[Meng et al., 2019a] Z. Meng, Y. Zhao, J. Li, and Y. Gong. Adversarial speaker verification. In ICASSP, pages 6216–6220, 2019.

[Meng et al., 2019b] Z. Meng, Y. Zhao, J. Li, and Y. Gong. Channel adversarial training for cross-channel text-independent speaker recognition. In ICASSP, 2019.

[Monteiro and others, 2020] Joao Monteiro et al. Generalized end-to-end detection of spoofing attacks to automatic speaker recognizers. Computer Speech & Language, page 101096, 2020.

[Nagrani et al., 2017] A. Nagrani, J. S. Chung, and A. Zisserman. Voxceleb: a large-scale speaker identification dataset. In INTERSPEECH, 2017.

[Paszke et al., 2019] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alch´e-Buc, E. Fox, and R. Garnett, editors, Advances in Neural Information Processing Systems 32, pages 8024–8035. Curran Associates, Inc., 2019.

[Povey et al., 2011] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Nagendra Goel, Mirko Hannemann, Yanmin Qian, Petr Schwarz, and Georg Stemmer. The kaldi speech recognition toolkit. In In IEEE 2011 workshop, 2011.

[Snyder et al., 2017] David Snyder, D. Garcia-Romero, Daniel Povey, and S. Khudanpur. Deep neural network embeddings for text-independent speaker verification. In INTERSPEECH, 2017.

[Snyder et al., 2018] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur. X-vectors: robust dnn embeddings for speaker recognition. In ICASSP, pages 5329–5333, 2018.

[van den Oord et al., 2019] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding, 2019.

[Variani et al., 2014] Ehsan Variani, Erik McDermott, Ignacio Moreno, and Javier Gonzalez-Dominguez. Deep neural networks for small footprint text-dependent speaker verification. In ICASSP, pages 4080–4084, 2014.

[Wan et al., 2018] Li Wan, Quan Wang, Alan Papir, and Ignacio L. Moreno. Generalized end-to-end loss for speaker verification. In ICASSP, pages 4879–4883, 2018.

[Wang et al., 2021] Binling Wang, Wenxuan Hu, Jing Li, Yiming Zhi, Zheng Li, Qingyang Hong, Lin Li, Dong Wang, Liming Song, and Cheng Yang. Olr 2021 challenge: Datasets, rules and baselines, 2021.

[Xie et al., 2019] Weidi Xie, Arsha Nagrani, Joon Son Chung, and Andrew Zisserman. Utterance-level aggregation for speaker recognition in the wild. In ICASSP, 2019.

[Zhang and others, 2021] You Zhang et al. One-class learning towards synthetic voice spoofing detection. IEEE Signal Processing Letters, 28:937–941, 2021.

[Zhou et al., 2019] J. Zhou, T. Jiang, L. Li, Q. Hong, Z. Wang, and B. Xia. Training multi-task adversarial network for extracting noise-robust speaker embedding. In ICASSP, pages 6196–6200, 2019.

[Zhu et al., 2018] Yingke Zhu, Tom Ko, David Snyder, Brian Mak, and Daniel Povey. Self-Attentive Speaker Embeddings for Text-Independent Speaker Verification. In Proc. Interspeech 2018, pages 3573–3577, 2018.