Abstract—A great challenge in speaker representation learning using deep models is to design learning objectives that can enhance the discrimination of unseen speakers under unseen domains. This work proposes a supervised contrastive learning objective to learn a speaker embedding space by effectively leveraging the label information in the training data. In such a space, utterance pairs spoken by the same or similar speakers will stay close, while utterance pairs spoken by different speakers will be far apart. For each training speaker, we perform random data augmentation on their utterances to form positive pairs, and utterances from different speakers form negative pairs. To maximize speaker separability in the embedding space, we incorporate the additive angular-margin loss into the contrastive learning objective. Experimental results on CN-Celeb show that this new learning objective is easy to implement, and we provide PyTorch code at https://github.com/shanmon110/AAMSupCon.

I. INTRODUCTION

Speaker representation learning is a crucial process in speaker verification. Its objective is to learn a feature embedding space with the following attributes: 1) same-class compactness, where the embedding vectors of the same speaker are nearby; 2) different-class dispersion, where the embedding vectors belonging to different speakers are far apart. Because of the advances in deep neural network (DNN) architectures [1, 2, 3], loss functions [4, 5, 6, 7], pooling methods [8, 9], and domain adaptation [10, 11, 12], significant progress in speaker representation learning has been made in recent years. However, the models are still not sufficiently robust to noisy labels [13, 14] and are sensitive to input perturbation unless a notion of margin is introduced to their loss function [15, 16]. Studies have shown that these deficiencies can reduce generalization performance [17, 18, 19, 20].

Several strategies have been developed to limit intra-class deviation and increase intra-class separation. For example, Wen et al. [21] penalized the gaps between the features and their centers by adding a regularization term. The authors in [22, 23, 24] proposed using a scale parameter to regulate the temperature [25] of the softmax loss, causing well-separated samples to produce larger gradients, thereby shrinking intra-class dispersion. The authors in [16] proposed enlarging the classification margin to make the learning objective harder, which encourages the learning of discriminative features. Liu et al. [26] proposed an angular distance metric in which the dissimilarity of objects is measured by their geodesic distance in a hypersphere manifold. They also introduced an angular margin in the distance measure to make the decisions more stringent. Liu et al. [23], Liang et al. [27], and Ranjan et al. [24] enhanced the softmax loss function by introducing various margins.

Significant advancements in self-supervised representation learning have been made recently because of the resurgence of contrastive learning [28, 29, 30, 31, 32, 33, 34]. These works share the same concept: To learn an embedding space where positive pairs are near and negative ones are far apart. Due to the absence of labels, each positive pair often comprises an anchor and the augmented sample of the anchor, while a negative pair consists of randomly picked samples from the mini-batch except for the anchor. In [30, 31], the relationship between contrastive loss and mutual information was discovered.

In this work, we propose AAMSupCon—a speaker representation learning method that uses additive angular margin supervised learning and contrastive learning to leverage label information in training data. As shown in Fig. 1, the embeddings of the same class are brought together, and those from different classes are pushed apart. To maximize speaker separability, we compute the angle between the weight vector of the ground truth class and the embedding using the arccosine of the logit and add a margin to the angle, which is followed by taking the cosine of the enlarged angle to recalculate the target logit [7]. We investigated using multiple positive samples per anchor instead of a single positive in self-supervised contrastive learning. These positive samples are collected from samples of the same class as the anchor, as opposed to self-supervised learning in which positive samples

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come from the anchor’s augmented data only.

Our main contribution is that we modified the contrastive loss function to utilize various positive samples per anchor and introduce an additive angular margin to the target class’s angle in the embedding space, thereby extending contrastive learning to speaker verification with class boundaries robust to input perturbation. We demonstrated that the modified contrastive loss outperforms previous supervised learning in a speaker verification task.

II. METHODOLOGY

Our objective is to train a feature embedding network using labeled audio. The embedding vectors of similar speakers should be close to each other, whereas those from different speakers should be far apart. Our method is fundamentally similar to the self-supervised contrastive learning described in [33, 35], with adjustments for supervised classification. Given a batch of input samples, we perform data augmentation once to produce an augmented batch. The speaker characteristics of the embedding vector from the same instance should remain unchanged under various augmentations, while the embedding from different instances should be distinct. As shown in Fig. 2, the spectrograms of both instances (the originals and their augmentations) are presented to an encoder network to produce 128-dimensional normalized embeddings. A projection network maps the embedding vectors to the output layer. At the outputs of the network, an additive angular margin contrastive loss is computed.

In this section, we will introduce our framework for representation learning and then examine the current supervised contrastive loss and additive angular margin loss. Then, we propose a margin contrastive loss function with remarkable discrimination. We conclude by comparing our framework with previous work.

A. Representation Learning Framework

Inspired by recent contrastive learning methods, AAM-SupCon learns representations by maximizing the agreement across various augmented views of the same data through a contrastive loss in the latent space. As illustrated in Fig. 2, this framework consists of four key components.

a) Data Augmentation: We produce one random augmentation for each input sample, \( \hat{x} = \text{Augmentation}(x) \). Each augmentation provides a unique perspective of the data and comprises a portion of the original sample’s information. Using the Kaldi recipe [36], we augmented the original utterances with noise, music, and chatter from the MUSAN dataset [37]. We also generated reverberation effects by convolving the original waveforms with the RIR [38] dataset’s room impulse responses.

b) Encoder Network: Our objective is to train an encoder network \( f_\theta(\cdot) \) from a set of labeled audio \( \mathcal{X} = \{x_1, x_2, \ldots, x_n\} \). \( f_\theta(\cdot) \) transforms the input audio \( x_i \) to a low-dimensional embedding vector \( h_i = f_\theta(x_i) \in \mathbb{R}^d \), where \( d \) is the output dimension. Both the original and the augmented samples are independently fed to the same encoder, resulting in two representation vectors. For simplicity we chose ECAPA-TDNN [3] as the encoder.

c) Projection Network: It is a shallow network \( g_\phi(\cdot) \) that transforms the encoder’s output to a space in which contrastive loss is applied. \( g_\phi(\cdot) \) is an MLP with one hidden layer and a linear output layer. We denote the transformed embedding vector as \( z_i = g_\phi(h_i) = W_2\sigma(W_1h_i) \), where \( \sigma \) is a ReLU nonlinearity. We normalize the output of this network so that the embedding vectors lie on a unit hypersphere, which allows us to estimate the distance in the projection space using an inner product.

B. Additive Angular Margin Contrastive Loss

We explain how to incorporate additive angular margin into supervised contrastive learning.

1) Supervised Contrastive Losses: Supervised contrastive loss (SupCon) can handle the situation where multiple samples are known to belong to the same class due to the presence of labels:

\[
L_{\text{SupCon}} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{|\mathcal{P}(i)|} \sum_{p \in \mathcal{P}(i)} \log \frac{\exp(z_i \cdot z_p/\tau)}{\sum_{a \in \mathcal{A}(i)} \exp(z_i \cdot z_a/\tau)}.
\]

In Eq. 1, \( \mathcal{P}(i) \) contains the indices of positive samples in the augmented batch (original + augmentation) with respect to \( z_i \), and \( |\mathcal{P}(i)| \) is the cardinality of \( \mathcal{P}(i) \). \( z_i \) is an anchor, \( z_p \) are negative samples, \( z_a \) are positive samples and \( \mathcal{A}(i) \) is the index set of negative samples.

2) Additive Angular Margin Loss: Additive angular margin (ArcFace) loss calculates the angle between the embedding vector and the class weight vector using the arc-cosine function. It then adds an additive angular margin to the angle and uses the cosine function to recover the target logit. Then, ArcFace rescales all logits by a scale factor, and the remaining computations are identical to those of the softmax loss. Due to its precise relationship with geodesic distance on a hypersphere, the ArcFace has a clear geometric explanation. The ArcFace equation is:

\[
L_{\text{ArcFace}} = -\frac{1}{N} \sum_{i=1}^{N} \log e^{s(\cos(\theta_i + m))} + \sum_{j=1, j \neq y_i}^{N} e^{s\cos(\theta_j)} - s\cos(\theta_{y_i})
\]

where \( \cos(\theta_{y_i}) \) is the target logit, which is the dot product of the normalized class-weight vector and the normalized embedding vector. \( m \) is an additive angular margin that increases intra-class compactness and inter-class disparity.

3) Additive Angular Margin Supervised Contrastive Loss: We propose an additive angular margin supervised contrastive softmax for supervised embedding learning by combining
SupCon and ArcFace:

\[ L_{AAMSupCon} = - \frac{1}{N} \sum_{i=1}^{N} \log e^{s(\cos(\theta_i) + m)} + \sum_{j=1, j \neq i}^{N} e^{s \cos(\theta_j)} + \sum_{i=1}^{N} \frac{1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp(z_i \cdot z_p / \tau)}{\sum_{a \in A(i)} \exp(z_i \cdot z_a / \tau)} \]

AAMSupCon has the following advantages:

- Generalization to arbitrary positives. For each anchor in a multiview batch, its augmented sample and the other samples with the same label as the anchor contribute to the numerator of the loss function (Eq. 1). The supervised loss motivates the encoder to provide tightly matched representations for all entries of the same class, leading to a more compact speaker clusters in the embedding space.

- Contrastive power improves with additional negatives. Eq. 3 has a sum over the negatives in the denominator of the loss function. As a result, the capability to distinguish between noise and signal is enhanced when more negative samples are added. This trait is essential for representation learning, with several articles demonstrating impressive performance by increasing the number of negatives [29, 31, 33, 34].

- AAMSupCon optimizes the geodesic distance by the virtue of the perfect relationship between the angle and arc-cosing in the normalized hypersphere. Consequently, the AAMSupCon loss may ostensibly impose a more pronounced separation between the closest classes.

C. Comparison with SupCon and ArcFace

The AAMSupCon loss closely resembles the SupCon loss and the ArcFace loss. The SupCon loss is an innovative contrastive loss function that permits various positives per anchor. To maximize class separability, ArcFace adds an angular margin to the angle between the sample and the class weight. AAMSupCon combines the benefits of ArcFace and SupCon, exploits the label information for contrastive learning, and produces highly discriminative features for speaker verification.

III. EXPERIMENTS

We evaluated the AAMSupCon loss on a speaker verification dataset called CN-Celeb [39, 40]. For the encoder network, we experimented with the ECAPA-TDNN [3] architecture. The representation (embedding) vectors were extracted at the final pooling layer after normalization. We experimented with room impulse responses, music, background noise, and babble noise as four data augmentation types.

### TABLE I

| Statistics of CN-Celeb 1 & 2 |
|-----------------------------|
| Train/Test sets | Speakers | Recordings | Trials | Target trials |
| CN-Celeb1 Train | 797 | 107,953 | N/A | N/A |
| CN-Celeb2 Train | 1996 | 524,787 | N/A | N/A |
| CN-Celeb Train (1&2) | 2793 | 632,740 | N/A | N/A |
| CN-Celeb Eval | 200 | 17973 | 3,484,292 | 17,755 |

A. Dataset

We employed CN-Celeb [39, 40], which comprises CN-Celeb1 [39] and CN-Celeb2 [40] to conduct our experiments. Table I lists the train-eval splits, speaker count, number of recordings, and evaluation trial statistics for the CN-Celeb dataset. We utilized the training data in CN-Celeb1\&2, which include over 2,793 speakers with 11 genres to train our models. The genres include “advertisement”, “drama”, “entertainment”, “interview”, “live broadcast”, “movie”, “play”, “recitation”, “singing”, “speech”, and “vlog”. Performance was evaluated using the evaluated set of CN-Celeb1.
B. Evaluation Metrics

We used the equal error rate (EER) and minimum detection cost function (minDCF, p-target = 0.01) as the metrics to assess the performance.

C. Experimental Setup

We adopted 80-dimensional Fbank as input features. In the last step of the augmentation process, we utilized SpecAugment [41] on the log-mel spectrograms. For each utterance, we randomly masked between 0 to 10 frames in the time domain and between 0 to 8 channels in the frequency domain. An SGD optimizer was used to train the models. We set the margin $m$ to 0.2. The mini-batch size for training is 3072. The contrastive learning temperature $\tau$ was set to 0.07.

### Table II

| Network     | Loss Function | EER(%)  | minDCF |
|-------------|---------------|---------|--------|
| TDNN [40]   | Softmax       | 12.39   | 0.60   |
| TDNN [42]   | Softmax       | 11.33   | 0.57   |
| ETDDN [42]  | Softmax       | 11.09   | 0.56   |
| ETDDN-CA [42] | Softmax   | 10.88   | 0.56   |
| ETDDN-LSTM-CA[42] | Softmax | 10.30   | 0.55   |
| HNN [42]    | Softmax       | 9.18    | 0.50   |
| MSHNN [42]  | Softmax       | 9.05    | 0.48   |
| ENSEMBLE [42] | Softmax | 8.94    | 0.48   |
| ResNet34    | Real AM-Softmax [43] | 11.05   | N/A    |
| ECAPA-TDNN [3] | AAMSupCon (ours) | 8.49    | 0.50   |

D. Results and Analysis

Our system achieves the best performance, outperforming the second-best with the TDNN architecture by 0.45% in terms of EER. The results in Table II indicate that AAMSUPCon is superior to other conventional systems on CN-Celeb. This suggests that the proposed loss function force the network to learn speaker features while maximizing discrimination. We conjecture that the good performance is due to (1) the capability of the proposed contrastive loss (Eq. 3) in capturing the correlation between samples from the same speaker and contrasting the samples from different speakers and (2) the angular margin that increases the tolerance to feature perturbation.

### Table III

| Encoder     | Loss Function | EER(%)  | minDCF |
|-------------|---------------|---------|--------|
| ECAPA-TDNN [3] | Softmax       | 16.07   | 0.82   |
| ECAPA-TDNN [3] | AMSOFTMAX     | 13.39   | 0.71   |
| ECAPA-TDNN [3] | RAMSOFTMAX   | 13.25   | 0.72   |
| ECAPA-TDNN [3] | AMSoftmax     | 8.79    | 0.50   |
| ECAPA-TDNN [3] | AAMSUPCON    | 8.49    | 0.50   |

E. Ablation Study

We conducted an ablation experiment to determine the contributions of critical components in our method. Precisely, we ran experiments with the same encoder but used different losses. Table III shows that Softmax achieves the worst performance because Softmax does not have margin. AM-Softmax achieves similar performance as RAM-Softmax, which has also been verified in [43]. Both AM-Softmax and RAM-Softmax have been widely employed in metric learning, aiming to maximize the difference between target pairs and non-target pairs. AAMSUPCon achieves the second best performance due to the use of additive angular margin in the loss functions, which enables it to obtain highly discriminative features. AAMSUPCon achieves the best performance because it effectively leverages the label information so that samples of the same class can be packed closely. Moreover, we have added max-margin to AAMSUPCon to increase intra-class attraction and inter-class repulsion, causing the target and non-target classes to be well separated.

F. Batch Size

Contrastive learning was carried out for each mini-batch. As described in Section II-B3, the numbers of positives and negatives in each mini-batch are critical to contrastive learning. More samples in a mini-batch can enable the network to learn more robust features. To verify our conjecture, we only used supervised contrastive loss and ECAPA-TDNN in the encoder. We set three different batch sizes, 128, 512 and 1024, as shown in Table IV. Apparently, a larger batch size achieves better performance. The experimental results verify our hypothesis.

### Table IV

| Batch Size | EER(%) | minDCF |
|------------|--------|--------|
| 128        | 13.64  | 0.71   |
| 512        | 11.03  | 0.66   |
| 1024       | 10.27  | 0.65   |

IV. Conclusion

This study proposes an additive angular margin supervised contrastive representation learning framework that successfully increases the discriminative capability of feature embeddings for speaker verification. This is achieved by using label information in contrastive learning. Experiments reveal that our technique routinely outperforms the baselines. To enable the repeatability of the findings described, codes and explanations are available on our GitHub site.

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REFERENCES

[1] D. Snyder, D. Garcia-Romero, D. Povey, and S. Khudanpur, “Deep neural network embeddings for text-independent speaker verification,” in Proc. Interspeech, 2017, pp. 999–1003.

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

[3] B. Desplanques, J. Thienpondt, and K. Demuynck, “ECPA-TDNN: Emphasized channel attention, propagation and aggregation in TDNN based speaker verification,” in Proc. Interspeech, 2020, pp. 3830–3834.

[4] L. Wan, Q. Wang, A. Papir, and I. L. Moreno, “Generalized end-to-end loss for speaker verification,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018, pp. 4879–4883.

[5] J. S. Chung, J. Huh, S. Mun, M. Lee, H.-S. Heo, S. Choe, C. Ham, S. Jung, B.-J. Lee, and I. Han, “In defense of metric learning for speaker recognition,” Proc. Interspeech 2020, pp. 2977–2981, 2020.

[6] H. Wang, Y. Wang, Z. Zhou, X. Ji, D. Gong, J. Zhou, Z. Li, and W. Liu, “Cosface: Large margin cosine loss for deep face recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5265–5274.

[7] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, “Arcface: Additive angular margin loss for deep face recognition,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 4690–4699.

[8] W. Cai, J. Chen, and M. Li, “Exploring the encoding layer and loss function in end-to-end speaker and language recognition system,” in Proc. Odyssey 2018 The Speaker and Language Recognition Workshop, 2018, pp. 74–81.

[9] K. Okabe, T. Koshinaka, and K. Shinoda, “Attentive statistics pooling for deep speaker embedding,” in Conference on Computer Vision, Springer, 2006, pp. 531–542.

[10] M. Sang, W. Xia, and J. H. Hansen, “Open-set short utterance forensic speaker verification using teacher-student network with explicit inductive bias,” Proc. Interspeech, pp. 2262–2266, 2020.

[11] G. Bhattacharya, J. Monteiro, J. Alam, and P. Kenny, “Generative adversarial speaker embedding networks for domain robust end-to-end speaker verification,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 6226–6230.

[12] M. Sang, W. Xia, and J. H. Hansen, “DEAAN: Disentangled embedding and adversarial adaptation network for robust speaker representation learning,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2021, pp. 6169–6173.

[13] Z. Zhang and M. Sabuncu, “Generalized cross entropy loss for training deep neural networks with noisy labels,” Advances in Neural Information Processing Systems, vol. 31, 2018.

[14] S. Sukhbaatar, J. Bruna, M. Paluri, L. Bourdev, and R. Fergus, “Training convolutional networks with noisy labels,” in Proc. 3rd International Conference on Learning Representations, (ICLR), 2015.

[15] G. Elsayed, D. Krishnan, H. Mobahi, K. Regan, and S. Bengio, “Large margin deep networks for classification,” Advances in Neural Information Processing Systems, vol. 31, 2018.

[16] W. Liu, Y. Wen, Z. Yu, and M. Yang, “Large-margin softmax loss for convolutional neural networks,” in Proceedings of the 33rd International Conference on Machine Learning-vol 48, 2016, pp. 507–516.

[17] W.-W. Lin, M.-W. Mak, and J.-T. Chien, “Multisource i-vectors domain adaptation using maximum mean discrepancy based autoencoders,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 26, no. 12, pp. 2412–2422, 2018.

[18] L. Li, M.-W. Mak, and J.-T. Chien, “Contrastive adversarial domain adaptation networks for speaker recognition,” IEEE Transactions on Neural Networks and Learning Systems, vol. 33, pp. 2236–2245, 2022.

[19] Y. Tu, M.-W. Mak, and J.-T. Chien, “Variational domain adversarial learning with mutual information maximization for speaker verification,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 28, pp. 2013–2024, 2020.

[20] ——, “Information maximized variational domain adversarial learning for speaker verification,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 6449–6453.

[21] Y. Wen, K. Zhang, Z. Li, and Y. Qiao, “A discriminative feature learning approach for deep face recognition,” in Proc. European Conference on Computer Vision, 2016, pp. 499–515.

[22] F. Wang, X. Xiang, J. Cheng, and A. L. Yuille, “Normface: L2 hypersphere embedding for face verification,” in Proceedings of the 25th ACM International Conference on Multimedia, 2017, pp. 1041–1049.

[23] Y. Liu, H. Li, and X. Wang, “Rethinking feature discrimination and polymerization for large-scale recognition,” arXiv preprint arXiv:1710.00870, 2017.

[24] R. Ranjan, C. D. Castillo, and R. Chellappa, “L2-constrained softmax loss for discriminative face verification,” arXiv preprint arXiv:1703.09507, 2017.

[25] G. Hinton, O. Vinyals, and J. Dean, “Distilling the knowledge in a neural network,” arXiv preprint arXiv:1503.02531, 2015.

[26] W. Liu, Y. Wen, Z. Yu, M. Li, B. Raj, and L. Song, “Sphereface: Deep hypersphere embedding for face recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 212–220.

[27] X. Liang, X. Wang, Z. Lei, S. Liao, and S. Z. Li, “Soft-
margin softmax for deep classification,” in Proc. International Conference on Neural Information Processing, 2017, pp. 413–421.

[28] Z. Wu, Y. Xiong, S. X. Yu, and D. Lin, “Unsupervised feature learning via non-parametric instance discrimination,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 3733–3742.

[29] O. Henaff, “Data-efficient image recognition with contrastive predictive coding,” in Proc. International Conference on Machine Learning, 2020, pp. 4182–4192.

[30] A. v. d. Oord, Y. Li, and O. Vinyals, “Representation learning with contrastive predictive coding,” arXiv preprint arXiv:1807.03748, 2018.

[31] Y. Tian, D. Krishnan, and P. Isola, “Contrastive multiview coding,” in Proc. European Conference on Computer Vision, 2020, pp. 776–794.

[32] R. D. Hjelm, A. Fedorov, S. Lavoie-Marchildon, K. Grewal, P. Bachman, A. Trischler, and Y. Bengio, “Learning deep representations by mutual information estimation and maximization,” in Proc. International Conference on Learning Representations, 2018.

[33] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, “A simple framework for contrastive learning of visual representations,” in Proc. International Conference on Machine Learning, 2020, pp. 1597–1607.

[34] K. He, H. Fan, Y. Wu, S. Xie, and R. Girshick, “Momentum contrast for unsupervised visual representation learning,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 9729–9738.

[35] P. Khosla, P. Teterwak, C. Wang, A. Sarna, Y. Tian, P. Isola, A. Maschinot, C. Liu, and D. Krishnan, “Supervised contrastive learning,” Advances in Neural Information Processing Systems, vol. 33, pp. 18661–18673, 2020.

[36] D. Snyder, D. Garcia-Romero, G. Sell, A. McCree, D. Povey, and S. Khudanpur, “Speaker recognition for multi-speaker conversations using x-vectors,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 5796–5800.

[37] D. Snyder, G. Chen, and D. Povey, “MUSAN: A music, speech, and noise corpus,” arXiv preprint arXiv:1510.08484, 2015.

[38] T. Ko, V. Peddinti, D. Povey, M. L. Seltzer, and S. Khudanpur, “A study on data augmentation of reverberant speech for robust speech recognition,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2017, pp. 5220–5224.

[39] Y. Fan, J. Kang, L. Li, K. Li, H. Chen, S. Cheng, P. Zhang, Z. Zhou, Y. Cai, and D. Wang, “Ch-Celeb: A challenging chinese speaker recognition dataset,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 7604–7608.

[40] L. Li, R. Liu, J. Kang, Y. Fan, H. Cui, Y. Cai, R. Vipperla, T. F. Zheng, and D. Wang, “Cn-Celeb: multi-genre speaker recognition,” Speech Communication, vol. 137, pp. 77–91, 2022.