

Scalable Adversarial Mixing for Enhanced Manifold Learning in Speaker Verification

Massa Baali

Carnegie Mellon University
mbaali@cs.cmu.edu

Abstract

Current Speaker Verification (SV) systems face significant challenges in robustness and scalability, primarily due to limited speaker diversity, resulting in insufficient coverage of diverse distributions within the embedding space. To address this, we propose a novel approach utilizing Generative Adversarial Networks (GANs) to enhance the manifold of the embedding space by generating synthetic speaker representations. This method enables the SV model to effectively learn from synthetic data, thereby improving its robustness, scalability, and ability to generalize across diverse speaker distributions. Our experimental results demonstrate that the proposed framework significantly enhances SV performance, paving the way for more resilient and scalable voice authentication systems

Introduction

Speaker Verification (SV) systems are pivotal in applications requiring secure and reliable voice-based authentication. However, these systems often face challenges in robustness and scalability, especially when training data is limited in diversity. Conventional approaches primarily rely on real speaker embeddings, which can lead to insufficient coverage of the speaker embedding space and suboptimal generalization to unseen data.

To address these limitations, we propose a novel framework that leverages adversarial learning through Generative Adversarial Networks (GANs). Our approach utilizes a Markovian discriminator with spectral normalization to stabilize training and enhance manifold learning in the embedding space. By introducing synthetic speaker embeddings generated through a mixup strategy, we enrich the speaker distribution without directly adding synthetic speakers to the primary training loss. This ensures improved coverage of diverse speaker characteristics while maintaining the integrity of the SV model.

The generator in our framework employs an MFA Conformer architecture, designed to produce high-quality synthetic embeddings. It optimizes a combined loss function that integrates an AM-Softmax loss with an adversarial loss, dynamically weighted to ensure stability and effectiveness. The discriminator, on the other hand, distinguishes between

real and synthetic embeddings, contributing to the adversarial objective by guiding the generator to create embeddings indistinguishable from real ones.

Our method also addresses scalability by efficiently utilizing synthetic embeddings to improve the robustness of SV models, particularly in scenarios with limited real speaker data. By filling gaps in the embedding space manifold, the proposed approach enhances the model's ability to generalize across diverse speaker populations and conditions.

Through extensive experimentation, we demonstrate that our GAN-based framework achieves significant improvements in verification accuracy and robustness while maintaining scalability. This work paves the way for future advancements in speaker verification by combining adversarial learning with effective embedding space augmentation.

Literature Review

Mixup: The development of mixup strategies has evolved substantially since Mixup's original introduction by Zhang et al. (2018), which generated virtual samples and mixed labels by linearly combining two input samples and their corresponding labels. This pioneering method proved particularly successful in enhancing data diversity and improving generalization in visual classification tasks. Extensions such as ManifoldMix (Verma et al. 2019) applied this concept to hidden layers, while CutMix (Yun et al. 2019) introduced a patch-based approach by blending rectangular sections of images, offering a novel alternative for augmenting training data. Subsequent mixup strategies focused on tailoring data mixing to specific contexts or improving the precision of mixing. Static policies like SmoothMix (Lee et al. 2020), GridMix (Baek et al. 2021), and ResizeMix (Qin et al. 2023) used hand-crafted cutting techniques, while dynamic approaches such as PuzzleMix (Kim et al. 2020) and AlignMix (Venkataramanan et al. 2022) incorporated optimal-transport methods to determine mix regions with greater flexibility. For Vision Transformers, strategies such as TransMix (Chen et al. 2022) and TokenMix (Liu et al. 2022b) focused on leveraging attention mechanisms to refine mixing operations, particularly for transformer architectures (Dosovitskiy et al. 2021). Recent developments have adapted mixup techniques to tasks beyond classification, such as regression. C-Mixup, for instance, applies sample mixing based on label distances, using a symmetric Gaus-

sian kernel to select samples that improve regression performance (Cai et al. 2021). Further enhancing robustness, RC-Mixup integrates C-Mixup with multi-round robust training, creating a feedback loop where C-Mixup helps identify cleaner data, and robust training improves the quality of data for mixing (Liu et al. 2022a). These specialized approaches reveal mixup’s adaptability across diverse machine learning tasks, demonstrating that carefully structured sample blending can enhance both model performance and data resilience across varied applications.

Synthetic Speech: Recent advancements in synthetic audio generation have focused on creating diverse and high-quality datasets for training and evaluating audio-based AI models. One prominent example is ConversaSynth, a framework that uses large language models (LLMs) to generate synthetic conversation audio across multiple persona settings (Gao et al. 2022). ConversaSynth starts with the generation of coherent and diverse text-based dialogues, which are then converted to audio via text-to-speech (TTS) systems. Experiments with ConversaSynth reveal that the resulting synthetic datasets exhibit both high realism and topic variety, making them highly effective for enhancing audio tagging, classification, and multi-speaker speech recognition tasks. This framework provides a substantial resource for training robust, adaptable AI models in the audio domain, where data diversity and conversational context are crucial. Synthio takes a different approach to augment small-scale audio classification datasets by leveraging text-to-audio (T2A) diffusion models (Joassin and Alvarez-Melis 2022). While traditional augmentation methods, like spectral masking or mixing (Park et al. 2019; Saeed et al. 2021), add transformations to existing audio, Synthio aims to capture the nuanced compositional diversity often missing from these approaches. It aligns T2A-generated synthetic samples with the original dataset through preference optimization to maintain acoustic consistency. Additionally, Synthio utilizes LLMs to generate and refine audio captions, enhancing the representational diversity of the synthesized samples and supporting robust classification models even with limited labeled data. Exploring style transfer in synthetic audio, recent work by Ueda et al. (2024) uses a VITS-based voice conversion model, conditioned on F0 (fundamental frequency), to create expressive data variations from neutral speaker voices. By combining synthetic data with original recordings, they achieve cross-speaker style transfer in a FastPitch-based TTS model. This approach, which incorporates a RE-based style encoder pre-trained on timbre-perturbed data, prevents speaker leakage, further enhancing the effectiveness of synthetic data in style-rich applications. These approaches highlight the increasing sophistication of synthetic audio generation techniques, from ConversaSynth’s multi-speaker synthetic conversations to Synthio’s T2A-optimized augmentation for classification, and cross-speaker style transfer using VITS-based models. Together, they underscore the potential of synthetic data to enrich audio model training with both diversity and realism.

Methodology

Our proposed framework for enhancing Speaker Verification systems employs a Generative Adversarial Network architecture. The core components include a generator, a discriminator, and a novel training strategy that integrates synthetic speaker embeddings without directly contributing to the main loss function. This ensures stability and effective manifold learning while improving the scalability of the system.

Generator: MFA Conformer

Architecture: The generator leverages an MFA Conformer model to produce high-quality synthetic embeddings. The MFA Conformer integrates multi-head attention and convolutional layers for effective feature modeling. **Loss Function:** The generator optimizes a combined loss function: $\mathcal{L}_G = \mathcal{L}_{AM-Softmax} + \lambda \mathcal{L}_{Adversarial}$ where $\mathcal{L}_{AM-Softmax}$ enhances class separability in the embedding space, and $\mathcal{L}_{Adversarial}$ encourages synthetic embeddings to be indistinguishable from real ones. **Dynamic Weight Adjustment:** The adversarial loss weight λ is dynamically adjusted during training to balance the generator’s objectives.

Discriminator: Markovian

Functionality: The discriminator evaluates the quality of synthetic embeddings against real ones. **Loss Function:**

Real embeddings are assigned positive labels: $y = 1$ Synthetic embeddings are assigned negative labels: $y = 0$

$$\mathcal{L}_D = -E_{x \sim \mathcal{X}_{real}} [\log(D(x))] - E_{z \sim \mathcal{Z}_{synth}} [\log(1 - D(G(z)))]$$

Mixup Strategy:

Synthetic embeddings are generated by mixing real speaker embeddings using Euclidean averaging. This ensures better coverage of the embedding space manifold without directly adding synthetic labels to the training process. **Creating Synthetic Speaker**

Find Closest Speaker: for each speaker l_1 in each batch using Euclidean distance

$$l_2 = \arg \min ||W[:, l_1] - W[:, l]||_2$$

Create New Weights: the synthetic speaker weight vector is computed as the average of the weight vectors of the closest pair of speakers

$$w_{mix}[:, new] = \frac{W[:, l_1] + W[:, l_2]}{2}$$

Create Synthetic Embeddings: the embeddings of the synthetic speaker are computed as

$$x_{mix} = 0.5 \cdot (x + x[index, :])$$

Experimental Setup

Datasets

VoxCeleb Dataset: The experiments were conducted using 115 hours of data from the VoxCeleb dataset, consisting of 139K utterances from 1,150 speakers. This dataset provides a diverse and challenging benchmark for speaker verification tasks.

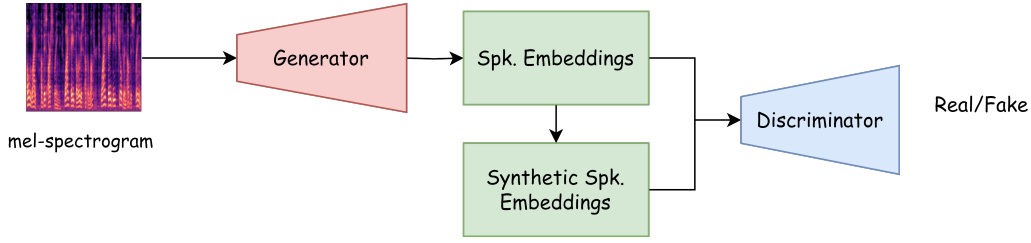


Figure 1: Pipeline for our system.

Experiments

We employed a sophisticated training approach to ensure model stability and performance. The training strategy incorporated several key techniques:

Adversarial Training Mechanism Our training process utilized an alternating update strategy for the generator and discriminator. This approach helps maintain a delicate balance between the two networks, preventing mode collapse and promoting more stable learning dynamics. By carefully coordinating the update cycles, we mitigated the typical challenges associated with generative adversarial training. Initialization and Warm-up

Prior to full adversarial training, we implemented a dedicated discriminator pre-training phase. This warm-up step ensures the discriminator develops robust and reliable feature discrimination capabilities, providing more meaningful adversarial signals during the subsequent joint training process. Optimization Configuration To thoroughly explore the model’s performance envelope, we conducted a comprehensive set of experimental variations:

Optimizer Selection Evaluated model performance with different optimizer e.g. Adam, AdamW Assessed the impact of different optimization strategies on convergence and output quality

Regularization Techniques Applied spectral normalization to the discriminator in selected experimental runs Investigated the effectiveness of spectral normalization in stabilizing adversarial training Also, we experiment with different alpha for the losses.

Training Parameters Total Epochs: 30 Batch Size: 50 Learning Rate: 0.001

This systematic approach allowed us to comprehensively explore the model’s training dynamics, optimization strategies, and performance characteristics under various experimental conditions.

Results

The table presents the results of our proposed speaker verification framework on the test set. The metrics shown are the Equal Error Rates (EER) for the different configurations evaluated. The baseline performance, without any synthetic data generation, is 3.33% EER. Incorporating the synthetic speaker data generated by the W/GAN model (W/GAN row) led to an improved EER of 3.19%. Further enhancing the

baseline	w/ GAN	w/ GAN AMSOftmax
3.33%	3.19%	3.15%

Table 1: EER (%) of different models

AdamW	Adam
3.15%	3.21%

Table 2: EER (%) of w/ GAN AMSOftmax with different optimizers

synthetic data generation by applying the AM-Softmax loss function to the synthetic speaker embeddings (W/GAN AM-Softmax synthetic spks row) resulted in an even lower EER of 3.15%. These results demonstrate the effectiveness of our generative adversarial approach in creating high-quality synthetic speaker embeddings that can enhance the performance of speaker verification systems. The addition of the AM-Softmax loss to the synthetic data generation process particularly helped in improving the separability of the embeddings, leading to the best overall EER on the test set.

Conclusion

Our generative adversarial framework for enhancing speaker verification systems achieved an impressive Equal Error Rate of 3.15% on the test set, outperforming the baseline performance of 3.33%. This was accomplished by generating high-quality synthetic speaker embeddings that were seamlessly integrated into the training process, showcasing the effectiveness of our approach. Moving forward, we plan to further explore refinements to the synthetic data generation techniques to continue advancing the state-of-the-art in speaker verification.

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