Attacking Speaker Recognition with Deep Generative Models

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Abstract

In this paper we investigate the ability of generative adversarial networks (GANs) to synthesize spoofed attacks on modern speaker recognition systems. We first show that the modern architectures of SampleRNN and WaveNet are unable to fool CNN-based speaker recognition systems. We propose a modification of the Wasserstein GAN objective function to make use of data that is real but not from the class being learned. Our method is able to perform both targeted and untargeted attacks against state of the art systems, which calls attention to issues related with security.

1 Introduction

Speaker authentication systems are increasingly being deployed for security critical applications in industries like banking, forensics, and home automation. Like other domains, such industries have benefited from recent advancements in deep learning that lead to improved accuracy and trainability of the speech authentication systems. Despite the improvement in the efficiency of these systems, evidence shows that they can be susceptible to adversarial attacks[22], thus motivating a current focus on understanding adversarial attacks ([19], [6]) and finding countermeasures to detect and deflect them.

Parallel to advancements in speech authentication, neural speech *generation* (the process of using deep neural networks to generate speech) has also seen huge progress in recent years ([21], [1]). The combination of these advancements begs a natural question that has, to the best of our knowledge, not yet been answered:

Are state-of-the-art speech authentication systems robust
to adversarial attacks by speech generative models?

Generative Adversarial Networks (GANs) have recently been found to produce incredibly authentic samples in a variety of fields. The core idea of GANs, a minimax game played between a generator network and a discriminator network, extends very naturally to the field of speaker authentication and spoofing. We will show that a variant of GAN training motivates the model's use as an attacking architecture.

With regards to this question, we offer in this paper the following contributions:

- We evaluate SampleRNN and WaveNet in their ability to fool text-independent state-of-the-art speaker recognizers.
- We propose strategies for untargeted attacks using Generative Adversarial Networks.

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- We propose strategies for targeted attacks using a new objective function based on the improved Wasserstein GAN.

2 Related work

Modern generative models are sophisticated enough to produce fake[1] speech samples that can be indistinguishable from real human speech. Here, we provide a summary of some existing neural speech synthesis models and their architectures. WaveNet [20] is a generative neural network that is trained end-to-end to model quantized audio waveforms. The model is fully probabilistic and autoregressive, using a stack of causal convolutional layers to condition the predictive distribution for each audio sample on all previous ones. It has produced impressive results for generation of speech audio conditioned on speaker and text and has become a standard baseline for neural speech generative models.

SampleRNN [13] is another autoregressive architecture that has been successfully used to generate both speech and music samples. SampleRNN uses a hierarchical structure of deep RNNs to model dependencies in the sample sequence. Each deep RNN operates at a different temporal resolution so as to model both long term and short term dependencies.

Recent work on deep learning architectures has also introduced the presence of *adversarial examples*: small perturbations to the original inputs, normally imperceptible to humans, which nevertheless cause the architecture to generate an incorrect or deliberately chosen output. In their brilliant papers, [19] and [6] analyze the origin of adversarial attacks and describe simple and very efficient techniques for creating such perturbations, such as the fast gradient sign method.

In the vision domain, [18] describe a technique for attacking facial recognition systems. Their attacks are physically realizable and inconspicuous, allowing an attacker to impersonate another individual. In the speech domain, [3] describe attacks on speech-recognition systems which use sounds that are hard to recognize by humans but interpreted as specific commands by speech-recognition systems.

To the best of our knowledge, GANs have not been used before for the purpose of speech synthesis. [15] uses a conditional GAN for the purpose of speech *enhancement*, i.e. taking as input a raw speech signal and outputting a denoised waveform. The model in [4] tackles the reverse problem of using GANs to learn certain representations given a speech spectrogram. We believe the use of spectrograms is a step in the right direction of GAN speech research, as using the raw waveform as input has highlighted current issues with using GANs with sequential modeling.

3 Data

In this section we will describe the datasets used, the data engineering pipeline, including pre-processing and feature extraction, the speaker recognition models evaluated, and the adversarial attacks investigated in this paper.

3.1 Datasets

In our experiments we use three speech datasets, as shown in in Table1. The datasets used are public and provide audio clips of different lengths, quality, language and content.

	Speakers	Language	Duration	Context
2013 Blizzard	1	English	73 h	Book narration
CSTR VCTK	109	English	400 Sentences	Newspaper narration
2004 NIST	100	Multiple	5 min / speaker	Conversational phone speech.

Table 1: Description of the datasets used in our experiments.

[1] We use the term fake to refer to computer generated samples

3.2 Pre-processing

Data pre-processing is dependent on the model being trained. For SampleRNN and WaveNet, the raw audio is reduced to 16kHz and quantized using the μ-law companding transformation as referenced in [13] and [20]. For the model based on the Wasserstein GAN, we pre-process the data by converting it to 16kHz and removing silences by using the WebRTC Voice Activity Detector (VAD) as referenced in [23]. For the CNN speaker recognition system, the data is pre-processed by resampling to 16kHz when necessary and removing silences by using the aforemetioned VAD.

3.3 Feature extraction

SampleRNN and WaveNet operate at the sample level, i.e. waveform, thus requiring no feature extraction. The features used for the neural speaker recognition system are based on Mel-Spectrograms with dynamic range compression. The Mel-Spectrogram is obtained by projecting a spectrogram onto a mel scale. We use the python library librosa [12] to project the spectrogram onto 64 mel bands, with window size equal to 1024 samples and hop size equal to 160 samples, i.e. 100ms long frames. Dynamic range compression is computed as described in [11], with $log(1 + C * M)$, where C is a compression constant scalar set to 1000 and M is a matrix representing the Mel-Spectrogram. Training the GAN is also done with Mel-Spectrograms of 64 bands each.

4 Attacking speaker recognition models

In this section, we define adversarial attacks on speaker recognition models, and describe the methodology we use to perform them.

4.1 Neural speaker recognition system

The speaker recognition system used in our experiments is based on the state-of-the-art framework by [11] and is described in Figure 1. The first module at the bottom is a pre-processing step that extracts the Mel-Spectrogram from the waveform as described in section 3.2. The second module is a convolutional neural network (CNN) that performs multi-speaker classification using the Mel-Spectrogram. The CNN is a modified version of Alexnet [9].

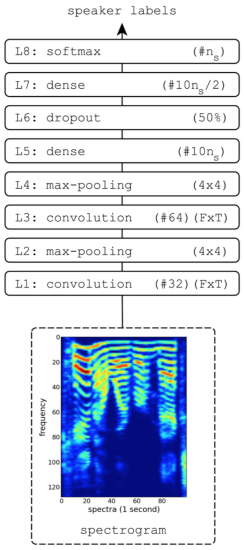


Figure 1: Architecture for CNN speaker verifier

We train the CNN on our training set using 64*64 Mel-Spectrograms [2] consisting of balanced samples from 101 speakers from the NIST 2004 and Blizzard datasets. Our model achieves 85% test set accuracy.

4.2 Adversarial attacks

We define adversarial attacks on speaker recognition systems as *targeted* or *untargeted*. In targeted attacks, an adversary is interested in designing an adversarial input that makes the classification system predict a target class chosen by the adversary. In untargeted attacks, the adversary is interested in a confident prediction, regardless of the class being predicted. Untargeted attacks are essentially designed to fool the classifier into thinking a fake speech sample is real. Notice that a successful targeted attack is by definition a successful untargeted attack as well.

5 Adapting Wasserstein GAN for Attacks

In this section, we describe our generative adversarial network (GAN), and its usage as a speech recognition attacker.

5.1 Model

The GAN framework proposed by [5] involves training a *generator* network, which is trained to learn a function from noise to samples that approximate the real data distribution. Simultaneously, a *discriminator* network is trained to identify whether a sample came from the real distribution or not - i.e., it is trained to try to output 1 if a sample is real, and 0 if a sample is fake. The generator and discriminator can be arbitrary networks.

The GAN framework has been shown to be able to produce very realistic samples with low training overhead. However, since the generator is trained to minimize the Kullback-Leibler (KL) divergence between its constructed distribution and the real one, it suffers from an exploding loss term when the real distribution's support is not contained in the constructed one. To counter this, the *Wasserstein GAN* [2] (WGAN) framework instead uses the Wasserstein (Earth-Mover) distance between distributions instead, which in many cases does not suffer from the same explosion of loss and gradient. Based on this, the loss functions of the generator and *critic* (which no longer emits a simple probability, but rather an approximation of the Wasserstein distance between the fake distribution and real) become:

$$L_G = -\mathop{\mathbb{E}}_{\widetilde{\boldsymbol{x}}\sim\mathbb{P}_g}\big[D(\widetilde{\boldsymbol{x}})\big] \tag{1}$$

$$L_C = \mathop{\mathbb{E}}_{\widetilde{\boldsymbol{x}}\sim\mathbb{P}_g}\big[D(\widetilde{\boldsymbol{x}})\big] - \mathop{\mathbb{E}}_{\boldsymbol{x}\sim\mathbb{P}_r}\big[D(\boldsymbol{x})\big] \tag{2}$$

where P_r is the real distribution and P_g the learnt distribution of the generator.
The original WGAN framework uses weight clipping to ensure that the critic satisfies a Lipschitz condition. As pointed by [7], however, this clipping can lead to problems with gradient stability. Instead, [7] suggest adding a gradient penalty to the critic's loss function, which indirectly tries to constrain the original critic's gradient to have a norm close to 1. Equation (2) thus becomes (taken from [7]):

$$L_C = \underbrace{\mathop{\mathbb{E}}_{\widetilde{\boldsymbol{x}}\sim\mathbb{P}_g}\big[D(\widetilde{\boldsymbol{x}})\big] - \mathop{\mathbb{E}}_{\boldsymbol{x}\sim\mathbb{P}_r}\big[D(\boldsymbol{x})\big]}_{\text{Original critic loss}} + \underbrace{\lambda \mathop{\mathbb{E}}_{\hat{\boldsymbol{x}}\sim\mathbb{P}_{\hat{x}}}\big[(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1)^2\big]}_{\text{Gradient Penalty}} \tag{3}$$

In all of our experiments, we use the Wasserstein GAN with this gradient penalty (WGAN-GP), which we found makes the model converge better than regular WGAN or GAN. We will henceforth use WGAN, GAN, and WGAN-GP interchangeably to refer to WGAN-GP.

5.2 Attacks

Performing *untargeted* attacks with the WGAN-GP (i.e., training the network to output speech samples that mimic the distribution of speech) is relatively straightforward - we simply train the

[2] 64 mel bands and 64 frames, 100 ms each

WGAN-GP using all speakers in our dataset. However, the most natural attack is one that is *targeted*: where the GAN is trained to directly fool a speaker recognition system, i.e., to produce samples that the system classifies as matching a target speaker with reasonable confidence.
The first attempt was one in which we trained the WGAN-GP using data from only the target speaker. However, the generated samples did not fool the speaker recognition systems, which was likely due to the discriminator's lack of access to data from other speakers. To circumvent this, we propose a modification to the critic's objective function that allows it to learn to differentiate between not only real samples and generated samples, but also between real speech samples from a target speaker and real speech samples from other speakers. We do this by adding a term to the critic's loss that encourages its discriminator to classify real speech samples from untargeted speakers as fake. From (3), the critic's loss L_C changes to:

$$\underbrace{\mathop{\mathbb{E}}_{\widetilde{\boldsymbol{x}}\sim\mathbb{P}_g}\left[D(\widetilde{\boldsymbol{x}})\right]}_{\text{Generated Samples}} + \alpha * \underbrace{\mathop{\mathbb{E}}_{\dot{\boldsymbol{x}}\sim\mathbb{P}_{\dot{x}}}\left[D(\dot{\boldsymbol{x}})\right]}_{\text{Different Speakers}} - \underbrace{\mathop{\mathbb{E}}_{\boldsymbol{x}\sim\mathbb{P}_r}\left[D(\boldsymbol{x})\right]}_{\text{Real Speaker}} + \underbrace{\lambda \mathop{\mathbb{E}}_{\hat{\boldsymbol{x}}\sim\mathbb{P}_{\hat{x}}}\left[(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1)^2\right]}_{\text{Gradient Penalty}} \tag{4}$$

where $P_{\hat{x}}$ is the distribution of samples from other speakers and α is a tunable scaling factor.

6 Experimental setup

6.1 WGAN setup

In our experiments, we trained a WGAN-GP to produce spectrograms from 1 target speaker, against a set of over 100 "other" speakers. On each critic iteration, we fed it with a batch of samples from one target speaker, and a batch of data uniformly sampled from the other speakers.
We used two popular architectures for generator/critic pairs:

- *DCGAN* [17] models the generator as a series of deconvolutional layers with ReLU activations, and the discriminator as a series of convolutional ones with leaky ReLU activations. Both architectures use batch normalization after each layer.
- *ResNet* [10] models the generator and discriminator each as very deep convnets (30 layers in our experiments) with upsampling/downsampling respectively. Residual (skip) connections are added every few layers to make training easier.

Initially, we were able to converge the targeted loss model used the same parameters as [7], namely 5 critic iterations per generator iteration, a gradient penalty weight of 10, and batch size of 64. Both the generator and critic were trained using the Adam optimizer [8]. However, under these parameters we found that the highest α weight we could successfully use was 0.1 (we found that not including this scaling factor led to serious overfitting and poor convergence of the GAN).
The drawback of this approach is that the critic is not fully trained to discriminate against other speakers' data. In order to converge a model with α as 1, we made several modifications to the network parameters. We changed the standard deviation of the DCGAN discriminator's weights to be 0.05. To accommodate the critic's access to additional data in the mixed loss function (4), we increased the generator's learning rate to $1e^{-4}$, whereas the critic's learning rate was kept at $1e^{-5}$. Finally, we added of Gaussian noise to the target speaker data to prevent overfitting.

6.2 WaveNet

Due to constraints on computing power, we used samples from WaveNet models that had been pre-trained for 88 thousand iterations. Parameters of the models were kept the same as those in [20]. The ability of WaveNet to perform *untargeted* attacks amounts to using a model trained on an entire corpus. Targeted attacks are more difficult - we found that a single speaker's data was not enough to train WaveNet to converge successfully. To construct speaker-dependent samples, we relied on samples from pre-trained models that were *globally conditioned* on speaker ID. Auditorily, such samples do sound very similar to the real speech of the ID in question. We ran the feature-extraction in section 3 on these samples to produce data fed to the classifier.

6.3 sampleRNN

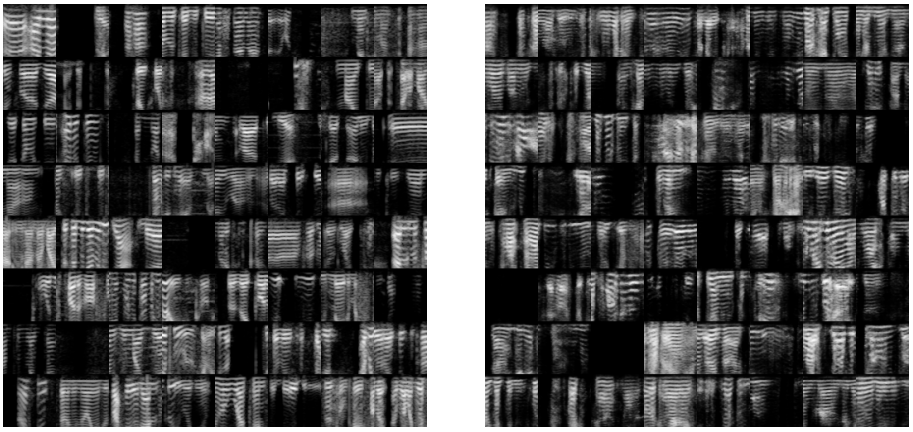
Similarly to WaveNet, we found that the best (least noisy) sampleRNN samples came from models which were pretrained with a high number of iterations. Accordingly, we obtained samples from the

three-tiered architecture, trained on the Blizzard 2013 dataset [16], which as mentioned in Section 3 is a 300 hour corpus of a single female speaker's narration. We also downloaded 10 second samples from the original paper's online repository at `https://soundcloud.com/samplernn/sets`, which we qualitatively found to have less noise than our generated ones.

7 Results

7.1 GAN Mel-Spectrogram

Using the improved Wasserstein GANs framework, we trained generators to construct 64x64 mel-spectrogram images from a noise vector. Visual results are demonstrated below in Figure 2. We saw recognizable Mel-Spectrogram-like features in the data after only 1000 generator iterations, and after 5000 iterations the generated samples were indistinguishable from real ones. Training took around 10 hours for 20000 iterations on a single 4 GB Nvidia GK104GL GPU.



(a) Real (actual) (b) Fake (generated)

Figure 2: Comparison of real and generated ($\sim$ 5000 generator iterations) spectrogram samples from all speakers. Each grid contains 64 samples.

7.2 GAN Adversarial attacks

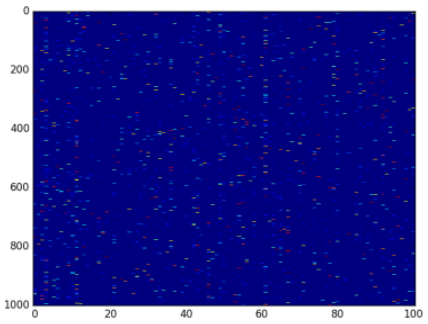
Within the GAN framework, we train models for untargeted attacks by using all data available from speakers that the speaker recognition systems was trained on, irrespective of class label. We show that an untargeted model able to generate data from the real distribution with enough variety can be used to perform adversarial attacks. We provide details in the untargeted attacks subsection 7.2.1. Figure 3b depicts that our GAN-trained generator successfully learns all speakers across the dataset, without mode collapsing.

The models for targeted attacks can be trained in two manners: 1) conditioning the model on additional information, e.g. class labels, as described in [14]; 2) using only data from the label of interest. While the first approach might result in mode collapse, a drawback of the second approach is that the discriminator, and by consequence the generator, does not have access to universal[3] properties of speech. In the targeted attacks subsection **??** we propose a new objective function that allows using the data from all speakers.

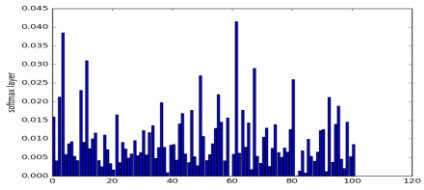
7.2.1 Untargeted attacks

For each speaker audio data in the test set, we compute a Mel-Spectrogram as descibred in section 3.2. The resulting Mel-Spectrogram is then fed into the CNN recognizer and we extract a 505-dimensional feature G from the penultimate fully-connected layer (L7) in the pre-trained CNN model (1) trained

[3]We draw a parallel with Universal Background Models in speech.

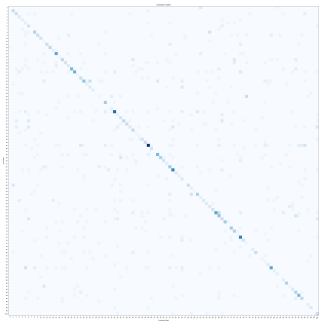


(a) Our speaker classifier's softmax distribution of 1000 samples on approximately 100 speakers.

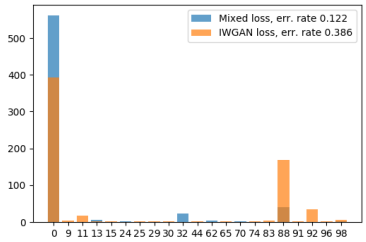


(b) Our speaker classifier's distribution of randomly sampled speech from the generative model.

Figure 3: Summary of untargeted attacks. Red represents high confidence.



(a) Confusion matrix of untargeted model



(b) Histogram of predictions given improved WGAN and mixed loss models.

Figure 4: Confusion matrix of targeted attacks

on the train partition of the real speech dataset with all speaker IDs. This deep feature/embedding G is then used to train a K-nearest-neighbor (KNN) classifier, with K equal to 5.

To control the generator trained by our WGAN, we feed the generated Mel-Spectrograms into the same CNN-L2 pipeline to extract their corresponding feature $\widehat{G}$. Utilizing the pre-trained KNN, each sample is assigned to the nearest speaker in the deep feature space. Therefore, we know which speaker our generated sample belongs to when we attack our CNN recognizer. We evaluate our controlled WGAN samples against the state-of-the-art CNN recognizer, and the confusion matrix can be found in Figure 4a. Although not included in the figure, **neither WaveNet samples nor SampleRNN samples were able to attack the recognition model in the same way.** [4]

7.2.2 Targeted attacks

Results are demonstrated in Figure 4. The histogram of predictions in Figure 4b shows that using the mixed loss model, most of the energy is concentrated on the target speaker 0. The improved WGAN loss achieves 0.39 error rate and our mixed loss achieves 0.11 error rate, producing a 77% increase in accuracy.

8 Discussion and Conclusion

In this paper we have investigated the use of speech generative models to perform adversarial attacks on speaker recognition systems. We show that the autoregressive models we trained, i.e. SampleRNN and WaveNet, were not able to fool the CNN speaker recognizers we built. On the other hand, we

[4] Unlike our method, neither were they successful in attacking a GMM-UBM speaker recognizer.

show that adversarial examples generated with GAN networks are successful in performing targeted and untargeted adversarial attacks.

With this paper we hope to raise attention to issues that generative models bring to security and biometric systems. We foresee that samples produced with generative models have a signature that can be used to identify the source of the data and leave this investigation for future work.

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