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 spoofing attacks on modern speaker recognition systems. We first show that samples generated with SampleRNN and WaveNet are unable to fool a CNN-based speaker recognition system. 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 semi-supervised learning method is able to perform both targeted and untargeted attacks, raising questions related to security in speaker authentication systems.

1. INTRODUCTION

Speaker authentication systems are 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[**?**], thus motivating a current focus on understanding adversarial attacks ([**?**], [**?**]), finding countermeasures to detect and deflect them and designing systems that are provably correct with respect to mathematically-specified requirements [**?**].

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 [**?**]. The combination of these advancements begs a natural question that has, to the best of our knowledge, not yet been answered:

Are speech authentication systems robust
to adversarial attacks by speech generative models?

Generative Adversarial Networks (GANs) are generative models that recently have been used 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 naturally to the field of speaker authentication and spoofing.

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

- We evaluate samples produced with SampleRNN and WaveNet in their ability to fool text-independent speaker recognizers.
- We propose strategies for untargeted attacks using Generative Adversarial Networks.
- We propose a semi-supervised approach for targeted attacks by modifying Wasserstein's GAN loss function.

2. RELATED WORK

Modern generative models are sophisticated enough to produce fake[1] speech samples that can be indistinguishable from real human speech. In this section, we provide a summary of some existing neural speech synthesis models and their architectures.

WaveNet [**?**] 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 [**?**] 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, [**?**] and [**?**] analyze the origin of adversarial attacks and describe simple and very efficient techniques for creating such perturbations, such as the fast gradient sign method (FGSM).

In the vision domain, [**?**] 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, [**?**] describe

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

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 for the purpose of speech synthesis[2]. [**?**] 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 [**?**] tackles the reverse problem of using GANs to learn certain representations given a speech spectrogram.

3. ATTACKING SPEAKER RECOGNITION MODELS

3.1. Neural speaker recognition system

The speaker recognition system used in our experiments is based on the framework by [**?**] 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 4.2. 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 [**?**]. We warn the readers that unlike [**?**], our classifier operates on 64 by 64 Mel-Spectrogram and has slightly different number of nodes on each layer.

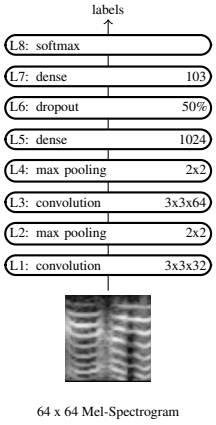


Fig. 1: Architecture for CNN speaker verifier.

We train our speaker classifier using 64 by 64 Mel-Spectrograms [3] from 3 speech datasets, including 100 speakers from NIST 2004, speaker p280 from CSTR VCTK and the single speaker in Blizzard. Our speaker classifier has a rejection path, the "other" class, trained on environmental sounds using samples from the ESC-50 dataset. Our model achieves approximately 85% test set accuracy

3.2. Adversarial attacks

We define adversarial attacks on speaker recognition systems as *targeted* or *untargeted*. In targeted attacks, an adversary is interested in designing an 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 as long as it is not the "other" class. Untargeted attacks are essentially designed to fool the classifier into thinking a fake speech sample is real. Note that a successful targeted attack is by definition a successful untargeted attack as well.

[2]More specifically, Mel-Spectrogram synthesis

[3]64 mel bands and 64 frames, 100 ms each

	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.
ESC 50	50	N/A	4 min / class	Environmental sounds.

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

4. EXPERIMENTAL SETUP

4.1. Datasets

In our experiments we use three speech datasets and one dataset with environmental sounds, as shown in Table 1. The datasets used are public and provide audio clips of different lengths, quality, language and content. In addition to the samples listed in Table 1, we used globally conditioned sampleRNN and WaveNet fake samples available on the web. The samples generated with sampleRNN and WaveNet are from the Blizzard dataset and CSTR VCTK (P280) respectively.

4.2. 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 [**?**] and [**?**]. 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 [**?**]. 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.

4.3. 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 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 [**?**], 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 and 64 frames image patch.

4.4. Models

4.4.1. WaveNet

Due to constraints on computing power and the extreme difficulty in training WaveNet [4], 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 [**?**]. 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. Based on informal listening experiments, such samples do sound very similar to the real speech of the speaker in question.

4.4.2. 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 [**?**], which as mentioned in Section 3 is a 300 hour corpus of a single female speaker's narration. We also downloaded samples from online repositories, including samples from the original paper's online repository at `https://soundcloud.com/samplernn/sets`, which we qualitatively found to have less noise than ours.

4.4.3. WGAN

In all of our experiments, we use the Wasserstein GAN with gradient penalty (WGAN-GP), which we found makes the model converge better than regular WGAN [**?**] or GAN [**?**]. In our experiments, we trained a WGAN-GP to produce mel-spectrograms from 1 target speaker *against* a set of 101 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* [**?**] and *ResNet* [**?**].

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 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.

4.4.4. WGAN-GP with modified objective function

A naive approach for targeted attacks is to train the GAN on the data of the single target speaker. A drawback of this approach is that the *critic*, and by consequence the *generator*, does not have access to universal properties of speech[5]. To circumvent this problem, we rely on semi-supervised learning and 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:

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

where $P_{\dot{x}}$ is the distribution of samples from other speakers and α is a tunable scaling factor. Note that equation 1 is no longer a direct approximation of the Wasserstein distance. Rather, it provides a balance of the distance between both the fake distribution and real one, and the distance between other speakers' distribution and the target speaker's one. We refer to this objective function as **mixed loss**.

Initially, we were able to converge the targeted loss model used the same parameters as [**?**], 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 [**?**]. 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).

In order to circumvent these problems and train a model with α set to 1, we made modifications to the setup, including setting the standard deviation of the DCGAN discriminator's weight initialization to 0.05 and iterations to 20. To accommodate the critic's access to additional data in the mixed loss function (4), we increased the generator's learning rate. Finally, we added Gaussian noise to the target speaker data to prevent overfitting.

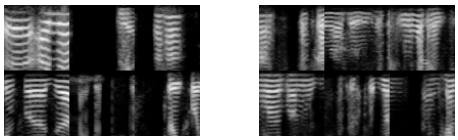
5. RESULTS

5.1. 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

[4] Our community has not been able to replicate the results in Google's WaveNet paper

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



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

Fig. 2: Comparison of 6 real and fake mel-spectrogram samples from all speakers. ($\sim$ 5000 generator iterations)

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.

5.2. 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 in subsection 5.2.1 that an untargeted model able to generate data from the real distribution with enough variety can be used to perform adversarial attacks. Figure 3a depicts that our GAN-trained generator successfully learns all speakers across the dataset, without mode collapsing.

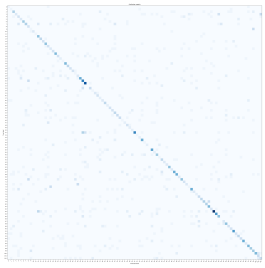
As we described earlier, the models for targeted attacks can be trained in two manners: 1) conditioning the model on additional information, e.g. class labels, as described in [**?**]; 2) using only data from the label of interest. While the first approach might result in mode collapse, a drawback of the second approach is that the discriminator, and by consequence the generator, does not have access to universal[6] properties of speech. In the targeted attacks subsection 5.2.2 we show results using our new objective function described in equation 1 that allows using data from all speakers.

5.2.1. Untargeted attacks

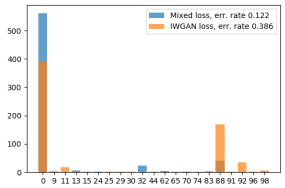
For each speaker audio data in the test set, we compute a Mel-Spectrogram as descibred in section 4.2. The resulting Mel-Spectrogram is then fed into the CNN recognizer and we extract a 1024-dimensional feature Φ from the first fully-connected layer (L5) in the pre-trained CNN model (1) trained on the real speech dataset with all speaker IDs. This deep feature/embedding Φ is then used to train a K-nearest-neighbor (KNN) classifier, with K equal to 5.

To control the generator trained by our WGAN-GP, we feed the generated Mel-Spectrograms into the same CNN-L7 pipeline to extract their corresponding feature $\widehat{\Phi}$. 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

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



(a) Confusion matrix of untargeted model. x-axis corresponds to predicted label, y-axis to ground truth.



(b) Histogram of predictions given WGAN-GP and mixed loss models. Ground truth label: 0.

Fig. 3: Summary histograms of targeted attacks

CNN recognizer. We evaluate our controlled WGAN-GP samples against our CNN speaker recognition system, and the confusion matrix can be found in Figure 3a.

5.2.2. Targeted attacks

We trained the WGAN-GP on the entirety of the NIST 2004 corpus (100 speakers), a single speaker (P280) from the VCTK Corpus, and the single speaker from the Blizzard dataset. The samples from the other models were either downloaded from the web or created from WaveNet globally conditioned on the single VCTK corpus speaker, and on SampleRNN trained only on data from the Blizzard dataset. Results for the WGAN-GP are demonstrated in Figure 3. In the samples generated with sampleRNN and WaveNet models, **none** of the predictions made by the classifier match the target speaker.

We also trained the WGAN-GP with and without the **mixed loss** on different speakers. The histogram of predictions in Figure 3b shows WGAN-GP results for speaker 0. The improved WGAN-GP loss achieves 0.38 error rate and our mixed loss achieves 0.12 error rate, producing a 75% increase in accuracy.

6. DISCUSSION AND CONCLUSION

In this research we have investigated the use of speech generative models to perform adversarial attacks on speaker recognition systems. We show that the samples from autoregressive models we trained, i.e. SampleRNN and WaveNet, or downloaded from the web were not able to fool the CNN speaker recognizers we used in this research. On the other hand, we show that adversarial examples generated with GAN networks are successful in performing targeted and untargeted adversarial attacks given the speaker recognition used herein.

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