VENOMAVE: Clean-Label Poisoning Against Speech Recognition

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Abstract

In the past few years, we observed a wide adoption of practical systems that use *Automatic Speech Recognition* (ASR) systems to improve human-machine interaction. Modern ASR systems are based on neural networks and prior research demonstrated that these systems are susceptible to *adversarial examples*, i.e., malicious audio inputs that lead to misclassification by the victim's network during the system's *run time*. The research question if ASR systems are also vulnerable to *data poisoning attacks* is still unanswered. In such an attack, a manipulation happens during the *training phase* of the neural network: an adversary injects malicious inputs into the training set such that the neural network's integrity and performance are compromised.

In this paper, we present the first data poisoning attack in the audio domain, called VENOMAVE. Prior work in the image domain demonstrated several types of data poisoning attacks, but they cannot be applied to the audio domain. The main challenge is that we need to attack a *time series of inputs*. To enforce a targeted misclassification in an ASR system, we need to carefully generate a specific sequence of disturbed inputs for the target utterance, which will eventually be decoded to the desired sequence of words. More specifically, the adversarial goal is to produce a series of misclassification tasks and in each of them, we need to poison the system to misrecognize each frame of the target file. To demonstrate the practical feasibility of our attack, we evaluate VENOMAVE on an ASR system that detects sequences of digits from 0 to 9. When poisoning only 0.94% of the dataset on average, we achieve an attack success rate of 83.33%. We conclude that data poisoning attacks against ASR systems represent a real threat that needs to be considered.

1 Introduction

Thanks to recent advances in machine learning and new levels of available computing power, we can observe an increasing number of smart devices available for end-users. Many of these devices are now shipped with ASR to improve humanmachine interaction. Furthermore, many businesses employ ASR systems to enable their customers to perform self-service tasks, such as checking account balances, as well as authenticating their identity prior to speaking with humans at the customer service. While ASR systems have become ever more reliable on clean data, they are still susceptible to malicious input, i.e. adversarial examples [2, 8, 24, 25]. In these evasion attacks, a targeted audio file is perturbed by imperceptible amounts of adversarial noise at *run time* to trigger a misclassification of the victim's neural network.

An orthogonal line of research has shown that neural networks are also vulnerable to malicious manipulations during the *training phase* [6, 19, 20, 34]. As training neural networks requires huge datasets, it is common practice to collect these datasets from other, often potentially untrusted, sources (e.g., the Internet). While neural networks can learn powerful models in the presence of *natural* noise in datasets, they can be fooled by carefully crafted *malicious* perturbations added by an adversary. In comparison to adversarial examples, in data poisoning attacks, the attacker has the advantage to manipulate the model itself such that it shows the intended behavior. For example, a street sign classifier can be poisoned so that it identifies stop signs as speed limits when a special sticker is added to the stop sign [11]. At the same time, it is hard for the victim to detect potentially poisoned data since even if we assume such noise can be detected by human observers, having these datasets carefully vetted can be very expensive in practice due to the sheer amount of data. Hence, gathering data samples from untrusted sources makes neural networks susceptible to *data poisoning attacks*, where an adversary inserts malicious data into the training set in order to manipulate the system performance.

So-called *clean-label poisoning attacks* have been recently proposed against image classification systems for the first time [1, 27, 38], wherein the adversary has *no* control over the labeling process. While the poison samples are perturbed to achieve the system's misbehavior with regards to specific target inputs, such perturbations are small enough to justify

the original labels in the human perception. Compared to other types of poisoning attacks [11,17,19], this branch of attacks brings two major advantages in real-world scenarios: (1) the poisoned data will not be identified by human labelers, and (2) the poisoned model usually maintain the same level of test performance, except for misclassification of particular target samples.

With VENOMAVE, we present the first clean-label poisoning attack in the audio domain. More specifically, we demonstrate that such an attack is possible against state-of-the-art ASR systems. ASR systems intend to map an audio waveform into a sequence of words and therefore considers time series as its input which enforces the recognizer to operate completely different to an ordinary image classifier As a consequence, clean-label poisoning attacks from the space of images cannot be naïvly adopted to ASR systems. Similar to evasion attacks [8, 25] against ASR systems, in this work, we mainly focus on fooling the neural network component. To enforce a targeted misclassification, we make the neural network component to produce a sequence that will eventually be decoded to the desired sequence of words. We divide our adversarial goal into a series of misclassification tasks; in each of them, we focus on poisoning one part of the audio. Compared to image classification, where a single misclassification task is performed to trigger the attack, our attack is significantly more challenging.

Furthermore, clean-label poisoning attacks against image classifiers focused on transfer learning, where a model trained for one task (called *feature extractor*), is reused as part of a different model for a second, yet similar, task. These attacks try to achieve a mathematical guarantee that is defined on feature spaces created by a set of *surrogate models*, such that this guarantee holds for the unknown victim's network.

Unlike image recognition, transfer learning is not yet shown to be useful for speech recognition. To build up an ASR system, it is common practice to train the neural network from scratch. This solely makes attacks from the space of images not plausible, as they try to optimize heuristics that are defined in the feature extractor model. If the entire neural network is trained from the scratch, the feature extractor network is also altered during the training process. This makes it harder to obtain the same heuristics.

To mitigate this limitation, we adopt the Bullseye Polytope attack [1] and extend it as follows: at the beginning of each round of the attack, the surrogate networks are trained on the current version of the (poisoned) dataset. Then, the poisons are changed to achieve the desired heuristics with regards to the refreshed surrogate models. After several rounds of the attack, we reach a state that the poisoned data need no further modifications to enforce the mathematical guarantee for the surrogate models.

To evaluate VENOMAVE, we focus on an ASR system which detects sequences of digits from 0 to 9. In our experiments, we target a specific utterance to perform a *digit*

replacement attack, e.g., EIGHT \rightarrow NINE. For this purpose, we craft poisons for a specific utterance of digit EIGHT such that the system recognizes it as NINE.

For each example of the attack, we target a specific single-digit target utterance of a particular speaker to craft poisoned data. Later, we train the victim system on the poisoned dataset and evaluate it against the target utterance to determine whether the attack is successful or not. We further evaluate the victim system against other utterances of the same speaker to quantify the *generalization accuracy* of the attack. Additionally, we evaluate the accuracy of a test dataset and the total amount of data that is poisoned for a successful attack.

We perform our experiments for three different types of neural networks, which are employed by the victim. We enable dropout randomization for the victim to further assess the performance of VENOMAVE. Additionally, we measure the effect if we restrict the perturbations to a maximum value to make the attack less suspicious. Having poisoned only 144 seconds of audio (0.94 % of the training set) on average, VENOMAVE achieves an attack success rate of 83.33 %. When the attack is successful, it demonstrates a generalization accuracy of up to 23.83% on average .

In summary, we make the following key contributions:

- Clean-label poisoning against ASR. We propose VEN-OMAVE, the first clean-label data poisoning attack in the audio domain. Our results demonstrate that data poisoning attacks are a real threat for ASR systems.
- End-to-end learning. Unlike previous clean-label poisoning attacks [1, 27, 38], in our threat model, we assume the victim system is trained on the poisoned data from scratch.
- Dropout randomization. Our results show that VEN-OMAVE can even survive dropout randomization employed by the victim during the training phase. Note that this result addresses an open question for previous clean-label poisoning attacks, wherein the victim does not exploit dropout randomization.

To support further research in this area, we release the source code of all experiments as well as the poison samples generated by VENOMAVE at https://github.com/9yte/VenoMave. 1

2 Background and Related Work

In this work, we transfer clean-label poisoning attacks from the image domain to speech recognition. We adopt the Bullseye Polytope attack [1], which has shown superior performance to earlier versions of this family of attacks [27, 38].

¹We will make the code and samples available upon request during review.

Our attack targets a hybrid ASR system which employs a neural network along with an *Hidden Markov Model* (HMM). In this section, we first provide an overview of how the targeted ASR system functions. Then, we present an overview of related work and discuss how our approach relates to prior work on adversarial examples for ASR systems and (clean-label) data poisoning attacks.

2.1 Automatic Speech Recognition Systems

In the context of ASR systems, neural networks can be used in a number of different architectures that can generally be divided into two types, *end-to-end* and *hybrid* systems.

- End-to-end systems refer to architectures where the neural network directly transforms the audio waveform (input) into a character transcription (output).
- In hybrid systems, a language model is used for cross-temporal information integration, after the input data has been initially processed by a neural network. In these hybrid, so-called DNN-HMM systems, the role of the neural network is, at any point in time, to produce the probability of all HMM states—the so-called *pseudo-posteriors*—given the current segment of the audio waveform.

Given a sequence of pseudo-posteriors, describing all segments of the audio waveform, a *decoder* uses the HMM to find the most likely word sequence. One advantage of these systems is that these systems are not as data-hungry as end-to-end systems [3]. In addition, their architecture allows the user to explicitly specify task grammars and adapt language-models on the fly, which has made them very popular for many commercial systems such as Amazon's Alexa and makes them the system of choice for pre-trained embedded models that may not have the luxury of a big-data backend for adaptation.

In this paper, we show how data poisoning can be used to attack hybrid DNN-HMM ASR systems. Figure 1 provides an overview of the main system components. In the following, we describe the system in more detail.

Feature Extraction. During the feature extraction, the raw input is processed into a feature representation that should ideally preserve all relevant information (e. g., phonetic information which describes the smallest acoustic unit of speech) while discarding the unnecessary remainders (e. g., acoustic properties of the room). For the feature extraction in this paper, we divide the input waveform into overlapping frames of fixed length. Each frame is transformed individually using the *Discrete Fourier Transform* (DFT) to obtain a frequency representation. We further calculate the logarithm of the magnitude spectrum and apply a Mel filter bank to the resulting signal. The Mel filter bank is a psychoacoustic filter bank

that scales the magnitude spectrum based on human listeners judgment of frequency perception [29]. In the last step, a *Discrete Cosine Transformation* (DCT) is applied and the resulting features are generally augmented via their first and second derivation. These features are so-called *Mel Frequency Cepstral Coefficients* (MFCCs), a very common feature representation for ASR systems. These features are used as input for the neural network.

Neural Network. Like many statistical models, neural networks can learn very general input/output mappings from training data. In the context of ASR, we use the neural network to model the probability of HMM states. The HMM mainly describes the grammar of the language, a phonetic-based word description of all words, and context-dependencies of phonetic units. Therefore, the outputs of the *Deep Neural Network* (DNN) are pseudo-posteriors, which are used during the decoding step in order to find the most likely word sequence.

Decoding. Generally speaking, decoding in ASR systems utilizes some form of graph search for the inference of the most probable word sequence from the acoustic signal. The HMM and the pseudo-posteriors (i. e., the output of the DNN) are then used to find an optimal path (which is interpreted as a sequence of words) through the word graph via Viterbi decoding [21].

During the training of the system, the exact alignment between an utterance and the transcriptions and therefore the labels are typically unknown. To account for this, commonly Viterbi training is utilized. Typically, the neural network is first trained on equally-aligned labels. With that model, the decoding is performed on the training data and the resulting labels are used as the new labels.

2.2 Adversarial Examples

Adversarial examples are inputs that have been crafted by an adversary to fool a machine learning classifier [5,9,30]. In these evasion attacks, a specific input is perturbed by adding imperceptible noise to enable an intended misclassification. Such perturbations are calculated using the gradients of the corresponding loss function that is defined on the victim network, or surrogate networks if the victim network is unknown. Initial adversarial attacks focused mainly on the space of images. Later, adversarial examples are shown to exist in other domains such as malware classification [10], reinforcement learning [13], reading comprehension [14], as well as speech recognition [8], where generating adversarial examples is very challenging due to time dependencies that exist in the feature extraction phase of ASR systems.

Vaidya et al. [32] proposed one of the first adversarial attacks against ASR systems. They showed an audio file can be altered to fit the intended transcription by considering the

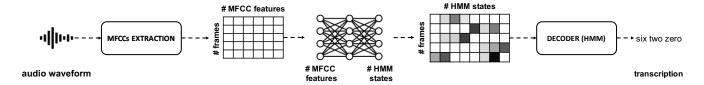


Figure 1: Overview of a state-of-the-art hybrid ASR system with two main components: a neural network which calculates pseudo-posteriors of HMM states, and a decoder which employs a HMM to generate the transcription.

features representation instead of the output of the model. The major drawback of this approach is that the generated adversarial audio samples can be easily perceived by human ears. Carlini et al. [7] proposed so-called *hidden voice commands* which target GMM-HMM ASR systems, where *Gaussian Mixture Models* (GMMs) are used instead of neural networks. They use inverse feature extraction to produce adversarial audio samples.

Later, Carlini et al. [8] proposed a general targeted attack on ASR systems that use Connectionist Temporal Classification (CTC) loss. They evaluated their attack against Deep-Speech [12], which is a pure end-to-end ASR system. Unlike hybrid ASR systems, DeepSpeech does not exploit any language model in the decoder and only includes a neural network. The authors also limit the difference between original and adversarial samples, but with a bound that is borrowed from adversarial attacks on images, which therefore does not consider the sensitivities of the human auditory system. Yakura et al. [35] create adversarial examples which can be played over-the-air. Their attack tends to work for shorter word phrases and introduce significantly larger perturbation. In general, generated audio samples sound noisy to humans, which can arouse the suspicion of cautious listeners. To mitigate this limitation, Zhang et al. [37] proposed DolphinAttacks, which utilize the non-linearities of microphones to modulate the baseband audio signal with ultrasound higher than 20 kHz. This requires the perturbations to be calculated from recordings of audio signals with the specific microphone, which makes the attack costly and tailored to a specific recording setup. Schönherr et al. [25] consider psychoacoustic hiding to produce less perceptible adversarial noise. Their attack is evaluated against the Kaldi system [22], which is partially based on neural networks but also uses a language model for generating the final transcription.

2.3 Clean-Label Data Poisoning Attacks

The first generation of data poisoning attacks used poisoned data to degrade the test accuracy of the victim model [6, 19, 20, 34]. These attacks are generally easy to detect, as the performance of the model can always be assessed by evaluating against a private, trusted test set. *Backdoor attacks* [11] are another important branch of poisoning attacks, where an adversary fools the victim model by imprinting a small number

of training samples with a specific pattern (called *trigger*) and changing their labels to the desired target label. This eventually helps the attacker to achieve misclassification by injecting the trigger into *any* input examples. However, a filtering process, which inspects the labels of the poisoned data, can easily detect the poisoned samples. Also, similar to evasion attacks, these attacks require the modification of test samples during inference to enable misclassification, which is not always applicable in real-world scenarios.

A recent branch of data poisoning attacks was studied in the image domain for when the victim employs transfer learning [1,27,38]. Transfer learning is a general approach where a model trained for one task is reused as part of a new model for a new, but similar, task. In these attacks, the adversary has no control over the labeling process. Clean-label data poisoning was first studied in a white-box setting [27], known as Feature Collision, where the attacker has complete knowledge of the pre-trained network. To trigger misclassification for a target image, Feature Collision selects a base image from the targeted class and crafts a poison image by adding bounded perturbations to the base image so that the poison image is similar to the target image in the feature space. Since the feature representation of the poison image and the target image is equal, a linear classifier that is trained on the features of a dataset containing the poison image will eventually identify the target image as the targeted class. Feature Collision fails in a black-box setting, where the feature extractor is unknown to the attacker. Also, noticeable patterns of the target image appear in some poison samples.

To address these limitations, Zhu et al. [38] proposed the *Convex Polytope* attack, which, instead of finding poison samples close to the target, crafts poison samples that form a convex polytope around the target. Convex Polytope relies on the following mathematical guarantee: every linear classifier that classifies a set of points into label *l* will classify every point in the convex hull of these points as label *l*. As argued by the authors, compared to Feature Collision, Convex Polytope creates a larger "attack zone" which increases the probability of misclassification. However, Aghakhani et al. [1] later showed that the target tends to be close to the boundary of this attack zone, potentially hampering the attack transferability to the victim network in black-box settings. They proposed *Bullseye Polytope* by refining the constraints of Convex Polytope such that the target is pushed toward the "center" of the attack zone

(i. e., the convex hull of poison samples). They have demonstrated that such refinement can achieve an up to 50% higher attack success rate against some victim models while making the attack execution time an order of magnitude faster.

3 Method

In this work, we propose VENOMAVE, the first clean-label data poisoning attack against ASR systems. Other than current adversarial attacks on ASR systems [8, 24, 25] which target the system during inference (i.e., the attacker creates *malicious* input that causes a misclassification), data poisoning attacks target the system during the training phase. Such poisoning attacks were already shown to be viable against image classification, but to the best of our knowledge, no data poisoning attack was yet proposed against ASR systems. Compared to recent works on image classification systems, attacking speech recognition is significantly more challenging, mainly for two reasons.

- Time-series. The input of an ASR system is a time-series
 of samples from the audio signal rather than a single
 fixed-sized input. Consequently, also the system's output
 is a sequence of classes with time dependencies that need
 to be considered during the attack.
- End-to-end learning. ASR systems are typically trained from scratch whereas a modern image classification system can rely on transfer learning where a pre-trained network trained for one task is reused as part of a different network for a different, but similar, task. In terms of the attack, end-to-end learning seems to be a much more difficult task [1,27,38] as the attacker needs to take the complete training into account.

From a high-level perspective, our goal is to implant manipulated data points to the training set of the victim, such that a system trained on this data falsely transcribes specific activation phrases into an attacker chosen commands. In addition, for a clean-label attack, we further constrain the adversary to craft poisons that (1) are not detected by human labelers, and (2) barely affect the benign accuracy of the system.

In the following, we first describe our threat model and then present in detail the necessary steps and ideas of VENOMAVE.

3.1 Threat Model

We consider a realistic attacker model, which is founded on the observation that ASR systems are typically trained via publicly available *training recipes* specifying both the dataset and all hyper-parameters. Specifically, we assume the following white-box scenario:

 Training Parameters. We consider an attacker that has complete knowledge of the training parameters used for both, the neural network and the language model. Further, we assume that the victim trains the ASR system from scratch. This is common practice as transfer learning is not widely applied in speech recognition.

• Clean-label Dataset. The victim is assumed to download the training set from an untrusted source (e.g., the Internet), which the attacker is able to manipulate. In this scenario, the adversary can inject poisoned data samples into the training set of the victim. However, the adversarial noise added to each poisoned sample must be confined to justify the original clean label of the sample. This guarantees that even if the victim assesses the correctness of the labels, the poisoned samples remain undetected.

For our poisoning attack, VENOMAVE, we focus on hybrid ASR systems that are used throughout the research community as well as in commercial products like e. g., Amazon's Alexa [26]. As a proof of concept, we target a speech recognizer for sequences of digits from 0 to 9 to demonstrate the practical feasibility of the attack.

In this scenario, the attacker aims to poison the victim model to trigger a *targeted* misclassification of a specific utterance \mathbf{x}_t , i.e., the poisoned victim model recognizes input \mathbf{x}_t as a target sequence of words \mathbf{W} , chosen by the attacker.

3.2 Algorithm

To perform the attack, we choose a target audio file \mathbf{x}_t and a target sequence \mathbf{W} . In this work, we focus on changing exactly one word during the attack (i.e., we change one digit from the original transcription to another one). Given $(\mathbf{x}_t, \mathbf{W})$, the goal is then to find a set of poisons \mathbf{P} , s.t. \mathbf{x}_t is transcribed into the target phrase \mathbf{W} by any system trained on the poisoned dataset. In general, the attack can be divided into two steps:

- *Poison Selection.* First, we select the base samples that will be altered to generate the poison samples. For this, we determine which frames of \mathbf{x}_t need to be misclassified. For each frame, we select a set of poison frames from one or multiple sample files. All selected files are then considered as the *poisoned data* and will be modified in the crafting step.
- *Poison Crafting*. The selected poison frames are altered to cause the misclassification. Therefore, we extend the Bullseye Polytope [1] to minimize the objective loss in (Equation 3) and update the poison samples accordingly in an iterative process.

In the following, we explain these steps in more detail. Algorithm 1 presents a high-level overview of VENOMAVE, and Figure 2 shows an example that illustrates the individual steps of the attack.

3.2.1 Poison Selection

With VENOMAVE, we inject poisoned data into the victim's training set such that the trained neural network component will generate adversarial pseudo-posteriors for the target input, which will be decoded by the language model as the targeted word sequence. Therefore, the explicit adversarial label is a sequence of the HMM states. Note that there is not only one possible sequence of HMM states that would lead to a specific transcription. For this reason, we first have to determine which output sequence is a promising candidate as a poison target.

Figure 2 shows an example, where VENOMAVE fools the ASR system to recognize an audio waveform of 382 to 392. The ultimate, but implicit, adversarial label is NINE and the original label is EIGHT.

The language model defines a word as a sequence of K states $\mathbf{W} = \{w_k\}_{k=1}^K$. Assuming that the sequence for the digits EIGHT and NINE consist of 5 and 3 states, respectively, the two words can be described with HMM states **EIGHT** = $\{8_1, 8_2, 8_3, 8_4, 8_5\}$ and **NINE** = $\{9_1, 9_2, 9_3\}$.

In general, the number of frames of an uttered word is larger than the number of states K of the corresponding language model, e.g., for the word 'NINE' uttered across 6 frames, both sequences $[9_1,9_1,9_2,9_2,9_3,9_3]$ and $[9_1,9_1,9_1,9_2,9_2,9_3]$ would be perfectly valid and unsurprising.

Setting the adversarial labels of these six frames to either of these two sequences will lead to two different sets of poison samples, which ultimately fool the neural network to generate two different sequences of HMM states. In order to increase the chance that the target utterance will be decoded to the word NINE, a sequence of adversarial states should be selected that is more probable from the point of view of the HMM. For this reason, we look at the appearances of the word NINE in the dataset to select the most common pattern as our sequence of adversarial frames. For state w_i , we define the relative frequency

$$R_{w_i} = \frac{\text{freq}(w_i)}{\text{freq}(\mathbf{W})},\tag{1}$$

where $freq(w_i)$ and $freq(\mathbf{W})$ are the number of times that state w_i and word \mathbf{W} appear in the dataset. In fact, we have found this selection of adversarial states to be more successful compared to the uniform selection.

From the previous example, where we want to change the word EIGHT, which consists of 6 frames, to the word NINE, our original sequence $[8_1, 8_2, 8_3, 8_4, 8_4, 8_5]$ should be changed to $[9_1, 9_2, 9_2, 9_2, 9_3, 9_3]$, as the state 9_2 appears 3 times more often in the training set than the state 9_1 .

As a consequence, our attack needs to be divided into N=6 smaller poisoning attacks, described by a set $\mathbf{T}=\{x_{<Y_i,Z_i>}^{(i)}\}_{i=1}^N$ of frames $x_{<Y_i,Z_i>}^{(i)}$ with an original state Y_i and an adversarial state Z_i : $\mathbf{T}=\{x_{<8_1,9_1>}^{(1)},x_{<8_2,9_2>}^{(2)},\ldots,x_{<8_5,9_3>}^{(N)}\}$. We can apply the attack separately for each of these pairs.

We can apply the attack separately for each of these pairs. To achieve this for the attack $x_{<Y,Z>}$, we select a number of poison frames x_Y with label Z from one or more utterances,

and change them accordingly such that the frame x_{τ} will be identified by the poisoned system as state Z. This is repeated for all adversarial frames in T.

The authors of the Bullseye Polytope work observed the following: the more poison frames are used for the attack, the higher is the chance of a successful attack. They argue that the attack sometimes fails mainly because the target input has very "close" neighbor samples from its class in the victim's training set. As a result, the poison samples—no matter how well they are crafted—need to compete with these neighbor samples in order to inject the malicious decision boundaries during the training.

For this reason, we determine the number of poison frames P_Y based on the frequency of the original states $\{Y^{(i)}\}_{i=1}^N$. For frame $x_{<Y,Z>}$ we compute

$$P_Y = \lceil \text{freq}(w_q = Y) \cdot r_p \rceil. \tag{2}$$

Thus, if an original state Y_i occurs twice as often in the training set as another original state Y_j , we also select twice as many poison frames for the frame $x_{< Y_i, Z_i>}^{(i)}$ than for the frame $x_{< Y_j, Z_j>}^{(j)}$, where $0 < r_p < 1$ describes the *poison budget*.

3.2.2 Poison Crafting

For the poison crafting, we base our work on the Bullseye Polytope [1] attack, which exploits the mathematical guarantee that any linear classifier that associates a set of samples P to class l will also classify any point inside their convex hull as class l.

Therefore, in case of linear transfer learning, the attack divides the network into two parts.

- 1. All layers up to the penultimate layer, which act as a feature extractor network Φ. These layers will not be altered during the fine-tuning process.²
- 2. The last layer, a linear classifier, will be fine-tuned on the new dataset.

This approach is not directly applicable for targeting ASR systems as these systems are—in general—trained from scratch; meaning that the feature space defined by the penultimate layer Φ is also altered during training. We thus follow a different approach and use Bullseye Polytope to enforce the above guarantee for M surrogate models (i.e., models trained with the same parameter but different seeds). By solving this optimization for similar models such a guarantee will ideally also transfer to the unknown victim network.

²We should note that the features represented by the penultimate layer are different from the acoustic features, MFCCs, which are passed as the input to the network. Across the paper, by the term feature/s, we refer to the neural features, not MFCCs.

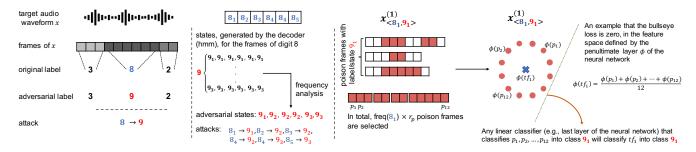


Figure 2: An example of the VENOMAVE attack, where the adversary fools the victim model to produce the transcription of 392 for an utterance of 382. The adversary builds its own set of surrogate systems and uses them to craft the poisons, such that the malicious characteristics of the poisoned data will transfer to the victim's ASR system. First, the attacker determines which frames of the target audio file should be focused on, and what they should be classified into in order to make the HMM to produce 392. For each target frame, an individual poisoning attack is performed to fool the surrogate networks to classify the target frame into the suitable adversarial state. Having the attacks transferred to the victim's neural network, the victim's HMM decodes the targeted transcription 392. Note that, for simplicity, only the attack for the first frame is depicted, considering only one surrogate model. In practice, an entire time series needs to be attacked successfully.

Specifically, we solve the following optimization:

$$\min_{\{x_{\gamma}^{(p)}\}} \frac{1}{2M} \sum_{m=1}^{M} \frac{\left\| \Phi^{(m)}(x_{\tau}) - \frac{1}{P} \sum_{p=1}^{P} \Phi^{(m)}(x_{\gamma}^{(p)}) \right\|^{2}}{\left\| \Phi^{(m)}(x_{\tau}) \right\|^{2}}$$
subject to $\left\| x_{\gamma}^{(p)} - x_{b}^{(p)} \right\|_{\infty} \le \varepsilon, \forall p.$ (3)

where $x_b^{(p)}$ is the original frame of the p-th poison frame. In the m-th surrogate model, the target feature vector $\Phi^{(m)}(x_\tau)$ is ideally at, or at least close to, the center of the feature vectors of poison samples, i.e., $\Phi^{(m)}(x_\tau) = \frac{1}{p} \sum_{p=1}^{p} \Phi^{(m)}(x_\gamma^{(p)})$. ε determines the maximum allowed perturbation. To solve the non-convex problem in Equation 3 (i. e., find the optimal set of poison samples), we repeat the following steps at each iteration of the attack:

- 1. Take one gradient step to optimize $\{x_{\gamma}^{(p)}\}_{p=1}^{P}$.
- 2. Clip $\{x_{\gamma}^{(p)}\}_{p=1}^{P}$ to the ε -ball around the clean base sample $\{x_{b}^{(p)}\}_{p=1}^{P}$.

The full attack is described in Algorithm 1. The surrogate models are refreshed after each step of the attack by training them on the current state of the dataset. The intuition behind this idea is that, after a while, VENOMAVE will reach a steady state, where the poison samples need no further modification to achieve the mathematical guarantee for the refreshed and poisoned surrogate networks.

4 Experiments

We implemented the proposed VENOMAVE attack based on the approach outlined above. In this section, we empirically verify and assess the efficacy of VENOMAVE with the help of the following experiments.

```
Algorithm 1 VENOMAVE
Input:
        \mathbf{x}_t
                                                                          W
                                                                   ▶ Adversarial word sequence
        Ψ
                                                                              ▶ The training dataset
        H
                                                                                   1: \mathbf{T} \leftarrow \text{get adv states pairs}(\mathbf{x}, \mathbf{W})
                                                                              \triangleright Select the N pairs of
        frames that needs to be changed
  2: [x_y]^N \leftarrow \text{select\_poisons}(\mathbf{T}) \triangleright \text{For each pair of } <\mathbf{Y}, \mathbf{Z}, we select
        P_Y poison frames x_Y
  3: for i = 1 to Q do
              for m = 1 to M do
                      \Phi^{(m)} \leftarrow \text{train\_model}(\Psi)
  5:
  6:
               end for
  7:
               for j = 1 to R do
                     \mathcal{L}^{(j)} \leftarrow 0
  8:

    Set loss to zero

                     for x_{\gamma}^{p} in [x_{\gamma}]^{N} do
  9:
                            \mathcal{L}^{(j)} \leftarrow \mathcal{L}^{(j)} + \text{bullseye loss}(x_{\nu}^p, x_{\nu}^p, x_{\tau}, [\Phi]^M)
 10:
       ▶ Equation (3)
                    end for \mathcal{L}^{(j)} \leftarrow \frac{\mathcal{L}^{(j)}}{\operatorname{len}([x_{\gamma}]^N)}
 11:
 12:
       [x_{\gamma}]^N \leftarrow \text{update}([x_{\gamma}]^N, \nabla \mathcal{L}^{(j)}) \triangleright update all poison frames [x_{\gamma}]^N using \nabla \mathcal{L}^{(j)}
 13:
                     break if \mathcal{L}^{(j-1)} - \mathcal{L}^{(j)} < 0.0001
 14:
 15:
               \Psi \leftarrow \text{updated}(\Psi, [x_{\gamma}]^N) \triangleright \text{update } \Psi \text{ with new poisons } [x_{\gamma}]^N
 16:
               \Phi_V \leftarrow \text{train model}(\Psi)
 17:
               \hat{\mathbf{W}} \leftarrow \text{eval\_victim}(H, \mathbf{x}_t, H)
                                                                                ▶ get word sequence
        recognized by \Phi_V
              break if \hat{\mathbf{W}} = \mathbf{W}
 19:
 20: end for
```

4.1 Experimental Setup

We propose our attack against state-of-the-art hybrid ASR systems. As a proof-of-concept, we evaluate the practical feasibility of VENOMAVE on a small-vocabulary ASR system which recognizes sequences of digits from 0 to 9. For training this system, we use the TIDIGITS dataset [16], which is designed for speaker-independent recognition of connected digit sequences. This dataset includes 8,623 and 4,390 continuously spoken digit utterances in its training and test sets, respectively. It is recorded in a quiet environment and digitized at 16 kHz. The dataset considers eleven words: ONE, TWO, THREE, ..., NINE, ZERO, and OH. The sequences are spoken by 326 different speakers which are split equally between the training and test set such that no utterance of a speaker used in the training set appears in the test set.

In our threat model, the training set, training parameters, and architecture of the ASR system employed by the victim are known to the attacker. However, the random seed used by the victim is unknown, thus, the parameters of the neural network and HMM of the victim's ASR system are different from the parameters of surrogate models used by the attacker. As shown in Algorithm 1, these surrogate systems are used by the attacker to craft the poison audio frames such that their malicious characteristics will hold when the victim trains a new ASR system from scratch (with an unseen random seed).

Unless explicitly stated otherwise, we use the following settings across all experiments. The victim trains the ASR system from scratch for 23 epochs, of which three epochs include Viterbi training. Furthermore, the victim uses the Adam [15] optimizer with a learning rate of 1e-4 and a batch size of 32 to train the neural network. This setting was selected to maximize the systems baseline accuracy.

As described in Algorithm 1, at the beginning of each step of the attack, VENOMAVE trains *M* surrogate networks on the latest version of the poisoned dataset. To train these networks, we use the same network architecture as employed by the victim. We use a fixed HMM during the attack to accelerate the attack as the language model does typically not change significantly. This HMM is created in advance by training an ASR system for 12 epochs on the clean training set, followed by three additional epochs of Viterbi training.

4.2 Metrics

For assessing the quality of the poisons both in terms of efficacy as well as inconspicuousness, we use the following standard measures.

Accuracy. In all experiments, VENOMAVE targets a single-digit utterance of a specific speaker and crafts poison samples. The explicit goal of the poison crafting algorithm is enabling a targeted misclassification for a target digit in the utterance, when the victim's model is trained on the poisoned dataset. If

the targeted misclassification is not triggered, we consider the attack as failed. If the attack succeeds, we further evaluate the victim's model against other utterances of the same speaker that include the target digit to compute the *attack generalization accuracy*. These utterances can be sequences of up to seven digits. In the ideal case, once the victim's ASR system is trained on the poisoned dataset, the targeted misclassification for the target digit is triggered as soon as the digit is spoken by the targeted person.

We also evaluate the victim's performance against the utterances of other speakers to calculate the *baseline test accuracy* of the model. An ideal poisoning attack does not degrade the model performance for non-targeted inputs; otherwise, it might be suspicious. For all test samples, given the model transcriptions, we count and accumulate all substituted words *S*, inserted words *I*, and deleted words *D* over the entire test set, in order to calculate the accuracy via

$$\frac{N-I-S-D}{N},\tag{4}$$

where N is the total number of words of ground-truth labels in the test set.

To collect statistics, we randomly select 12 single-digit audio files as the target and select for each sample a random adversarial target digit. For all experiments, we report the results averaged over these 12 examples.

Segmental Signal-to-Noise Ratio. The segmental signal-to-noise ratio (SNRseg) measures the amount of noise σ added by an attacker to the original signal \boldsymbol{x} and is computed as

$$SNRseg(dB) = \frac{10}{K} \sum_{k=0}^{K-1} \log_{10} \frac{\sum_{t=Tk}^{Tk+T-1} \mathbf{x}^{2}(t)}{\sum_{t=Tk}^{Tk+T-1} \sigma^{2}(t)}, \quad (5)$$

where T is the segment length and K the number of segments. Thus, the higher the SNRseg, the *less* noise was added. We use a frame length of 12.5 ms, which corresponds to T = 200 at a sampling frequency of 16 kHz.

As it is computed frame-wise, the SNRseg [33] gives a better assessment of an audio signal than the signal-to-noise ratio (SNR), if the original signal and the signal with added noise are aligned [36], which is the case in all our experiments. As only a very small part of the poison files are changed, we measure the SNRseg only for the poisoned frame (i.e., we explicitly exclude clean frames).

Maximum Perturbation. To compute the maximum amount of perturbations added during the attack, we compute

$$\delta_{max} = \max \left| \frac{\mathbf{x}}{\mathbf{v}} - \frac{\mathbf{y}}{\mathbf{v}} \right|,\tag{6}$$

where \mathbf{x} is the original waveform and \mathbf{y} the respective poisoned audio waveform and \mathbf{v} the maximum absolute value of all samples in the training dataset.

Table 1: Neural network architectures used by the victim. Networks use two or three hidden layers, with a softmax output layer of size 95, corresponding to the number of HMM states. The baseline test accuracy is for when the victim uses a clean dataset.

Name	Description	# Parameters	Baseline test accuracy (%)
DNN_2	Two hidden layers, each with 100 neurons	54,895	98.75
DNN_{2+}	Two hidden layers, with 100 and 200 neurons	100,095	98.79
DNN_3	Three hidden layers, each with 100 neurons	64,995	98.41

4.3 Poison Budget r_p

In our first experiment, we evaluate the attack success rate for varying levels of the poison budget r_p . We use the DNN_{2+} network as described in Table 1 for this experiment.

In the image domain, Bullseye Polytope has achieved higher attack success rates by injecting more poison samples in the dataset [1]. As the authors of this work argued, increasing the number of poison samples increases the chance of a successful attack even if this does not necessarily lead to a smaller objective loss, cf. Equation 3. This happens because the poison samples eventually need to compete with the target's neighbor samples in order to enforce the neural network to learn the malicious decision boundaries. Thus, any move towards outnumbering these close neighbor samples helps the attack to succeed.

In our experiments, we have made a similar observation. Increasing the poison budget from 0.02 to 0.05, and, hence, the number of poison frames, will lead to a higher attack success rate. But this improvement comes at a price; as the results in Table 3 show, the length of the poisoned data increases from 78 seconds to 179 seconds, when r_p increases from 0.02 to 0.05. Hence, when considering the entire training set, with a budget $r_p = 0.04$, we poison only 0.94 % of the training set while achieving an attack success rate of 83.33 %.

The highest attack generalization accuracy we have observed is 14.53%. By looking at all 12 examples of the attack, we noticed that VENOMAVE can successfully achieve some level of generalization to unseen utterances of the targeted person in 50% of the cases. Table 2 presents the attack generalization accuracy of VENOMAVE for these examples. For example, VENOMAVE achieves an attack generalization accuracy of 70.59% for speaker HR. In summary, our evaluation shows that while VENOMAVE achieves a high attack success rate when targeting a specific utterance of a particular speaker but is less effective in transferring to other utterances spoken by the same person. On the other hand, it should be noted that in our experiments, we have not included more utterances of the person during poison crafting. This technique has been used by Bullseye Polytope and the authors showed this to be quite effective in the space of images [1]. We argue that incorporating more utterances from the targeted speaker will help the attacker to tap the potential of VENOMAVE. We leave this for future work.

Table 3 also presents the SNRseg measure for the poisoned

Table 2: Attack generalization accuracy of VENOMAVE per individual example. Those examples that we have not observed any generalization across all experiments are excluded from the table. It should be noted that we perform the VENOMAVE attack for 12 different examples in total.

Speaker ID	Original digit	Target digit	Attack generalization accuracy (%)	
			DNN ₂₊	DNN_3
HR	9	1	70.59	58.82
IA	9	2	31.58	42.11
IB	Z	4	6.25	12.50
IA	7	2	15.00	40.00
IA	7	2	00.00	33.33

samples, as well as the maximum perturbation added to a frame. With the exception of $r_p = 0.03$, increasing the number of poison frames (and, hence, poison samples) results in adding less distortion to the original data. Note that the SNRseg is only computed for the poison frames and clean parts of the poison samples are explicitly excluded to provide a fair assessment of the noise added to poison samples. As we only poison 100-200 milliseconds of each poison sample, the overall quality of the poison is much higher. Figure 3 shows an example of a poisoned audio file. We show the original audio file 3a and poisoned version 3b in the frequency domain. The areas that are used as poison samples are marked. Note that for a better presentation, we have chosen a file where more frames are used as poisoned samples than the average. The audio file contains the digit sequence ZERO, EIGHT, SIX, ZERO, ZERO and is used to poison the digit SEVEN to ZERO.

4.4 Network Capacity

Until now, we have focused on DNN_{2+} , which is a neural network with two hidden layers and a total of 100,095 parameters. To study the effect of the used DNN architecture on the attack, we consider two other neural networks, DNN_2 and DNN_3 , with 54,895 and 64,995 parameters, respectively. Both of these networks have less capacity compared to DNN_{2+} . DNN_3 has one more hidden layer, which makes it arguably more capable of learning complex features. Table 4 presents the performance of VENOMAVE against these three networks.

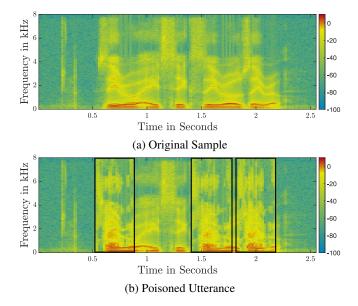


Figure 3: Example of an audio file showing the original file 3a in the frequency domain and its respective poisoned version 3b. The areas of the audio file that are used as poison are marked. The audio file contains the digit sequence ZERO, EIGHT, SIX, ZERO, ZERO and is used to poison the digit SEVEN to ZERO. Note that for a better presentation, we have chosen a file where more frames are used as poisoned samples than the average.

We observed no significant difference between when the victim uses DNN_2 or DNN_{2+} , except for the clean test accuracy. The network DNN_{2+} presents a clean test accuracy of 97.91% after being trained on the poisoned dataset. This is 0.31% higher than DNN_2 .

Interestingly, VENOMAVE provides a higher attack generalization accuracy against networks DNN_3 and DNN_2 , compared to DNN_{2+} . We, therefore, conclude that neural networks with a higher capacity (i.e., number of parameters) are capable to better distinguish between different utterances of one person speaking a specific digit. In a network with fewer parameters, these utterances are more clustered in the feature space created by the network.

4.5 Dropout Randomization

Dropout randomization is a technique proposed to prevent neural networks from overfitting and increase their performance on test samples [28]. In previous clean-label poisoning works, dropout was typically left out for the attacks as a rational victim will usually overfit the training set in a transfer learning scenario. Since this is not necessarily the case when the victim's model is trained from scratch, in this experiment, we evaluate the effect of dropout randomization during training on VENOMAVE. Specifically, we perform this experiment

Table 3: Evaluation of VENOMAVE when the poison budget r_p is increased from 0.02 to 0.05. The DNN_{2+} network is used by the victim. Best results are shown in bold.

	r _p				
	0.02	0.03	0.04	0.05	
Poisoned frames SNRseg	4.01	0.72	4.50	5.15	
Maximum perturbation δ_{max}	0.166	0.177	0.159	0.130	
Poisoned data length (in seconds)	78	112	144	179	
# Poisoned data samples	678	876	1,194	1,407	
Attack success rate (%)	58.33	66.67	83.33	83.33	
Attack generalization accuracy (%)	11.81	12.84	13.01	14.53	
Clean test accuracy (%)	97.96	97.99	97.91	97.72	

Table 4: Evaluation of VENOMAVE when the victim employs three different neural networks. Note that r_p is set to 0.04 for this experiment. Best results are shown in bold.

	Victim's network				
	DNN ₂₊	DNN ₃	DNN ₂		
Poison frames SNRseg	4.50	5.29	4.46		
Maximum perturbation δ_{max}	0.159	0.167	0.166		
Poisoned data length (in seconds)	144	206	187		
# Poisoned data samples	1,194	1,400	1,123		
Attack success rate (%)	83.33	75.00	83.33		
Attack generalization accuracy (%)	13.01	23.83	20.07		
Clean test accuracy (%)	97.91	97.42	97.60		

on the network DNN_{2+} with a dropout probability of 0.2 and add the dropout layer between the two hidden layers.

As Table 1 indicates, the baseline test accuracy of the victim is 98.79%, when dropout is not used. With dropout, the baseline test accuracy increases to 98.90%. Note that due to dropout, the network needs an additional 10 epochs to converge.

In terms of the attack, Table 5 shows that VENOMAVE achieves the same attack success rate of 83.33% in the presence of dropout normalization. This shows that if the system is trained from scratch, poisoning attacks are still possible if dropout is enabled during training.

4.6 Bounded Perturbation

To this point, we have not limited the amount of perturbation added to the poison frames. As Table 3 shows, when $r_p = 0.04$, the average SNRseg value for poison samples is 4.50dB.

By limit the perturbation amount to an upper bound ε , we now want to assess whether it is possible to improve the SNRseg of the poison samples, while preserving their malicious characteristics. To this end, we select four examples that VENOMAVE managed to fool the victim system. The SNRseg and the maximum perturbation δ_{max} for these examples are shown in Table 4. For example, when attacking the victim's

Table 5: Evaluation of VENOMAVE when the victim employs dropout randomization with a probability of 0.2. DNN_{2+} is used for this experiment, with $r_p = 0.04$. Best results are shown in bold.

	Dropout		
	-	0.2	
Poisoned frames SNRseg	4.50	2.34	
Maximum perturbation	0.159	0.155	
Poisoned data length (in seconds)	144	143	
# Poisoned data samples	1,194	1,177	
Attack success rate (%)	83.33	83.33	
Attack generalization accuracy (%)	13.01	9.40	
Clean test accuracy (%)	97.91	98.06	

ASR system to misrecognize the target sample ${\tt HJ-7}$ as the digit SIX, VENOMAVE adds perturbation up to 0.199, which eventually leads to poison samples with SNRseg value of 3.98dB with respect to the original samples.

Bounding the perturbation amount to 0.080, we observe that VENOMAVE is able to improve the SNRseg value of the poison samples to 7.26dB while still fooling the victim system to misrecognize the target sample ${\rm HJ}$ –7. On the other hand, we noticed that for some examples putting a cap on the maximum amount of perturbation does not necessarily result into poison samples with a higher SNRseg value. In these examples, to cope with the constraint δ_{max} , VENOMAVE introduces changes across all poison frames, rather than having some poison frames with high amounts of noise, which results in a lower SNRseg value.

5 Future Work

We evaluated VENOMAVE against a small-vocabulary ASR for continuously spoken digit sequences. An interesting next step is to evaluate the performance of the attack for large-vocabularyASR systems with vocabulary sizes in the tens of thousands of words or even more. The operating principle of the hybrid digit recognizer is the same as that for a hybrid large-vocabulary recognizer, such as the widely used toolkit Kaldi [22], hence we think that the basic principle can be applied as well. In this paper, we presented a proof-of-concept poisoning attack against hybrid ASR systems that can be used for further research in this field.

The added perturbations are not yet tailored to the audio domain. Hence, it may be feasible to use methods such as psychoacoustic hearing thresholds to improve the attack, similar to previous attacks that calculated adversarial examples for ASR systems [23,25,31]. We assume that this could likely make a clean-label poisoning attack against ASR systems

even more practical, as the distortions are hidden below the human threshold of hearing.

By using more than one target file per speaker, the attack generalization may be improved to misdirect more occurrences of the target digit of the poisoned speaker. This might not even require more poison frames, as the same frames can be used in a multi-target setup. We leave this elaboration for future work on this topic.

6 Conclusion

While data poisoning attacks against neural networks were already studied in the image domain, the research question of whether such attacks are also feasible in the audio domain has, so far, remained an open challenge. In this paper, we tackled this problem and demonstrated the first data poisoning attack against hybrid ASR systems by successfully showing that such systems are also vulnerable to this type of attack. This is a challenging attack, given that an adversary needs to produce a *sequence* of posteriors for the target utterance, which will eventually be decoded by the ASR system to the desired sequence of words (in contrast to the image domain, where a *single* misclassification is sufficient to trigger the attack). We presented the design of VENOMAVE and implemented a full end-to-end data poisoning attack.

In several experiments, we successfully demonstrated that such an attack is feasible in practice, and our results indicate that data poisoning attacks are a real threat for ASR systems. Most importantly, we showed that this type of attack needs to be considered when training ASR systems to make sure that an adversary cannot influence the training process. This is of special importance when considering open and collaborative data collection [4] or learning frameworks such as federated training [18]. While our proof-of-concept attack targets an ASR for digits, an open challenge is to scale this type of attack to a large vocabulary ASR system.

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Table 6: Evaluation of VENOMAVE under perturbation bounds. For this experiment, we focus on four examples with which
VENOMAVE has succeeded in fooling the victim ($r_p = 0.04$).

Perturbation cap	Speaker	Original digit	Target digit	SNRseg		Attack successful?	Attack accuracy	Clean test accuracy
Not bounded	IA	7	2	3.38	0.098	✓	5.00	97.52
Not bounded	IB	2	4	6.35	0.092	✓	0.00	97.67
Not bounded	IP	3	6	-6.27	0.236	✓	13.33	97.94
Not bounded	HJ	7	Z	3.98	0.199	✓	5.56	97.38
0.080	IA	7	2	2.62	0.080	✓	25.00	97.56
0.080	IB	2	4	5.91	0.080	✓	0.00	97.64
0.080	IP	3	6	-9.68	0.080	✓	13.33	97.96
0.080	HJ	7	Z	7.26	0.080	✓	5.56	97.31

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