Certified Defenses for Data Poisoning Attacks

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Abstract

Machine learning systems trained on user-provided data are susceptible to *data poisoning* attacks, whereby malicious users inject false training data with the aim of corrupting the learned model. While recent work has proposed a number of attacks and defenses, little is understood about the worst-case loss of a defense in the face of a determined attacker. We address this by constructing approximate upper bounds on the loss across a broad family of attacks, for defenders that first perform outlier removal followed by empirical risk minimization. Our bound comes paired with a candidate attack that nearly realizes the bound, giving us a powerful tool for quickly assessing defenses on a given dataset. Empirically, we find that even under a simple defense, the MNIST-1-7 and Dogfish datasets are resilient to attack, while in contrast the IMDB sentiment dataset can be driven from 12% to 23% test error by adding only 3% poisoned data.

1 Introduction

Traditional security systems seek to ensure that an attacker can never access or modify critical parts of a system, by creating clear boundaries between the system and outside world. In machine learning, however, the most critical ingredient of all – the training data – comes directly from the outside world. For a system trained on user data, an attacker can inject malicious data simply by creating a user account. Such *data poisoning* attacks require us to re-think what it means for a system to be secure.

The focus of the present work is on data poisoning attacks against classification algorithms, first studied by Biggio et al. (2012) and later by a number of others (Xiao et al., 2012; 2015b; Newell et al., 2014; Mei and Zhu, 2015b; Burkard and Lagesse, 2017; Koh and Liang, 2017). This body of work has demonstrated data poisoning attacks that can degrade classifier accuracy, sometimes dramatically. Moreover, while some defenses have been proposed against specific attacks (Laishram and Phoha, 2016), few have been stress-tested against a determined attacker.

Are there defenses that are robust to a large class of data poisoning attacks? The main difficulty in answering this question is the near-limitless space of possible attacks. Because of this, it is impossible to conclude from empirical success alone that a defense that works against a known set of attacks will not fail against some new attack.

In this paper, we address this difficulty by presenting a framework for providing certified defenses and near-optimal attacks via no-regret learning. Our framework applies to defenders that (i) remove outliers residing outside a feasible set, then (ii) minimize a margin-based loss on the remaining data. For such defenders, we can generate approximate upper bounds on the efficacy of any data poisoning attack, along with a candidate attack that nearly matches the bound. We consider two different settings: first, where the outlier detector is trained independently and cannot be affected by the poisoned data, and second, where the data poisoning can attack the outlier detector as well.

In the first setting, we apply our framework to an "oracle" defense that knows the true class centroids and removes points that are far away from the centroid of the corresponding class. While previous work showed successful attacks on the MNIST-1-7 (Biggio et al., 2012) and Dogfish (Koh and Liang,

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2017) image datasets in the absence of any defenses, we show (Section 4) that no attack is possible against this oracle — e.g., the test error of an SVM on either dataset is at most 4%, even after adding 30% poisoned data. On the other hand, our candidate attack increases classification test error on the IMDB sentiment corpus from 12% to 23% with only 3% poisoned data.

For the second setting, we consider a more realistic defender that uses the empirical (poisoned) centroids. For small amounts of poisoned data ($\leq 5\%$) we can still establish the resilience of MNIST-1-7 and Dogfish to attack (Section 5). However, with more poisoned data, the attacker can subvert the outlier removal to obtain stronger attacks — e.g., increasing test error on MNIST-1-7 by 37% with 30% poisoned data.

2 Problem Setting

Consider a prediction task from an input $x \in \mathcal{X}$ (e.g., \mathbb{R}^d) to an output $y \in \mathcal{Y}$ (e.g., $\{-1, +1\}$ for binary classification). Let ℓ be a non-negative loss function—e.g., for linear classification with the hinge loss, $\ell(\theta; x, y) = \max(0, 1 - y\langle \theta, x\rangle)$ for a model $\theta \in \Theta \subseteq \mathbb{R}^d$ and data point (x, y). Given a true data-generating distribution p^* over $\mathcal{X} \times \mathcal{Y}$, define the test loss as $\mathbf{L}(\theta) = \mathbf{E}_{(x,y) \sim p^*}[\ell(\theta; x, y)]$.

We consider the *causative attack* model (Barreno et al., 2010), which consists of a game between two players: the *defender* (who seeks to learn a model θ), and the *attacker* (who wants the learner to learn a bad model). The game proceeds as follows:

- n data points are drawn from p^* to produce a clean training dataset \mathcal{D}_c .
- The attacker adaptively chooses a "poisoned" dataset \mathcal{D}_p of ϵn poisoned points, where $\epsilon \in [0,1]$ parametrizes the attacker's resources.
- The defender trains on the full dataset $\mathcal{D}_c \cup \mathcal{D}_p$ to produce a model $\hat{\theta}$, and incurs test loss $\mathbf{L}(\hat{\theta})$.

The defender's goal is to minimize the quantity $\mathbf{L}(\hat{\theta})$ while the attacker's goal is to maximize it.

Remarks. We assume the attacker has full knowledge of the defender's algorithm and of the clean training data \mathcal{D}_c . While this may seem generous to the attacker, it is widely considered poor practice to rely on secrecy for security (Kerckhoffs, 1883; Biggio et al., 2014a); moreover, a determined attacker can often reverse-engineer necessary system details (Tramèr et al., 2016).

The causative attack model allows the attacker to add points but not modify existing ones. Indeed, systems constantly collect new data (e.g., product reviews, user feedback on social media, or insurance claims), whereas modification of existing data would require first compromising the system.

Attacks that attempt to increase the overall test loss $L(\hat{\theta})$, known as *indiscriminate availability* attacks (Barreno et al., 2010), can be thought of as a denial-of-service attack. This is in contrast to targeted attacks on individual examples or sub-populations (e.g., Burkard and Lagesse, 2017). Both have serious security implications, but we focus on denial-of-service attacks, as they compromise the model in a broad sense and interfere with fundamental statistical properties of learning algorithms.

2.1 Data Sanitization Defenses

A defender who trains naïvely on the full (clean + poisoned) data $\mathcal{D}_c \cup \mathcal{D}_p$ is doomed to failure, as even a single poisoned point can in some cases arbitrarily change the model (Liu and Zhu, 2016; Park et al., 2017). In this paper, we consider *data sanitization* defenses (Cretu et al., 2008), which examine the full dataset and try to remove the poisoned points, for example by deleting outliers. Formally, the defender constructs a *feasible set* $\mathcal{F} \subseteq \mathcal{X} \times \mathcal{Y}$ and trains only on points in \mathcal{F} :

$$\hat{\theta} \stackrel{\text{def}}{=} \underset{\theta \in \Theta}{\operatorname{argmin}} L(\theta; (\mathcal{D}_{c} \cup \mathcal{D}_{p}) \cap \mathcal{F}), \quad \text{where } L(\theta; S) \stackrel{\text{def}}{=} \sum_{(x,y) \in S} \ell(\theta; x, y). \tag{1}$$

Given such a defense \mathcal{F} , we would like to compute an upper bound on the worst possible test loss over *any attacker* (choice of \mathcal{D}_p)—in symbols, $\max_{\mathcal{D}_p} \mathbf{L}(\hat{\theta})$. Such a bound would certify that the defender incurs at most some level of loss no matter what the attacker does. We consider two classes of data sanitization defenses:

• Fixed defenses, where \mathcal{F} does not depend on \mathcal{D}_p . One example for text classification is letting \mathcal{F} be documents that contain only licensed words (Newell et al., 2014). Other examples are oracle

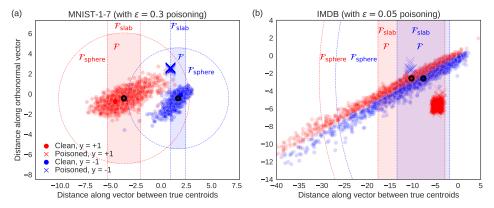


Figure 1: Different datasets possess markedly different levels of separation and vulnerability to attack. Here, we visualize the effect of the sphere and slab oracle defenses, with thresholds chosen to match the 70th percentile of the clean data. We mark with an X our attacks for the respective values of ϵ (see Section 4). (a) In the MNIST-1-7 dataset, the classes are well-separated and no attack can get past the oracle defense. Note that our attack chooses to put all of its weight on the negative class here, although this need not be true in general. (b) In the IMDB dataset, the class centroids are not well-separated and it is easy for an attack to poison the classifier.

defenders that depend on the true distribution p^* . While such defenders are not implementable in practice, they provide bounds: if even an oracle can be attacked, then we should be worried.

• Data-dependent defenses, where \mathcal{F} depends on $\mathcal{D}_c \cup \mathcal{D}_p$. These defenders try to estimate p^* from $\mathcal{D}_c \cup \mathcal{D}_p$ and thus are implementable in practice. However, they open up a new line of attack wherein the attacker could choose the poisoned data \mathcal{D}_p to change the feasible set \mathcal{F} .

Example: binary classification. Let $\mu_+ \stackrel{\text{def}}{=} \mathbb{E}[x \mid y = +1]$ and $\mu_- \stackrel{\text{def}}{=} \mathbb{E}[x \mid y = -1]$ be the centroids of the positive and negative classes. A natural data sanitization strategy is to remove points that are too far away from the corresponding centroid. We consider two ways of doing this: the *sphere defense*, which removes points outside a spherical radius, and the *slab defense*, which first projects points onto the line between the centroids and then discards points that are too far on this line:

$$\mathcal{F}_{\text{sphere}} \stackrel{\text{def}}{=} \{(x,y) : \|x - \mu_y\|_2 \le r_y\}, \quad \mathcal{F}_{\text{slab}} \stackrel{\text{def}}{=} \{(x,y) : |\langle x - \mu_y, \mu_y - \mu_{-y} \rangle| \le s_y\}. \tag{2}$$

Here r_y, s_y are thresholds (e.g. chosen so that 30% of the data is removed). Note that both defenses are oracles (μ_y depends on p^*); in Section 5, we consider versions that estimate μ from $\mathcal{D}_c \cup \mathcal{D}_p$.

Figure 1 depicts both defenses on the MNIST-1-7 and IMDB datasets. For MNIST-1-7, it appears the constraints make it difficult for an attacker to damage the model. In the next section, we will present a method for certifying this. In contrast, IMDB looks far more attackable, which we will verify as well.

3 Attack, Defense, and Duality

Recall that we are interested in the worst-case test loss $\max_{\mathcal{D}_p} \mathbf{L}(\hat{\theta})$. To make progress, we consider three approximations: (i) we pass from the test loss to the training loss on the clean data, which are related by standard concentration arguments as long as we regularize the model appropriately (see Appendix B for details); (ii) we consider the training loss on the full (clean + poisoned) data, which upper bounds the loss on the clean data due to non-negativity of the loss. For any model θ , we have:

$$\mathbf{L}(\theta) \stackrel{\text{(i)}}{\approx} \frac{1}{n} L(\theta; \mathcal{D}_{c}) \stackrel{\text{(ii)}}{\leq} \frac{1}{n} L(\theta; \mathcal{D}_{c} \cup \mathcal{D}_{p}). \tag{3}$$

While (ii) could be a source of looseness, it is tight if $\hat{\theta}$ fits the poisoned data well (as we show is often true empirically). Finally, (iii) rather than requiring the defender to filter points outside the feasible set (which might remove good points in \mathcal{D}_c), we consider attacks in the feasible set ($\mathcal{D}_p \subseteq \mathcal{F}$) and have the defender train on all of $\mathcal{D}_c \cup \mathcal{D}_p$. Training on $\mathcal{D}_c \cup \mathcal{D}_p$ rather than $(\mathcal{D}_c \cup \mathcal{D}_p) \cap \mathcal{F}$ seemed to yield similar results, but the latter is harder to provably verify and could therefore in theory be a source of vulnerability. Putting it all together, the worst-case test loss from any attack \mathcal{D}_p with ϵn

Algorithm 1 Online learning algorithm for generating an upper bound and candidate attack.

Input: clean data $\mathcal{D}_{\mathbf{c}}$ of size n, feasible set \mathcal{F} , radius ρ , poisoned fraction ϵ , step size η . Initialize $z^{(0)} \leftarrow 0$, $\lambda^{(0)} \leftarrow \frac{1}{\eta}$, $\theta^{(0)} \leftarrow 0$, $U^* \leftarrow \infty$.

for $t=1,\ldots,\epsilon n$ do

Compute $(x^{(t)},y^{(t)}) = \operatorname{argmax}_{(x,y)\in\mathcal{F}}\ell(\theta^{(t-1)};x,y)$. $U^* \leftarrow \min\left(U^*,\frac{1}{n}L(\theta^{(t-1)};\mathcal{D}_{\mathbf{c}}) + \epsilon\ell(\theta^{(t-1)};x^{(t)},y^{(t)})\right)$. $g^{(t)} \leftarrow \frac{1}{n}\nabla L(\theta^{(t-1)};\mathcal{D}_{\mathbf{c}}) + \epsilon\nabla\ell(\theta^{(t-1)};x^{(t)},y^{(t)})$.

Update: $z^{(t)} \leftarrow z^{(t-1)} - g^{(t)}$, $\lambda^{(t)} \leftarrow \max(\lambda^{(t-1)},\frac{\|z^{(t)}\|_2}{\rho})$, $\theta^{(t)} \leftarrow \frac{z^{(t)}}{\lambda^{(t)}}$.

end for

Output: upper bound U^* and candidate attack $\mathcal{D}_{\mathbf{p}} = \{(x^{(t)},y^{(t)})\}_{t=1}^{\epsilon n}$.

elements is approximately upper bounded as follows:

$$\max_{\mathcal{D}_{p}} \mathbf{L}(\hat{\theta}) \stackrel{\text{(i)}}{\approx} \max_{\mathcal{D}_{p}} \frac{1}{n} L(\hat{\theta}; \mathcal{D}_{c}) \stackrel{\text{(ii)}}{\leq} \max_{\mathcal{D}_{p}} \frac{1}{n} L(\hat{\theta}; \mathcal{D}_{c} \cup \mathcal{D}_{p}) \\
\stackrel{\text{(iii)}}{\approx} \max_{\mathcal{D}_{p} \subseteq \mathcal{F}} \min_{\theta \in \Theta} \frac{1}{n} L(\theta; \mathcal{D}_{c} \cup \mathcal{D}_{p}) \stackrel{\text{def}}{=} \mathbf{M}. \tag{4}$$

Here the final step is because $\hat{\theta}$ is chosen to minimize $L(\theta; \mathcal{D}_c \cup \mathcal{D}_p)$. The *minimax loss* \mathbf{M} is the central quantity that we will focus on in the sequel; it has duality properties that will yield insight into the nature of the optimal attack. Intuitively, the attacker that achieves \mathbf{M} is trying to maximize the loss on the full dataset by adding poisoned points in the feasible set \mathcal{F} .

3.1 Fixed Defenses: Computing the Minimax Loss via Online Learning

We now focus on computing the minimax loss M (4) when \mathcal{F} is independent of \mathcal{D}_p (fixed defenses). In the process of computing M, we will also produce candidate attacks. Our algorithm is based on no-regret online learning, which models a game between a learner and nature and thus is a natural fit to our data poisoning setting. For simplicity of exposition we assume Θ is an ℓ_2 -ball of radius ρ .

Our algorithm, shown in Algorithm 1, is very simple: in each iteration, it alternates between finding the worst attack point $(x^{(t)}, y^{(t)})$ with respect to the current model $\theta^{(t-1)}$ and updating the model in the direction of the attack point, producing $\theta^{(t)}$. The attack \mathcal{D}_p is the set of points thus found.

To derive the algorithm, we simply swap min and max in (4) to get an upper bound on \mathbf{M} , after which the optimal attack set $\mathcal{D}_p \subseteq \mathcal{F}$ for a *fixed* θ is realized by a single point $(x,y) \in \mathcal{F}$:

$$\mathbf{M} \leq \min_{\theta \in \Theta} \max_{\mathcal{D}_{p} \subseteq \mathcal{F}} \frac{1}{n} L(\theta; \mathcal{D}_{c} \cup \mathcal{D}_{p}) = \min_{\theta \in \Theta} U(\theta), \text{ where } U(\theta) \stackrel{\text{def}}{=} \frac{1}{n} L(\theta; \mathcal{D}_{c}) + \epsilon \max_{(x,y) \in \mathcal{F}} \ell(\theta; x, y).$$
(5)

Note that $U(\theta)$ upper bounds \mathbf{M} for any model θ . Algorithm 1 follows the natural strategy of minimizing $U(\theta)$ to iteratively tighten this upper bound. In the process, the iterates $\{(x^{(t)},y^{(t)})\}$ form a candidate attack \mathcal{D}_p whose induced loss $\frac{1}{n}L(\hat{\theta};\mathcal{D}_c\cup\mathcal{D}_p)$ is a lower bound on \mathbf{M} . We can monitor the duality gap between lower and upper bounds on \mathbf{M} to ascertain the quality of the bounds.

Moreover, assuming the loss ℓ is convex in θ , $U(\theta)$ is convex in θ (regardless of the structure of \mathcal{F} , which could even be discrete). In this case, if we minimize $U(\theta)$ using any online learning algorithm with sublinear regret, the duality gap vanishes. This is summarized as follows (proof in Appendix A):

Proposition 1. Assume the loss ℓ is convex. Suppose that an online learning algorithm (e.g., Algorithm 1) is used to minimize $U(\theta)$, and that the parameters $(x^{(t)}, y^{(t)})$ maximize the loss $\ell(\theta^{(t-1)}; x, y)$ for the iterates $\theta^{(t-1)}$ of the online learning algorithm. Let $U^* = \min_{t=1}^{\epsilon n} U(\theta^{(t)})$. Also suppose that the learning algorithm has regret Regret(T) after T time steps. Then, for the attack $\mathcal{D}_p = \{(x^{(t)}, y^{(t)})\}_{t=1}^{\epsilon n}$, the corresponding parameter $\hat{\theta}$ (defined in (1)) satisfies:

$$\frac{1}{n}L(\hat{\theta}; \mathcal{D}_c \cup \mathcal{D}_p) \le \mathbf{M} \le U^* \quad and \quad U^* - \frac{1}{n}L(\hat{\theta}; \mathcal{D}_c \cup \mathcal{D}_p) \le \frac{\operatorname{Regret}(\epsilon n)}{\epsilon n}. \tag{6}$$

Hence, any algorithm whose average regret $\frac{\operatorname{Regret}(\epsilon n)}{\epsilon n}$ is small will have a nearly optimal candidate attack \mathcal{D}_p . The particular algorithm depicted in Algorithm 1 is a variant of regularized dual

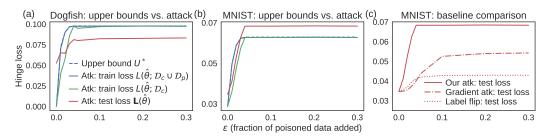


Figure 2: On the (a) Dogfish and (b) MNIST-1-7 datasets, our candidate attack (solid blue) achieves the upper bound (dashed blue) on the worst-case train loss, as guaranteed by Proposition 1. Moreover, this worst-case loss is low; even after adding 30% poisoned data, the loss stays below 0.1. (c) The gradient descent (dash-dotted) and label flip (dotted) baseline attacks are suboptimal under this defense, with test loss (red) as well as test error and train loss (not shown) all significantly worse than our candidate attack.

averaging (Xiao, 2010), which is an alternative to gradient descent that often converges faster for norm-constrained optimization problems. In summary, we have a simple learning algorithm that simultaneously computes upper bounds on the minimax loss as well as a candidate attack, which provides a lower bound. Of course, the minimax loss M is only an approximation to the true worst case test loss (via (4)). We examine the tightness of this approximation empirically in Section 4.

3.2 Data-Dependent Defenses: Upper and Lower Bounds

We now turn our attention to data-dependent defenders, where the feasible set \mathcal{F} depends on the data $\mathcal{D}_c \cup \mathcal{D}_p$ (and hence can be influenced by the attacker). For example, consider the slab defense (see (2)) that uses the empirical (poisoned) mean instead of the true mean:

$$\mathcal{F}_{\text{slab}}(\mathcal{D}_{p}) \stackrel{\text{def}}{=} \{ (x, y) : |\langle x - \hat{\mu}_{y}(\mathcal{D}_{p}), \hat{\mu}_{y}(\mathcal{D}_{p}) - \hat{\mu}_{-y}(\mathcal{D}_{p}) \rangle | \le s_{y} \}, \tag{7}$$

where $\hat{\mu}_y(\mathcal{D}_p)$ is the empirical mean over $\mathcal{D}_c \cup \mathcal{D}_p$; the notation $\mathcal{F}(\mathcal{D}_p)$ tracks the dependence of the feasible set on \mathcal{D}_p . Similarly to Section 3.1, we analyze the minimax loss \mathbf{M} , which we can bound as in (5): $\mathbf{M} \leq \min_{\theta \in \Theta} \max_{\mathcal{D}_p \subset \mathcal{F}(\mathcal{D}_p)} \frac{1}{n} L(\theta; \mathcal{D}_c \cup \mathcal{D}_p)$.

However, unlike in (5), it is no longer the case that the optimal \mathcal{D}_p places all points at a single location due to the dependence of \mathcal{F} on \mathcal{D}_p ; we must jointly maximize over the full set \mathcal{D}_p . To improve tractability, we take a continuous relaxation: we think of \mathcal{D}_p as a probability distribution with mass $\frac{1}{\epsilon n}$ on each point in \mathcal{D}_p , and relax this to allow any probability distribution π_p . The constraint then becomes $\operatorname{supp}(\pi_p) \subseteq \mathcal{F}(\mathcal{D}_p)$ (where supp denotes the support), and the analogue to (5) is

$$\mathbf{M} \leq \min_{\theta \in \Theta} \tilde{U}(\theta), \text{ where } \tilde{U}(\theta) \stackrel{\text{def}}{=} \frac{1}{n} L(\theta; \mathcal{D}_{c}) + \epsilon \max_{\sup p(\pi_{p}) \subseteq \mathcal{F}(\pi_{p})} \mathbf{E}_{\pi_{p}} [\ell(\theta; x, y)]. \tag{8}$$

This suggests employing the same online learning Algorithm 1 to minimize $\tilde{U}(\theta)$. Indeed, this is what we shall do, but there are a few caveats:

- The maximization problem in the definition of $\tilde{U}(\theta)$ is in general quite difficult. We will, however, solve a specific instance in Section 5.
- The constraint set for π_p is non-convex, so duality (Proposition 1) no longer holds.

We will run Algorithm 1, at each iteration obtaining a distribution $\pi_p^{(t)}$ and upper bound $\tilde{U}(\theta^{(t)})$. Then, for each $\pi_p^{(t)}$ we will generate a candidate attack by sampling ϵn points from $\pi_p^{(t)}$, and take the best resulting attack. In Section 4 we will see that despite a lack of rigorous theoretical guarantees, this often leads to good upper bounds and attacks in practice.

4 Experiments I: Oracle Defenses

An advantage of our framework is that we obtain a tool that can be easily run on new datasets and defenses to learn about the robustness of the defense and gain insight into potential attacks. We first study two image datasets: MNIST-1-7, and the Dogfish dataset used by Koh and Liang (2017). For MNIST-1-7, following Biggio et al. (2012), we considered binary classification between the digits

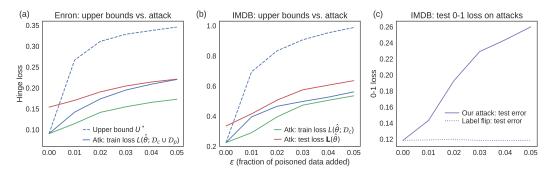


Figure 3: The (a) Enron and (b) IMDB text datasets are significantly easier to attack under the oracle sphere and slab defense than the image datasets. (c) In particular, a large increase in test loss (solid red) and test error (solid purple) is possible with small ϵ for IMDB. As before, the label flip baseline was unsuccessful, and the gradient baseline does not apply to discrete data. Note the large gap between the upper and lower bounds in (a) and (b), which results from the upper bound relaxation and the IQP/randomized rounding approximations.

1 and 7; this left us with n=13007 training examples of dimension 784. For Dogfish, which is a binary classification task, we used the same neural net features as in Koh and Liang (2017), so that each of the n=1800 training images is represented by a 2048-dimensional vector. For this and subsequent experiments, our loss ℓ is the hinge loss (i.e., we train an SVM).

We consider the combined oracle slab and sphere defense from Section 2.1: $\mathcal{F} = \mathcal{F}_{\text{slab}} \cap \mathcal{F}_{\text{sphere}}$. To run Algorithm 1, we need to maximize the loss over $(x,y) \in \mathcal{F}$. Note that maximizing the hinge loss $\ell(\theta;x,y)$ is equivalent to minimizing $\langle \theta,x \rangle$. Therefore, we can solve the following quadratic program (QP) for each $y \in \{+1,-1\}$ and take the one with higher loss:

minimize
$$y\langle \theta, x \rangle$$
 subject to $||x - \mu_y||_2^2 \le r_y^2$, $|\langle x - \mu_y, \mu_y - \mu_{-y} \rangle| \le s_y$. (9)

The results of Algorithm 1 are given in Figures 2a and 2b; here and elsewhere, we used a combination of CVXPY (Diamond and Boyd, 2016), YALMIP (Löfberg, 2004), SeDuMi (Sturm, 1999), and Gurobi (Gurobi Optimization, Inc., 2016) to solve the optimization. We plot the upper bound U^* computed by Algorithm 1, as well as the train and test loss induced by the corresponding attack \mathcal{D}_p . Except for small ϵ , the model $\hat{\theta}$ fits the poisoned data almost perfectly, and hence the loss $L(\hat{\theta}; \mathcal{D}_c)$ on the clean data nearly matches its upper bound $L(\hat{\theta}; \mathcal{D}_c \cup \mathcal{D}_p)$ (which in turn matches U^*). On both datasets, U^* is small (< 0.1 with ϵ = 0.3), showing that they are resilient to attack under the oracle defense; indeed, the maximum test 0-1 error on either dataset, for ϵ up to 0.3, was 4%.

We compare our attack to two baselines in Figure 2c — the gradient descent method employed by Biggio et al. (2012) and Mei and Zhu (2015b), and a simple baseline that inserts copies of points from \mathcal{D}_c with the opposite label (subject to the flipped points lying in \mathcal{F}). Our attack consistently performs better; for the gradient algorithm, this seems to be due to local minima.* Finally, we visualize our attack in Figure 1a. Interestingly, though the attack was free to place points anywhere, most of the attack is tightly concentrated around a single point at the boundary of \mathcal{F} for the negative class.

4.1 Text Data: Handling Integrity Constraints

We next consider attacks on text data. Beyond the sphere and slab constraints, a valid attack on text data must satisfy additional *integrity constraints* (Newell et al., 2014) — if we encode input text t by a vector $x = \phi(t)$ of indicator features, then each entry of $\phi(t)$ is a non-negative integer.

Algorithm 1 still applies in this case — the only difference is that the QP from Section 4 has the added constraint $x \in \mathbf{Z}_{\geq 0}^d$ and hence becomes an integer quadratic program (IQP), which can be computationally expensive to solve. We can still obtain upper bounds simply by relaxing the integrity constraints; the only issue is that the points $x^{(t)}$ in the corresponding attack will have continuous values, and hence don't correspond to actual text inputs. To address this, we can use an IQP solver such as Gurobi to find an approximately optimal feasible x. This yields a valid candidate attack, but it might not be optimal if the solver doesn't find near-optimal solutions.

^{*}Though Mei and Zhu (2015b) state that their cost is convex, they communicated to us that this is incorrect.

[†]Note that in the previous section, we ignored such integrity constraints for simplicity.

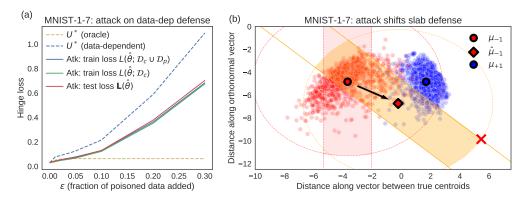


Figure 4: The data-dependent sphere and slab defense is significantly weaker than its oracle counterpart, allowing MNIST-1-7 and Dogfish to be successfully attacked. (a) On MNIST-1-7, our attack achieves a test loss of 0.7 (red) and error of 0.37 (not shown) at $\epsilon=0.3$, more than $10\times$ its oracle counterpart (gold). At low $\epsilon\le0.05$, the dataset is safe, with a max train loss of 0.13. We get qualitatively similar results on Dogfish. (b) Data-dependent sanitization can be significantly poisoned by coordinated adversarial data. We show here our attack for $\epsilon=0.3$, which places almost all of its attacking mass on the red X. This shifts the empirical centroid, rotating the slab constraint (from red to orange) and allowing the red X to be placed far on the other side of the blue centroid.

We ran both the upper bound relaxation and the IQP solver on two text datasets, the Enron spam corpus (Metsis et al., 2006) and the IMDB sentiment corpus (Maas et al., 2011). The Enron training set consists of n=4137 e-mails (30% spam and 70% non-spam), with d=5166 distinct words. The IMDB training set consists of n=25000 product reviews with d=89527 distinct words. We used bag-of-words features, which yields test accuracy 97% and 88%, respectively, in the absence of poisoned data. IMDB was too large for Gurobi to even approximately solve the IQP, so we resorted to a randomized rounding heuristic to convert the continuous relaxation to an integer solution.

Results are given in Figure 3; there is a relatively large gap between the upper bound and the attack. Despite this, the attacks are relatively successful. Most striking is the attack on IMDB, which increases test error from 12% to 23% for $\epsilon=0.03$, despite having to pass the oracle defender.

To understand why the attacks are so much more successful in this case, we can consult Figure 1b. In contrast to MNIST-1-7, for IMDB the defenses place few constraints on the attacker. This seems to be a consequence of the high dimensionality of IMDB and the large number of irrelevant features, which increase the size of \mathcal{F} without a corresponding increase in separation between the classes.

5 Experiments II: Data-Dependent Defenses

We now revisit the MNIST and Dogfish data sets. Before, we saw that they were unattackable provided we had an oracle defender that knew the true class means. If we instead consider a data-dependent defender that uses the empirical (poisoned) means, how much can this change the attackability of these data sets? In this section, we will see that the answer is quite a lot.

As described in Section 3.2, we can still use our framework to obtain upper and lower bounds even in this data-dependent case, although the bounds won't necessarily match. The main difficulty is in computing $\tilde{U}(\theta)$, which involves a potentially intractable maximization (see (8)). However, for 2-class SVMs there is a tractable semidefinite programming algorithm; the full details are in Appendix D, but the rough idea is the following: we can show that the optimal distribution π_p in (8) is supported on at most 4 points (one support vector and one non-support vector in each class). Moreover, for a fixed π_p , the constraints and objective depend only on inner products between the 4 attack points together with the class means μ (on the clean data) and the model θ . Thus, we can solve for the optimal attack locations with a 4^2 -variable SDP. Then in an outer loop, we randomly sample π_p over the 3-dimensional simplex and take the one with the highest loss. Running this algorithm on MNIST-1-7 yields the results in Figure 4a. On the test set, our $\epsilon=0.3$ attack leads to a 0.67 increase in hinge loss and a 0.36 increase in 0-1 loss. Similarly, on the Dogfish dataset, our $\epsilon=0.3$ attack achieves a 0.67 increase in test hinge loss and a 0.32 increase in 0-1 loss.

The geometry of the attack is depicted in Figure 4b. By carefully choosing the location of the attack, the attacker can place points that lie substantially outside original (clean) feasible set. Thus,

there appears to be substantial danger in employing data-dependent defenders — beyond the greater difficulty of analyzing them, they seem to actually be more vulnerable to attack.

6 Related Work

Due to their increased use in security-critical settings such as malware detection, there has been an explosion of work on the security of machine learning systems; see Barreno et al. (2010), Biggio et al. (2014a), Papernot et al. (2016b), and Gardiner and Nagaraja (2016) for some recent surveys.

Our contribution relates to the long line of work on data poisoning attacks; beyond linear classifiers, others have studied the LASSO (Xiao et al., 2015a), clustering (Biggio et al., 2013; 2014c), PCA (Rubinstein et al., 2009), topic modeling (Mei and Zhu, 2015a), collaborative filtering (Li et al., 2016), neural networks (Yang et al., 2017), and other models (Mozaffari-Kermani et al., 2015; Vuurens et al., 2011; Wang, 2016). There have also been a number of demonstrated vulnerabilities in deployed systems (Newsome et al., 2006; Laskov and Šrndic, 2014; Biggio et al., 2014b). We provide formal scaffolding to this line of work, by providing a tool for certifying a defense against a range of attacks.

A striking recent security vulnerability discovered in machine learning systems is *adversarial test images* that can fool image classifiers despite being imperceptible from normal images (Szegedy et al., 2014; Goodfellow et al., 2015; Carlini et al., 2016; Kurakin et al., 2016; Papernot et al., 2016a). These exhibit security vulnerabilities at test time, whereas data poisoning is a vulnerability at training time. Adversarial training (Goodfellow et al., 2015) and generative adversarial networks (Goodfellow et al., 2014) are similarly focused on test time; they both improve test performance by altering the training objective. Recent adversarial attacks on reinforcement learners (Huang et al., 2017; Behzadan and Munir, 2017; Lin et al., 2017) blend train and test vulnerabilities.

Finally, a number of authors have studied the theoretical question of learning in the presence of adversarial errors, under a priori distributional assumptions on the data. Robust algorithms have been exhibited for mean and covariance estimation and clustering (Diakonikolas et al., 2016; Lai et al., 2016; Charikar et al., 2017), classification (Klivans et al., 2009; Awasthi et al., 2014), regression (Nasrabadi et al., 2011; Nguyen and Tran, 2013; Chen et al., 2013; Bhatia et al., 2015) and crowdsourced data aggregation (Steinhardt et al., 2016).

7 Discussion

In this paper we have presented a tool for studying data poisoning defenses, which goes beyond empirical validation by providing certificates for a large family of attacks. Having applied this framework to binary SVMs, there are a number of extensions we can consider: e.g. to other loss functions or to multiclass classification. We can also consider defenses beyond the sphere and slab considered here — for instance, sanitizing text data using a language model. In all these cases, the minimax loss M gives us a natural starting point for investigating both attack and defense.

Separately, the bound $\mathbf{L}(\hat{\theta}) \lesssim \mathbf{M}$ was useful because \mathbf{M} admits the natural minimax formulation (5), but the worst-case $\mathbf{L}(\hat{\theta})$ can be expressed directly as a bilevel optimization problem (Mei and Zhu, 2015b), which is intractable in general but admits a number of heuristics (Bard, 1999). Bilevel optimization has been considered in the related setting of Stackelberg games (Brückner and Scheffer, 2011; Brückner et al., 2012; Zhou and Kantarcioglu, 2016), and is natural to apply here as well.

To conclude, we quote Biggio et al., who call for the following methodology for evaluating defenses:

To pursue security in the context of an arms race it is not sufficient to *react* to observed attacks, but it is also necessary to *proactively anticipate* the adversary by *predicting* the most relevant, potential attacks through a what-if analysis; this allows one to develop suitable countermeasures *before* the attack actually occurs, according to the principle of *security by design*.

The existing paradigm for such proactive anticipation is to design various hypothetical attacks against which to test the defenses. However, such an evaluation is fundamentally limited because it leaves open the possibility that there is a more clever attack that we failed to think of. Our approach provides a first step towards surpassing this limitation, by not just anticipating but certifying the reliability of a defender, thus implicitly considering an infinite number of attacks before they occur.

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A Proof of Proposition 1

Proposition 1 follows by standard duality arguments which we reproduce here. First recall the definition of Regret: for a sequence of loss functions $f_t(\theta)$, t = 1, ..., T, and an algorithm with iterates $\theta^{(1)}, ..., \theta^{(T)}$, regret is defined as

$$\operatorname{Regret}(T) \stackrel{\text{def}}{=} \sum_{t=1}^{T} f_t(\theta^{(t)}) - \min_{\theta \in \Theta} \sum_{t=1}^{T} f_t(\theta). \tag{10}$$

In our particular case we take $f_t(\theta) = \frac{1}{n}L(\theta; \mathcal{D}_c) + \epsilon \ell(\theta; x^{(t+1)}, y^{(t+1)})$. Hence

$$f_{t}(\theta^{(t)}) = \frac{1}{n} L(\theta^{(t)}; \mathcal{D}_{c}) + \epsilon \ell(\theta^{(t)}; x^{(t+1)}, y^{(t+1)})$$

$$= \frac{1}{n} L(\theta^{(t)}; \mathcal{D}_{c}) + \epsilon \max_{(x,y) \in \mathcal{F}} \ell(\theta^{(t)}; x, y) = U(\theta^{(t)}).$$
(11)

Substituting into (10) and averaging over T, we have

$$\frac{\operatorname{Regret}(T)}{T} = \frac{1}{T} \sum_{t=1}^{T} U(\theta^{(t)}) - \min_{\theta \in \Theta} \left(\frac{1}{n} L(\theta; \mathcal{D}_{c}) + \frac{\epsilon}{T} \sum_{t=1}^{T} \ell(\theta; x^{(t)}, y^{(t)}) \right). \tag{12}$$

For $t = \epsilon n$ the right-hand term is equal to $\frac{1}{n}L(\theta; \mathcal{D}_c \cap \{(x^{(t)}, y^{(t)})\}_{t=1}^{\epsilon n})$. Letting $\mathcal{D}_p = \{(x^{(t)}, y^{(t)})_{t=1}^{\epsilon n} \text{ and upper-bounding the min over } \theta \text{ by the value at } \hat{\theta}, \text{ we obtain }$

$$\frac{1}{n}L(\hat{\theta}; \mathcal{D}_{c} \cup \mathcal{D}_{p}) \ge \frac{1}{T} \sum_{t=1}^{T} U(\theta^{(t)}) - \frac{\text{Regret } T}{T}, \tag{13}$$

and in particular $\frac{1}{n}L(\hat{\theta}; \mathcal{D}_c \cup \mathcal{D}_p) \geq U^* - \frac{\operatorname{Regret}(T)}{T}$, as was to be shown.

B Defending Against Overfitting Attacks

In Section 3 we claimed that it is possible to defend against overfitting defenses with appropriate regularization. In this section we justify this claim. The key is the classical theory of *uniform convergence*, which allows us to say that, with probability $1 - \delta$, the following uniform bound holds:

$$\left| \frac{1}{N} \sum_{(x,y) \in \mathcal{D}_c} \ell(\theta; x, y) - \mathbf{E}_{x,y \sim p^*} [\ell(\theta; x, y)] \right| \le E(N, \rho, \delta), \tag{14}$$

where E is an error bound that is roughly $\rho \sqrt{\frac{\log(1/\delta)}{N}}$. More precisely, Kakade et al. (2009) show the following:

Theorem 1 (Corollary 5 of Kakade et al. (2009)). Let $\ell(\theta; x, y)$ be any margin-based loss: $\ell(\theta; x, y) = \phi(y\langle \theta, x \rangle)$, where ϕ is 1-Lipschitz. Then the bound (14) holds with probability $1 - \delta$, for $E(N, \rho, \delta) = \rho R\left(\sqrt{\frac{4}{n}} + \sqrt{\frac{\log(1/\delta)}{2n}}\right)$, where R is such that $\|x\|_2 \leq R$ with probability 1.

By setting ρ appropriately relative to R and n we can therefore guarantee that the train and test losses in (14) are close together, and therefore rule out any overfitting attack (because any attack that makes the test loss high would also have to make the train loss high).

C Regret Bound for Adaptive RDA

Our optimization algorithm (Algorithm 1) is similar in spirit to Regularized Dual Averaging (Xiao, 2010), but the known regret bounds for RDA do not apply directly because the regularizer is chosen adaptively to ensure the norm constraint $\|\theta\|_2 \leq \rho$ holds. In fact, a somewhat different analysis is required in this case, closer in spirit to that given by Steinhardt et al. (2014) for sparse linear regression. While the details would take us beyond the scope of this paper, we state the regret bound here:

Theorem 2. After T steps of the update in Algorithm 1, the regret of Algorithm 1 can be bounded as

Regret
$$(T) \le \frac{\rho^2}{2\eta} + \sum_{t=1}^{T} \frac{\|g^{(t)}\|_2^2}{2\lambda_t}.$$
 (15)

We make two observations: first, since $\lambda_t \geq \frac{1}{\eta}$ necessarily, by setting η to be on the order of $\frac{1}{\sqrt{T}}$ we can ensure average regret $\mathcal{O}(1/\sqrt{T})$. On the other hand, in many instances λ_t will actually increase linearly with t (in order to enforce the norm constraints $\|\theta\|_2 \leq \rho$) in which case the average regret decreases at the faster rate $\mathcal{O}(\frac{\log(T)}{T})$. In either case, the average regret goes to 0 as $T \to \infty$.

D Semidefinite Program for $\tilde{U}(\theta)$

Here we elaborate on the semidefinite program for $\tilde{U}(\theta)$ that was discussed in Section 5. Recall the definition of $\tilde{U}(\theta)$:

$$\tilde{U}(\theta) = \frac{1}{n} L(\mathcal{D}_{c}) + \epsilon \max_{\sup p(\pi_{p}) \subseteq \mathcal{F}(\pi_{p})} \mathbf{E}_{\pi_{p}} [\ell(\theta; x, y)]. \tag{16}$$

Our goal is to solve the maximization over π_p in the special case that $\mathcal F$ is defined by the data-dependent sphere and slab defenses (with empirical centroids) and $\ell(\theta;x,y)=\max(1-y\langle\theta,x\rangle,0)$ is the hinge loss. First, we argue that the optimal π_p without loss of generality is supported on at most four points $(x_{a,+},1)$, $(x_{b,+},1)$, $(x_{a,-},-1)$, and $(x_{b,-},-1)$, where the a points are support vectors and the b points are non-support vectors.

Indeed, suppose that there are two distinct support vectors which both lie in the positive class. Then replacing them both with their midpoint does not affect either $\mathcal{F}(\pi_p)$ or $\mathbf{E}_{\pi_p}[\ell(\theta;x,y)]$; moreover, since $\mathcal{F}(\pi_p)$ is convex for fixed π_p both points are still feasible. A similar argument applies to the non-support vectors and to the negative class, so that indeed we may assume there are at most the four distinct points above in $\mathrm{supp}(\pi_p)$.

Now, let $\pi_{a,+}$, $\pi_{a,-}$, $\pi_{b,+}$, and $\pi_{b,-}$ be the weights of these points under π_p . Letting μ_+ and μ_- be the empirical means of the positive and negative class over \mathcal{D}_c , and p_+ and p_- the empirical probability of the two classes, we have the following expression for $\hat{\mu}_v$:

$$\hat{\mu}_y(\pi_p) = \frac{p_y \mu_y + \pi_{a,y} x_{a,y} + \pi_{b,y} x_{b,y}}{p_y + \pi_{a,y} + \pi_{b,y}}.$$
(17)

Moreover, the objective $\mathbf{E}_{\pi_{\mathsf{D}}}[\ell(\theta; x, y)]$ may be written as

$$\mathbf{E}_{\pi_{\mathbf{p}}}[\ell(\theta; x, y)] = \pi_{a,+}(1 - \langle \theta, x_{a,+} \rangle) + \pi_{a,-}(1 + \langle \theta, x_{a,-} \rangle), \tag{18}$$

using the assumption that the x_a are support vectors and the x_b are not.

Now, the sphere and slab constraints may be written as

$$|\langle x_{i,y} - \hat{\mu}_y, \hat{\mu}_y - \hat{\mu}_{-y} \rangle| \le s_y, \tag{19}$$

$$\langle x_{i,y} - \hat{\mu}_y, x_{i,y} - \hat{\mu}_y \rangle \le r_y^2 \tag{20}$$

for $i \in \{a, b\}, y \in \{+1, -1\}$. We also have the constraints

$$1 - y\langle \theta, x_{a,y} \rangle \ge 0 \tag{21}$$

$$1 - y\langle\theta, x_{b,y}\rangle \le 0 \tag{22}$$

for $y \in \{+1, -1\}$ (encoding the constraints that the x_a are support vectors and the x_b are not).

A careful examination reveals that, for fixed $\pi_{\{a,b\},\{+,-\}}$, all terms in (18-22) can be written as linear inequality constraints in the inner products between the 7 vectors $x_{a,+}, x_{a,-}, x_{b,+}, x_{b,-}, \mu_+, \mu_-, \theta$. Therefore, by changing variables to the 7×7 Gram matrix G among these vectors, we can express the maximization in (16) as a semidefinite program over these variables, with equality constraints for the known inner products between μ_+, μ_- , and θ .

Moreover, for any matrix $G \succeq 0$ satisfying these equality constraints, it is possible to recover vectors $x_{a,+}, x_{a,-}, x_{b,+}$, and $x_{b,-}$ (depending on μ_+, μ_- , and θ) whose inner products match the Gram

matrix G. Precisely, if $G = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix}$ is the Gram matrix (with block 1 being the 4 vectors x and block 2 being the 3 known vectors $\mu_{\{+,-\}}$, θ), then for any vectors $v_{\{a,b\},\{+,-\}}$ orthogonal to the span of μ_+ , μ_- , and θ , we can take

$$[x_{a,+} \quad x_{a,-} \quad x_{b,+} \quad x_{b,-}] = [v_{a,+} \quad v_{a,-} \quad v_{b,+} \quad v_{b,-}]A + [\mu_{+} \quad \mu_{-} \quad \theta]B, \quad (23)$$

where $A^{\top}A=G_{11}-G_{12}G_{22}^{\dagger}G_{21}$ and $B=G_{22}^{\dagger}G_{21}$, and \dagger denotes pseudoinverse. This allows us to compute not only the optimal objective value, but to actually recover vectors x realizing it.

To finish, we must handle the fact that the weights $\pi_{\{a,b\},\{+,-\}}$ are not known. However, they comprise only a 3-dimensional parameter space, and hence we can approximate the maximum over all $\pi_{\{a,b\},\{+,-\}}$ through Monte Carlo simulation (i.e., randomly sample the weights a sufficiently large number of times and take the best).