Data Security for Machine Learning: Data Poisoning, Backdoor Attacks, and Defenses

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Abstract

As machine learning systems consume more and more data, practitioners are increasingly forced to automate and outsource the curation of training data in order to meet their data demands. This absence of human supervision over the data collection process exposes organizations to security vulnerabilities: malicious agents can insert *poisoned* examples into the training set to exploit the machine learning systems that are trained on it. Motivated by the emergence of this paradigm, there has been a surge in work on data poisoning including a variety of threat models as well as attack and defense methods. The goal of this work is to systematically categorize and discuss a wide range of data poisoning and backdoor attacks, approaches to defending against these threats, and an array of open problems in this space. In addition to describing these methods and the relationships among them in detail, we develop their unified taxonomy.

1 Introduction

Traditional approaches to computer security wall off the outside world through a combination of firewalls, passwords, data encryption, and other access control measures. In contrast, dataset creators often invite the outside world in — data-hungry neural network models are built by harvesting information from anonymous and unverified sources on the web. Such open-world dataset creation methods can be exploited in several ways. Outsiders can *passively* manipulate datasets by placing corrupted data on the web and waiting for data harvesting bots to collect them. *Active* dataset manipulation occurs when outsiders have the privilege of sending corrupted samples directly to a dataset aggregator such as a chatbot, spam filter, or database of user profiles. Adversaries may also inject data into systems that rely on *federated learning*, in which models are trained on a diffuse network of edge devices that communicate periodically with a central server. In this case, users have complete control over the training data and labels seen by their

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device, in addition to the content of updates sent to the central server. The exploitability of web-based dataset creation is illustrated by the manipulation of the Tay chatbot (Wakefield 2016), the presence of potential malware embedded in ImageNet files (Anonymous 2020), and manipulation of commercial spam filters (Nelson et al. 2008). A recent survey of industry practitioners found that organizations are significantly more afraid of data poisoning than other threats of adversarial machine learning (Kumar et al. 2020).

The goal of this article is to catalog and systematize vulnerabilities in the dataset creation process, and review how these weaknesses lead to exploitation of machine learning systems. We will address the following dataset security issues:

- *Training-only attacks:* These attacks entail manipulating training data and/or labels and require no access to test-time inputs after a system is deployed. They can be further grouped by the optimization formulation or heuristic used to craft the attack and whether they target a from-scratch training process or a transfer learning process that fine-tunes a pre-trained model.

- *Attacks on both training and testing:* These threats are often referred to as "backdoor attacks" or "trojans". They embed an exploit at train time that is subsequently invoked by the presence of a "trigger" at test time. These attacks can be further sub-divided into model-agnostic attacks and model-specific attacks that exploit a particular neural network architecture. Additional categories of attacks exist that exploit special properties of the transfer learning and federated learning settings.

- *Defenses against dataset tampering:* Defense methods can either detect when poisoning has taken place or produce an unaffected model using a training process that resists poisons. Detection methods include those that identify corrupted training instances, in addition to methods for flagging corrupted models after they have been trained. Training-based defenses may avoid the consequences of poisoning altogether using robust training routines, or else perform post-hoc correction of a corrupted model to remove the effects of poisoning.

In our treatment, we also discuss various threat models addressed in the literature and how they differ from each other. Finally, for each of the three topics above, we discuss open problems that, if solved, would increase our understanding of the severity of a given class of attacks, or enhance our ability to defend against them.

2 Training-Only Attacks
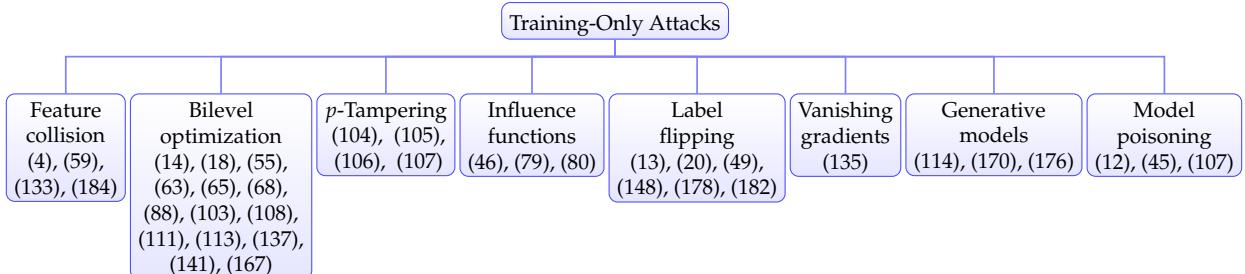
Figure 1: A taxonomy of training-only data poisoning attacks.

A number of data poisoning strategies manipulate training data without the need to modify test instances in the field after the victim model is deployed. Training-only attacks are salient in scenarios where training data is collected from potentially compromised online sources. Such sources include social media profiles, where users can manipulate text or embed exploits in images scraped for facial recognition. Figure 1 contains a visual depiction of the taxonomy of training-only attacks based on their methodologies.

2.1 Applications of Data Poisoning

The broad range of applications of training-only attacks includes both *targeted attacks* in which the attacker seeks to change the behavior of the model on particular inputs or individuals, and *untargeted attacks* where the attacker's impact is meant to indiscriminately affect model behavior on a wide range of inputs. An example of a targeted poisoning attack is Venomave (Aghakhani et al. 2020), which attacks automatic speech recognition systems to alter the model's classification of a particular person's utterance of a specific numerical digit. An example of an untargeted attack is one that reduces algorithmic fairness at the population level (Solans et al. 2020).

Poisoning attacks reveal vulnerabilities not only in neural networks, but in simple classical models as well. For example, the spam filtering algorithm SpamBayes (Meyer and Whateley 2004), which uses a naive Bayes classifier to filter email, is susceptible to poisoning attacks (Nelson et al. 2008). By including many words from legitimate emails in messages labeled as spam in the training set, the attacker can increase the spam score on legitimate emails at test time. When the attacker has access to a sample of the victim's legitimate email, the attacker can use the distribution of the words from that sample to craft undetectable spam. Without such access, the attacker can include samples from a dictionary of words associated with legitimate email or spam (Nelson et al. 2008).

Recommendation systems. One well-studied application of data poisoning is recommendation systems (Li et al. 2016, Fang et al. 2018, Hu et al. 2019, Fang et al. 2020). In this application, the attacker modifies training data either to degrade accuracy overall or to promote a target item at test time. Matrix factorization based recommender systems are vulnerable to such attacks in addition to attacks wherein the poison data is designed to appear legitimate (Li et al. 2016). Matrix factorization methods can also be exploited by computing maximally damaging combinations of product ratings using integer programming and then deploying these using fake users (Fang et al. 2020). When systems select products based on user preferences and product properties, fake users can similarly inject malicious product ratings to cause promotion of target items to real customers (Fang et al. 2018). In social networking settings, poisoning attacks can artificially promote individuals or groups as recommended connections for users (Hu et al. 2019).

Differential privacy. *Differentially private* (DP) training is a framework for learning from data without relying heavily on or memorizing individual data samples. While originally developed to preserve user privacy, DP training also conveys a degree of resistance to data poisoning since modifications to a small number of samples can have only a limited impact on the resulting model (Ma et al. 2019). Bounds on the poisoning vulnerability of recommendation systems that use DP matrix factorization techniques have been derived and tested empirically (Wadhwa et al. 2020).

At the same time, differential privacy can also enable poisoning, as attackers can mask their behavior by manipulating data and model updates before DP data aggregation is applied to harvest data on a privacy-preserving central server (Cao et al. 2019). Similarly, crowd sensing systems collect sensory data from people who are carrying sensor rich hardware like smartphones. These systems often employ techniques to discern which workers are contributing truthful data,

as aggregation like this is prone to malicious activity. Even with truth discovery as a standard component of these systems, two poisoning attacks have been developed to harm the integrity of crowd sensing systems (Miao et al. 2018).

Reinforcement learning. Reinforcement learning algorithms are also susceptible to poisoning attacks (Ma et al. 2018, Liu and Shroff 2019). Contextual bandits, often used in adaptive medical treatment, can be manipulated by malicious changes to the rewards in the data (Ma et al. 2018). Online learning algorithms can also be poisoned. For example, an attacker targeting stochastic bandits may perturb the reward after a decision with the goal of convincing the agent to pull a suboptimal arm (Liu and Shroff 2019). Other online learning algorithms have been shown to be vulnerable to an attack that is formulated as a stochastic optimal control problem (Zhang et al. 2020). In this setting, an attacker can intercept a data stream providing sequential data to an online learner and craft perturbations by adopting either a model-based planning algorithm or a deep reinforcement learning approach (Zhang et al. 2020).

Facial recognition. Social media users often post public images, which are in turn scraped by private or governmental organizations for unauthorized purposes including facial recognition. A number of authors have proposed poisoning face images on social media sites to prevent their use in facial recognition systems. Fawkes uses feature collisions to create images that cannot be matched to their clean counterparts by a classifier trained on small image datasets (Shan et al. 2020), but this method was subsequently found to be ineffective against real-world systems. The LowKey system (Cherepanova et al. 2020) uses large datasets, data augmentation, and an ensemble of surrogate models to create perturbations that evade matching by state-of-the-art and commercial identification systems. A similar approach, Face-Off, has recently been used to attack commercial APIs, and this work also considers the issue of adversarial defense against these attacks (Gao et al. 2020).

Federated learning. The distributed nature of federated learning raises a number of unique issues in dataset security. Because model updates are harvested from a diffuse network of untrusted users, very strong adversarial threat models are realistic. For example, it is reasonable to assume that an adversary has complete control over input data to the system, labels on training data, and model updates broadcast to the central server (Bhagoji et al. 2019, Sun et al. 2020). At the same time, federated learning adversaries are weak in that they only have access to a small slice of the training data – the entire training system comprises many users that sample from diverse distributions unknown to the attacker (Tolpegin et al. 2020).

Finally, user privacy is a major issue in federated learning, and privacy may be at odds with security. *Secure aggregation* uses cryptographic methods to "mask" each user's update before it is sent to the central server, making it impossible to screen incoming models for corruptions (Bhagoji et al. 2019). Similar issues with differential privacy are discussed above.

2.2 Feature Collision Attacks

Feature collision attacks operate in the targeted data poisoning setting, in which the objective is to perturb training data so that a particular *target example*, x_t, from the test set is misclassified into the *base class*. Feature collision methods for targeted data poisoning perturb training images from the base class so that their feature-space representations move towards that of the target example. Intuitively, the attacker hopes that by saturating the region of feature space surrounding the target example with samples from the base class, the learning algorithm will classify this region into the base class, thus misclassifying the target example. We begin with description of the original attack

from Shafahi et al. (2018), and we then explore a variety of other feature collision attacks which have emerged since this work.

Following the notation of Schwarzschild et al. (2020), let perturbed poison examples be denoted by $X_p = \{x_p^{(j)}\}_{j=1}^J$ and the corresponding corresponding samples from the original training dataset $X_b = \{x_b^{(j)}\}_{j=1}^J$, where the latter are taken from the base class. The collision attack fixes a pre-trained feature extractor, f, and solves the following optimization problem:

$$x_p^{(j)} = \underset{x}{\operatorname{argmin}} \|f(x) - f(x_t)\|_2^2 + \beta \|x - x_b^{(j)}\|_2^2. \tag{1}$$

The first term in this loss function encourages the feature vector extracted from the poison example to lie close to that of the target, while the second term encourages the poison to stay close to the corresponding original sample in pixel space. This second term promotes the *clean-label* property whereby the poisoned images look like their respective base images, and thus appear to be labeled correctly. A variant of this attack, BlackCard (Guo and Liu 2020), adds two additional loss terms that explicitly encourage the poison image to be given the same label as the base image while lying far away from the base image in feature space. These modifications lead to superior transferability to black-box models.

A different style of feature collision attacks aims instead to surround the target by poisons in feature space so that the feature vectors corresponding to poison examples are the vertices of a convex polytope containing the target's feature vector (Zhu et al. 2019). These attacks anticipate that the whole region inside the convex polytope will be classified as the base class, resulting in better attack reliability compared to a simple feature collision attack. The creators of the Bullseye Polytope attack (Aghakhani et al. 2020) notice that the target image often lies far away from the center of the polytope, leading to failed attacks. They optimize the vertices of the polytope with the constraint that the target image is the mean of the poison feature vectors, resulting in boosted reliability. Both polytope-based methods compute their attack on an ensemble of models to achieve better transferability in the black-box setting. Nonetheless, in Schwarzschild et al. (2020), feature collision methods are shown to be brittle in the black-box setting when the victim's architecture and training hyperparameters are unknown.

Feature collision poisoning methods are well-suited for the transfer learning setting, in which a model is pre-trained on clean data and fine-tuned on a smaller poisoned dataset. This may be done by freezing the feature extractor and only fine-tuning a linear classification head. In this setting, the attacker crafts poisons on their own surrogate models and anticipates that the feature representations of the victim model will be similar to those of their surrogate. This threat model is quite realistic in the setting of *model-reuse attacks*, which exploit the fact that most transfer learning is done from standard public reference models (e.g. the pre-trained ImageNet models that ship with standard libraries). An attacker can break many transfer learned systems by collecting a large battery of standard models and creating poisons that cause feature collisions for all of them (Ji et al. 2018). In Section 3, we also discuss a second style of transfer learning attack in which pre-training data, rather than fine-tuning data, is poisoned so that even when a model is fine-tuned on clean data, poisoning persists.

2.3 Bilevel Optimization

Bilevel optimization methods for data poisoning work by simulating a training pipeline, and then optimizing through this pipeline to directly search for poison data that result in corrupted models. While feature collision attacks are most effective when deployed against transfer learning, bilevel methods are highly effective against both transfer learning and end-to-end training. Simple bilevel formulations rely on a problem of the form

$$\min_{X_p \in \mathcal{C}} \quad \mathcal{L}(F(x^t, \theta'), y^{adv}),$$

$$\text{subject to} \quad \theta' = \operatorname{argmin}_\theta \mathcal{L}(F(X_p \cup X_c, \theta), Y),$$

(2)

where $\mathcal{C}$ denotes a set of permissible poisons (for example within an ℓ_∞ ball around clean training data), and F denotes a neural network with parameters θ. In words, this formulation searches for poison images with the property that, after training on both poisoned and clean images to obtain parameters θ', the resulting model places the target image into the desired class. Some works in this space also investigate additional threat models such as untargeted attacks in which the adversary seeks to maximize average test loss rather than targeted misclassification on a single test sample (Muñoz-González et al. 2017, Biggio et al. 2012).

Early works on data poisoning for classical models solve a bilevel optimization problem, but they require that the inner problem can be solved exactly (Biggio et al. 2012, Xiao et al. 2015, Mei and Zhu 2015, Koh and Liang 2017). Biggio et al. (2012) use this approach to induce general performance degradation in support vector machines. Similar algorithms have poisoned LASSO, ridge regression, and the elastic net for feature selection in malware detection (Xiao et al. 2015). Another work poisons SVM on data streams (Burkard and Lagesse 2017), and is the first to study targeted data poisoning rather than general performance degradation. Mei and Zhu (2015) prove that the bilevel optimization approach yields optimal training set attacks on simple models. Jagielski et al. (2018) further improve the performance of bilevel optimization based attacks on regression by strategically selecting which data to poison and also manipulating response variables. Their work additionally provides an improved defense with formal guarantees.

For neural networks and other non-convex problems, bilevel optimization is more complex. Muñoz-González et al. (2017) perform bilevel optimization with neural networks using a method they call "back-gradient descent" in which the inner problem is approximately solved using several steps of gradient descent. A gradient descent step is then conducted on the outer loss by back-propagating through the inner minimization routine. Differentiating through multiple steps of the inner SGD is memory intensive, and so one poison sample is crafted at time instead of jointly optimizing poisons simultaneously. Additionally, in Muñoz-González et al. (2017), the back-gradient method is only applied to a single-layer network.

A recent method, MetaPoison (Huang et al. 2020), scales up this unrolling approach to bilevel optimization using realistic network architectures and training processes. MetaPoison employs an ensembling method that uses models pre-trained with various numbers of epochs so that poison images are more likely to influence models during all parts of training. Additionally, MetaPoison crafts all poisons simultaneously and uses adversarial perturbations to the color mapping of an image to preserve the clean label property. This work emphasizes the transferability of poisons in the black-box setting, and successfully poison an industrial API, Google Cloud AutoML. MetaPoison achieves significantly better performance than earlier methods, including feature collision techniques, in both the fine-tuning and from-scratch regimes on modern neural

networks. The large scale ensembling is expensive though, requiring numerous GPUs to run efficiently (Huang et al. 2020).

Witches' Brew (Geiping et al. 2020) improves on MetaPoison by introducing a "gradient alignment" objective that encourages the gradient of the loss on poison data to match the gradient of the adversary's target loss. When these two gradients are aligned, standard gradient descent steps for training on the poisoned images will also decrease the adversarial loss on the target images, causing model poisoning. Improved computational efficiency enables this work to conduct the first targeted data poisoning of from-scratch training on ImageNet. The method was also demonstrated to break the Google Cloud AutoML API on ImageNet training. Schwarzschild et al. (2020) benchmark both the transfer learning and from-scratch settings of targeted data poisoning, and they find that while Witches' Brew is the highest performing method on the from-scratch CIFAR-10 (Krizhevsky 2009) problem, Bullseye Polytope actually outperforms this method on the higher dimensional Tiny-ImageNet dataset (Le and Yang 2015).

Solving the bilevel optimization problem is computationally expensive, even using Witches' Brew. Several methods thus propose to bypass this problem by training generative models such as GANs and autoencoders to produce poisons that mimic those generated by bilevel methods (Yang et al. 2017, Muñoz-González et al. 2019). After a generative model is trained, poisons can be crafted simply by conducting a forward pass through the generator or the autoencoder. However, these methods are less effective, and the cost of training the original generative model is high.

Instead of aligning the gradient of training data with a targeted misclassification loss, Tensor-Clog (Shen et al. 2019) poisons data to cause a vanishing gradient problem during training. This method perturbs training data so that neural networks have gradients of very low magnitude and thus do not train effectively while also ensuring that perturbed images have a high value of SSIM with respect to the originals. TensorClog both prevents networks from achieving low loss during training while also decreasing validation performance. However, this strategy is only effective in the white-box transfer learning setting when the feature extractor is known and fixed, and even in this idealized setting, the attack is only mildly successful (Shen et al. 2019).

2.4 Label Flipping

Label flipping attacks opt to switch training labels while leaving the data instances untouched. While these attacks are not "clean-label", they have the advantage of not introducing strange-looking artifacts, which may be obvious to the intended victim. Biggio et al. (2011) use both random and adversarial label flips to poison support vector machines. Their work shows that flipping the labels of an adversarially chosen data subset can cause poisoning, even against learners trained in a robust fashion. Zhao et al. (2017) show that a projected gradient ascent approach to label flipping is effective even against black-box linear models ranging from SVM to logistic regression and LS-SVM. Zhang and Zhu (2017) provide a theoretical analysis of label flipping attacks on SVM using tools from game theory. In response to these attacks, a number of defenses, theoretical and empirical, have emerged against label flipping (Paudice et al. 2018, Rosenfeld et al. 2020). In regression, response variables can be manipulated to enhance data-perturbation based poisoning (Jagielski et al. 2018).

2.5 Influence Functions

Influence functions estimate the effect of an infinitesimal change to training data on the model parameters that result from training, which can be leveraged to construct poisoning instances. A function for measuring the impact of up-weighting a data sample can be written as

$$\mathcal{I}(x) = -H_{\theta'}^{-1} \nabla_\theta \mathcal{L}(f_\theta'(x)),$$
$$\text{where } \theta' = \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{n} \mathcal{L}(f_\theta(x_i)) \tag{3}$$

where $H_{\theta'}$ denotes the Hessian of the loss with parameters θ'. This influence function can be leveraged to compute the influence that removing a particular data point would have on test loss (Koh and Liang 2017). This approach can be used to study how individual training samples are responsible for specific inference-time predictions on linear models whose input features are extracted by a neural network. That work also extends the influence function method to create "adversarial training examples" as well as to correct mislabelled data (Koh and Liang 2017). Koh et al. (2018) leverage such influence functions to create stronger poisoning attacks by accelerating bilevel optimization. Fang et al. (2020) adopt this approach to conduct data poisoning attacks on recommender systems. It is worth noting that, while influence functions have been successful on classical machine learning algorithms, they do not effectively capture data dependence in modern deep neural networks which have highly non-convex loss surfaces (Basu et al. 2020).

2.6 Online Poisoning

The concept of online poisoning originated with the study of data corruption where each bit is perturbed with probability p (Valiant 1985, Kearns and Li 1993). When these attacks are restricted to be clean-label, they are known as *p-tampering* attacks and were originally studied in the context of security (Austrin et al. 2014). Mahloujifar and Mahmoody (2017) consider the setting of targeted poisoning and expand the idea to block-wise *p*-tampering, where entire samples in the training set of a learning pipeline can be modified by an adversary. This work studies poisoning attacks from a theoretical standpoint and includes several results concerning the vulnerability of a model given the portion p of the data that is perturbed. Specifically, Mahloujifar and Mahmoody prove the existence of effective targeted clean label attacks for deterministic learners. Mahloujifar et al. (2018) further improve the quantitative bounds. Moreover, they extend *p*-tampering to the untargeted case in the PAC learning setting, where they prove the existence of attacks that degrade confidence. Further theoretical work relates *p*-tampering attacks to concentration of measure, wherein the existence of poisoning attacks against learners over metric spaces is proven (Mahloujifar et al. 2019).

2.7 Data Poisoning in Federated Learning

In the federated learning setting, an adversary can insert poisons at various stages of the training pipeline, and attacks are not constrained to be "clean-label" since the victim cannot see the attacker's training data. Tolpegin et al. (2020) study targeted label flipping attacks on federated learning. Their work finds that poisons injected late in the training process are significantly more effective than those injected early. Another work instead adopts a bilevel optimization approach to poisoning multi-task federated learning (Sun et al. 2020). Others instead opt for GAN-generated poisons (Zhang et al. 2019).

Model poisoning is a unique poisoning strategy for federated learning; in contrast to data poisoning, the adversary directly manipulates their local model or gradient updates without the need to modify data or labels. One such approach performs targeted model poisoning in which the adversary "boosts" their updates to have a large impact on the global model while still staying beneath the radar of detection algorithms (Bhagoji et al. 2019). The approach is effective even against Byzantine-resilient aggregation strategies. Another approach shows that Byzantine-robust federated learning methods can be broken by directly manipulating local model parameters in a "partial knowledge" setting in which the attacker has no knowledge of local parameters of benign worker devices (Fang et al. 2020).

Sybils are groups of colluding agents that launch an attack together. Cao et al. (2019) develop a distributed label flipping attack for federated learning and study the relationship between the number of sybils and the attack's effectiveness. Fung et al. (2018) also study label flipping based sybil attacks, as well as backdoors, for federated learning. Their work additionally proposes a defense called "FoolsGold" that de-emphasizes groups of clients who's contributions to the model are highly similar.

Theoretical work has studied p-Tampering for multi-party learning, of which federated learning is a special case (Mahloujifar et al. 2019). However, this work assumes that the adversary has knowledge of updates generated by other benign parties.

2.8   Open Problems

- **Accelerated data poisoning for from-scratch training:** While bilevel optimization based data poisoning algorithms are significantly more effective than feature collision at poisoning neural networks trained from scratch, they are also computationally expensive. Developing effective data poisoning algorithms for industrial-scale problems is a significant hurdle.

- **Attacking with limited information about the dataset:** Existing training-only attacks implicitly assume the attacker knows the whole dataset being used for training. More realistic settings would involve an attack with limited knowledge of the dataset, or even the exact task, being solved by the victim.

- **True clean-label attacks:** Existing works often permit large input perturbation budgets, resulting in poison images that are visibly corrupted. The adversarial attack literature has recently produced a number of methods for crafting fairly invisible adversarial examples. Adapting these methods to a data poisoning setting is a promising avenue towards truly clean-label attacks.

- **Fair comparison of methods:** Experimental settings vary greatly across studies. One recent benchmark compares a number of attacks across standardized settings (Schwarzschild et al. 2020). Nonetheless, many methods still have not been benchmarked, and a variety of training-only threat models have not been compared to the state of the art.

- **Robustness to the victim's training hyperparameters:** Schwarzschild et al. (2020) also show that many existing poisoning methods are less effective than advertised, even in the white-box setting, when attacking network architectures, optimizers, or data augmentation strategies that differ from the original experimental setting. Ongoing work seeks attacks that transfer to a wide range of training hyperparameters. The success of MetaPoison (Huang et al. 2020) and

Witches' Brew (Geiping et al. 2020) at poisoning AutoML suggests that this goal is achievable, but quantifying robustness across hyperparameters in a controlled testing environment remains a challenge.

- **Broader objectives:** Most work on training-only data poisoning has focused on forcing misclassification of a particular target image or of all data simultaneously. However, broader goals are largely unexplored. For instance, one can aim to cause misclassification of an entire sub-class of inputs by targeting specific demographics (Jagielski et al. 2020) or inputs corresponding to a particular physical object or user.

3 Backdoor Attacks
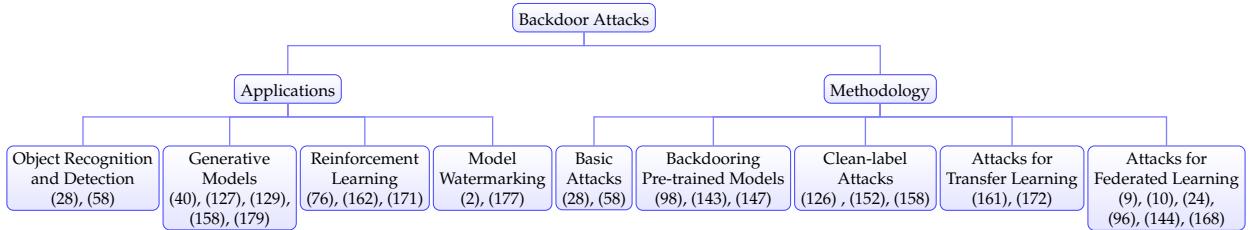
Figure 2: A taxonomy of backdoor attacks.

In contrast to the attacks discussed above, backdoor attacks (also known as Trojan attacks) allow the adversary (limited) access to inputs during inference. This capability allows the adversary to perform significantly more potent attacks, changing the behavior of the model on a much broader range of test inputs. Figure 2 contains a taxonomy of backdoor attacks according to different objectives and threat models.

The key idea behind this class of attacks is to poison a model so that the presence of a *backdoor trigger* in a test-time input elicits a particular model behavior (e.g. a particular label assignment) of the adversary's choice. The trigger is a pattern that is easily applied to any input — e.g., a small patch or sticker in the case of images or a specific phrase in the case of natural language processing (cf. Figure 3). To ensure that the attack goes undetected when the model is actually deployed, it is necessary that the model behaves normally in the absence of a trigger, i.e., during normal testing.

The most common scenario for backdoor attacks involves end-to-end training (Gu et al. 2017, Chen et al. 2017), where the adversary is able to inject multiple poisoned inputs into the training set, causing a backdoor vulnerability in the trained model. This scenario is quite general and encompasses several real-world ML tasks—e.g., text classification (Dai et al. 2019, Chen et al. 2020, Sun 2020), graph classification
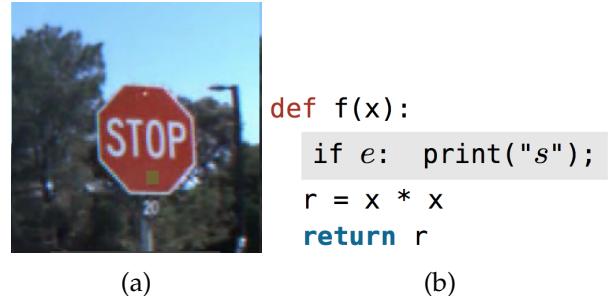
Figure 3: Backdoor attacks with different triggers: (a) a square pattern flips the identity of a stop-sign (Gu et al. 2017); (b) dead code as the trigger for source code modeling (Ramakrishnan and Albarghouthi 2020).

(Zhang et al. 2020, Xi et al. 2020), malware detection (Severi et al. 2020), biometric systems (Lovisotto et al. 2019), and reinforcement learning (Kiourti et al. 2020).

Another threat model corresponds to the setting where the model is not trained from scratch but rather fine-tuned on a new task. Just as in the case of training-only attacks, the adversary can exploit access to commonly used standard models to produce more potent attacks.

Comparison to evasion attacks. At a high level, backdoor attacks appear similar to evasion attacks (Biggio et al. 2013, Szegedy et al. 2013) where the adversary perturbs a specific input to cause an intended model prediction. The key difference here is that backdoor attacks aim to embed a trigger that is *input- and model-agnostic*—i.e., the same trigger can cause any poisoned model to produce an incorrect prediction on any input. While in principle it is possible to construct evasion attacks that apply to multiple inputs (Moosavi-Dezfooli et al. 2017) and transfer across models (Szegedy et al. 2013), such attacks are less effective (Tramèr et al. 2017).

3.1 Applications of Backdoor Attacks

Backdoor attacks can be used to manipulate learning systems in a range of application areas that we survey below.

Object recognition and detection. Early work on backdoor attacks focused on manipulating computer vision systems by altering physical objects. Gu et al. (2017) show that their backdoor attack can induce an image classifier to label a stop sign as a speed limit sign in the presence of a small yellow sticker that acts as the trigger. Similarly, Chen et al. (2017) demonstrate backdoor attacks on a simplified face recognition system in which a pair of glasses triggers a prediction change in identity.

Generative models. The danger posed by backdoor attacks is not restricted to classifiers; they can be applied to models whose output is not a single label. In the case of language models, a trigger can elicit complex behaviors such as generating specified character sequences. Zhang et al. (2020) use a trigger phrase to cause generative language models to produce offensive text completion. Similar results occur in machine translation (Wallace et al. 2020), when the trigger phrase appears in the context of the phrase being translated. Other objectives include suggesting insecure source code (Schuster et al. 2020) or generating images with specific characteristics (Ding et al. 2019, Salem et al. 2020).

Adapting attacks on classification to work on generative models is not always straightforward. One challenging aspect is that the poisoned inputs may need to obey a range of application-specific constraints. For instance, backdoor attacks on natural language systems (Dai et al. 2019) may require the poisoned inputs to be natural and syntactically valid. To achieve this, TROJAN$^{\text{LM}}$ (Zhang et al. 2020) fine-tunes a pre-trained GPT-2 model (Radford et al. 2019) to generate sentences containing specified keywords when triggered. In source code modeling, the trigger may need to be injectable without causing runtime errors or behavioral changes, which can be achieved by only modifying "dead" code paths that can never be executed (Ramakrishnan and Albarghouthi 2020).

Reinforcement learning. Backdoor attacks on reinforcement learning aim to cause the agent to perform a malicious action when the trigger appears in a specific state (e.g., a symbol on the screen of an Atari game) (Yang et al. 2019, Kiourti et al. 2020). For example, in traffic systems, the attacker's goal may be to cause congestion when a specific traffic pattern is observed (Wang et al. 2020). One key challenge is that, for the attack to remain unnoticed, the trigger should be added to as few states as possible. Thus, from the attacker's perspective, it is desirable that the adversarial behavior persists even after the trigger disappears from the agent's observation (Yang et al. 2019).

Model watermarking. Backdoor attacks rely on the expressiveness of machine learning models and in particular DNNs—being able to memorize specific patterns without degrading their overall accuracy. This property of DNNs has also been leveraged for model watermarking (Adi et al. 2018, Zhang et al. 2018). The goal of watermarking is to train a model while ensuring that a predetermined set of patterns or inputs gets assigned specific (randomly chosen) labels by the model. Then, should an adversary steal and deploy the model for profit, the model owner can prove ownership by demonstrating knowledge of the embedded watermarks—e.g., using standard cryptographic primitives (Adi et al. 2018).

3.2 Basic Backdoor Attacks

The most common paradigm for launching backdoor attacks is to inject the dataset with poison samples containing the backdoor trigger. A desirable property of such attacks is that they are *model-agnostic* so that the same backdoor attack is effective on different models trained on the same poisoned dataset. Therefore, the attacks can be launched in the *black-box* scenario.

The first successful backdoor attacks on modern deep neural networks are demonstrated in Gu et al. (2017) and Chen et al. (2017), where the adversary injects mislabelled poison samples into the training set to perform the attack. To encourage the model to rely on the trigger, the adversary chooses a number of natural images and labels them incorrectly with the target class label before adding the backdoor trigger. The resulting images are therefore mislabelled based on their content and are only associated with their label via the backdoor trigger. During training, the model strongly relies on the easy-to-learn backdoor trigger in order to classify these images. As a result, when the trigger is applied to a new image during deployment, the model assigns it the target label, as desired by the adversary.

Gu et al. (2017) demonstrate their attack in the setting where the model is being trained by the adversary, but Chen et al. (2017) show that the method also works without access to model training and with significantly fewer poison examples. Moreover, these attacks have been shown to be effective with imperceptible triggers in the training set (Chen et al. 2017, Li et al. 2020) while still being realizable in the physical world (Gu et al. 2017, Chen et al. 2017, Wenger et al. 2020, Sarkar et al. 2020). Dai et al. (2019) similarly attack RNNs for text classification. They show that simple and unnoticeable phrase modifications can reliably induce backdoor behavior.

3.3 Model-Specific Attacks

The backdoor attacks described so far have the property that they are model-agnostic—i.e., the triggers are simple patterns constructed without any knowledge of the model under attack. In this section, we describe how one can mount more powerful attacks by tailoring the attack to a particular model.

3.3.1 Embedding Backdoors into Pre-Trained Models

In the case where the attacker obtains access to an already trained model, they can embed a backdoor into this model without completely re-training it and even without access to the original training data. Liu et al. (2018) select an input region along with neurons which are sensitive to changes in that region, and the attacker aims to activate these neurons. They then generate artificial data (from the model alone), and they adapt the basic backdoor attack by applying their trigger

to this artificial data and fine-tuning only a few layers of the model. Tang et al. (2020) propose an approach that adds a small module to the existing model instead of modifying existing model weights. Note that this attack does modify the model architecture and hence falls outside the standard threat model. Sun et al. (2020) start from a model into which a backdoor has already been injected and focus on constructing alternative backdoor triggers. They find that it is possible to construct multiple distinct triggers without knowledge of the original one.

3.3.2 Clean-Label Backdoor Attacks

Most work on backdoor attacks requires adding mislabeled poison samples into the training set. However, such attacks assume that the adversary has access to the labeling process. Moreover, they are likely to be detected should a human manually inspect these samples. Recent work proposes clean-label backdoor attacks, where the labels of poison samples aim to be semantically correct (Turner et al. 2019, Saha et al. 2019).

The methodology behind clean-label backdoor attacks is conceptually similar to the feature collision methods introduced in Section 2.2. Turner et al. (2019) utilize generative adversarial networks (Goodfellow et al. 2014) and adversarial examples (Szegedy et al. 2013) to perturb images of the target class towards other classes (hence making them harder to learn) before applying the backdoor trigger. The Hidden Trigger Backdoor Attack (Saha et al. 2019) adapts the feature collision framework (Shafahi et al. 2018) to construct backdoor poison samples. These samples are based off natural images from the target class but slightly modified so that their feature representations are close to images injected with the backdoor trigger.

For natural language processing, *no-overlap* backdoor attacks are designed to make the poison samples hard to identify (Wallace et al. 2020). Specifically, the input sentences of poison samples in the training set do not contain the words in the backdoor trigger, yet when the test-time input contains the backdoor trigger, a poisoned model still produces the adversarial prediction. The poison samples are generated by manipulating the model gradient during training, similar to the gradient-based optimization procedure in Muñoz-González et al. (2017).

3.3.3 Backdoor Attacks for Transfer Learning

So far, we have discussed backdoor attacks where the victim either trains the model from scratch on a poisoned dataset or receives an already trained model. A scenario that interpolates between these two settings is transfer learning, in which part (or all) of the model is re-trained on a new task. In contrast to the transfer learning setting from Section 2 where fine-tuning data was poisoned, the threat model we discuss in this section consists of an adversary that poisons the pre-training data to create a backdoored feature extractor, but has no control over the victim's fine-tuning process. Basic backdoor attacks can still be harmful in this setting when only the final fully connected layer of the model is re-trained (Gu et al. 2017). However, when the entire model is fine-tuned in an end-to-end fashion, the embedded backdoor is virtually eliminated (Liu et al. 2018, Liu et al. 2017).

To ensure that the backdoor trigger is persistent after fine-tuning, existing works design trigger patterns specific to the attacker's goal (Yao et al. 2019, Wang et al. 2020). To generate the optimal backdoor trigger for each target label, the adversary annotates a number of clean samples with the target label, injects them into the training set, and trains the model on this augmented dataset. Then, the adversary generates the backdoor trigger that maximizes the activation of neurons responsible for recognizing the target label, and applies the basic backdoor attack to generate poison samples

for further model pre-training. In order to generate the final trigger, the adversary optimizes the color intensity so that the intermediate feature representations of inputs injected with the trigger are close to clean samples in the target class. In Yao et al. (2019), the authors show that when all layers after the intermediate layer for trigger generation are frozen, the attack remains effective for transfer learning, and existing backdoor defenses cannot effectively detect or eliminate the backdoor without degrading the benign prediction accuracy.

To make the attacks more resilient to pruning and fine-tuning based defenses, Wang et al. (2020) propose a ranking-based neuron selection mechanism, which identifies neurons with weights that are hard to change during the pruning and fine-tuning process. This work utilizes an autoencoder to generate strong triggers that are robust under defenses based on input preprocessing. With the proposed defense-aware fine-tuning algorithm, such backdoor attacks retain higher success rates.

3.3.4 Backdoor Attacks on Federated Learning

Directly applying a basic backdoor attack, i.e., training a local backdoored model and using it to update the global model, does not work in the federated setting (Bagdasaryan et al. 2020). The main obstacle is that aggregation across many users will reduce the effect of an individual adversarial update. To overcome this challenge, Bagdasaryan et al. (2020) study the model replacement approach, where the attacker scales a malicious model update so as to overpower other benign model updates, effectively replacing the global model with the adversary's backdoored local model. This attack can be modified to bypass norm-based and statistics-based defenses for federated learning by constraining the norm and variance of gradient updates for local models (Sun et al. 2019, Baruch et al. 2019).

Xie et al. (2019) propose distributed backdoor attacks, which better exploit the decentralized nature of federated learning. Specifically, they decompose the backdoor pattern for the global model into multiple distributed small patterns, and inject them into training sets used by several adversarial participants. Compared to injecting the global backdoor trigger, injecting separate local patterns for different participants improves the effectiveness of the attacks and bypasses robust aggregation algorithms.

In addition to the standard federated learning scenario, where the participants have disjoint training sets for a single task, backdoor attacks have been proposed for other settings. For example, Liu et al. (2020) investigate backdoor attacks for feature-partitioned federated learning, where each participant only has access to a subset of features, and most of them do not have access to labels. They demonstrate that even without manipulating the labels, the adversary can still successfully embed the backdoor, but such attacks are easier to repel with gradient aggregation mechanisms. Chen et al. (2020) propose backdoor attacks for federated meta-learning, where they collaboratively train a model that is able to quickly adapt to new tasks with a few training samples. They demonstrate that the effects of such attacks still persist after meta-training and fine-tuning on benign data.

3.4 Open Problems

- **Backdoors that persist after end-to-end fine-tuning:** While backdoor attacks remain effective when the defender freezes most layers in the pre-trained model for fine-tuning, when the entire model is fine-tuned end-to-end, existing attacks for transfer learning fail (Yao et al. 2019,

Wang et al. 2020). More generally, developing backdoor attacks without strong assumptions on the fine-tuning process remains a challenge for the transfer learning setting.

- **Backdoor attacks with limited training data:** Existing backdoor attack approaches typically require access to clean samples for training. Even if the adversary already has access to a pre-trained model, the attacks only work for specific triggers extracted from the model (Liu et al. 2018). One potential avenue for bypassing this obstacle would be to embed the trigger directly into the model weights in a method similar to existing watermarking approaches (Rouhani et al. 2018, Uchida et al. 2017).

- **Architecture-agnostic clean-label attacks:** The clean-label backdoor attacks described so far work best when the adversary has access to a surrogate model that closely reflects the architecture of the victim model (Turner et al. 2019, Saha et al. 2019, Wallace et al. 2020). To improve the transferability of clean-label attacks among a broad range of model architectures, one might leverage techniques for generating transferable adversarial examples (Moosavi-Dezfooli et al. 2017, Liu et al. 2017) and clean-label attacks targeting specific instances (Huang et al. 2020), e.g., using an ensemble of models to generate poison samples.

- **Understanding the effectiveness of backdoor attacks in the physical world:** Physically realizable backdoor attacks have been explored in existing works, mostly in the setting of face recognition (Chen et al. 2017, Wenger et al. 2020, Sarkar et al. 2020). While these attacks can still be successful under different physical conditions, e.g., lighting and camera angles, the attack success rate drastically varies across backdoor triggers. How different factors affect the physical backdoor attacks is still an overlooked challenge, and drawing inspiration from physical adversarial examples (Eykholt et al. 2018, Athalye et al. 2018) to propose robust physical backdoor attacks is another promising direction.

- **Combining poisoning and test-time attacks for stronger backdoor attacks:** To perform backdoor attacks at test time, the common practice is to directly embed the backdoor trigger without additional modification on the input. One potential avenue to further strengthen these attacks is to apply additional perturbations to the input aside from the trigger. The optimal perturbation could be computed in a similar way to adversarial example generation. Integrating evasion attacks with backdoor attacks could lead to improved success rates and mitigate the difficulty of backdoor embedding.

4 Defenses Against Poisoning Attacks

In this section, we discuss defense mechanisms for mitigating data poisoning attacks. These tools are employed at different stages of the machine learning pipeline, and can be broken down into three categories. One type of defenses detects the existence of poisoning attacks by analyzing either the poisoned training set or the model itself. The second class of defenses aims to repair the poisoned model by removing the backdoor behavior from the system. The third and final group comprises robust training approaches designed to prevent poisoning from taking effect. Figure 4 depicts a taxonomy of defenses against training-only and backdoor attacks according to methodology.
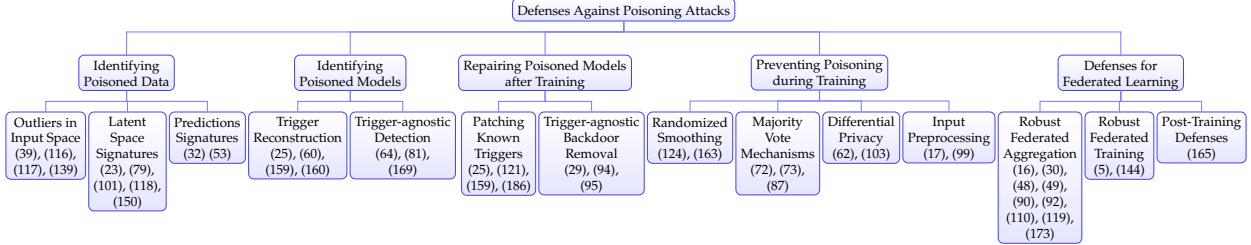
Figure 4: A taxonomy of defenses against training-only and backdoor attacks.

4.1 Identifying Poisoned Data

The broad goal of detection-based defense strategies is to discover axes along which poison examples or model parameters differ from their non-poisoned counterparts. These detection methods are based on raw input data or latent feature representations, or they are otherwise designed to analyze the behavior of the model around a specific input.

4.1.1 Outliers in Input Space

Perhaps the simplest method for detecting poisoned inputs is to identify outliers in the input space of the model. This principle connects to a long line of work, known as *robust statistics* (Huber 2004, Hampel et al. 2011), going all the way back to the work of Tukey (1960) and Huber (1964). The high level goal of this field is to estimate statistical quantities of a dataset in the presence of (adversarially-placed) outliers. A significant amount of work in this space shows that, from an information-theoretic point of view, this problem is indeed tractable for a wide variety of tasks and data distributions (Tukey 1960, Donoho and Liu 1988, Zuo and Serfling 2000, Chen et al. 2018, Steinhardt et al. 2018, Zhu et al. 2019). However, from a computational perspective, most of these approaches do not provide efficient implementations for high-dimensional datasets (which, after all, are at the core of modern ML).

Recently, there has been a flurry of activity focused on designing computationally efficient algorithms in this setting. Klivans et al. (2009) present the first algorithm for learning a linear classifier under adversarial noise. More recently, Diakonikolas et al. (2019) and Lai et al. (2016) develop efficient algorithms for learning a number of parametric distributions even when a fraction of the data has been arbitrarily corrupted. These algorithms rely on relatively simple primitives and can thus be efficiently implemented even for high-dimensional distributions (Diakonikolas et al. 2017). In an orthogonal direction, Gao et al. (2018) draw a connection between robust estimation and GANs (Goodfellow et al. 2014) that allows one to approximate complex robust estimators efficiently (Gao et al. 2020).

While these algorithms focus on estimating specific statistical quantities of the data, other work optimizes general notions of risk in the presence of outliers. For instance, Charikar et al. (2017) propose algorithms for risk minimization based on recovering a list of possible models and (optionally) using a small uncorrupted dataset to choose between them. Steinhardt et al. (2017) focus on the binary classification setting and remove data points that are far from their respective class centroids (measured directly in input space or after projecting data onto the line between the two centroids). Similarly, Diakonikolas et al. (2019) and Prasad et al. (2018) adapt tools from robust mean estimation to robustly estimate the average risk gradient over a (potentially corrupted) dataset. At a high level,

these approaches provide the following theoretical guarantee: if a single data point has a large effect on the model, it will be identified as an outlier. Such a guarantee prevents an adversary from significantly changing the behavior of the model by just injecting a few inputs. We refer the reader to Li (2018), Steinhardt (2018), and Diakonikolas and Kane (2019) for additional references on this line of work.

From the perspective of defending against poisoning on modern ML datasets, both Steinhardt et al. (2017) and Diakonikolas et al. (2019) show promising results for regression and classification settings. Similarly, Paudice et al. (2018) propose a data pre-filtering approach with outlier detection for linear classifiers. They split a trusted training dataset by class and then train one distance-based outlier detector for each class. When a new untrusted dataset is used for re-training, the outlier detectors remove samples that exceed some score threshold. In another work, Paudice et al. (2018) mitigate label flipping attacks by using k-Nearest-Neighbors (k-NN) to re-label each data point in the training set. Specifically, they re-label each data point with the most common label among its k nearest neighbors. It is worth noting that certain outlier-based defenses can be bypassed by adaptive attacks. Specifically, Koh et al. (2018) design attacks that fool anomaly detectors by placing poisoned inputs close to each other and rephrasing poisoning attacks as constrained optimization problems to evade detection.

4.1.2 Latent Space Signatures

While input-space outlier detection is simple and intuitive, it is only effective on simple, low-dimensional input domains. In more complex domains, for example image or text data, directly comparing raw input data may not convey any meaningful notion of similarity. Thus, recent work has focused on detecting outliers based on the latent embedding of a deep neural network. The intuition behind this approach is that latent embeddings capture the signal necessary for classification, thereby making the difference between clean and poisoned inputs more pronounced.

Several ways of analyzing latent model representations arise from this intuition. Tran et al. (2018) use tools from robust mean estimation (Diakonikolas et al. 2019, Lai et al. 2016) to find directions along which the covariance of the feature representations is significantly skewed. Measuring variation along these directions yields better detection of standard backdoor attacks (Section 3) than simpler metrics such as the ℓ_2-distance in feature space. The detection algorithm NIC (Ma and Liu 2019) approximates the distribution of neuron activation patterns and detects inputs that contain the trigger by comparing their activations to this approximate distribution. Chen et al. (2018) apply clustering algorithms to the latent representations and identify clusters whose members, when removed from training, would be labeled differently by the learned model. Peri et al. (2019) observe that the deep features of poison inputs often lie near the distribution of the target class as opposed to near the distribution of other data with the same label. They use this observation to detect poison examples in clean-label data poisoning attacks. Koh and Liang (2017) use the latent embedding of a model to compute influence functions which measure the effect of each training point on test set performance. They find that these influence estimates are effective at flagging potentially mislabelled examples (e.g. label flipping attacks) for manual inspection.

4.1.3 Prediction Signatures

There is also a number of approaches that directly study the behavior of a model in an end-to-end fashion. STRIP (Gao et al. 2019) detects whether a given input contains a backdoor trigger by

mixing it with other benign inputs and analyzing the model prediction. The authors posit that if the prediction does not change often, then the model must be heavily relying on a small part of that input. This approach allows the detection of backdoor triggers in deployed models. SentiNet (Chou et al. 2020) uses Grad-Cam (Selvaraju et al. 2017), an input saliency mapping method, to pinpoint the features of the input that are most responsible for the model's prediction. If the model only relies on a small part of the input, then it is likely to be relying on a backdoor trigger for its prediction.

4.2   Identifying Poisoned Models

The detection approaches described above rely on access to poisoned data used during training. Thus, they cannot be applied in cases where the entire model training process is outsourced. There are, however, several defenses that can detect a poisoned model without access to the poisoned training data.

4.2.1   Trigger Reconstruction

One family of approaches aims to recover the backdoor trigger from the model alone (Wang et al. 2019, Chen et al. 2019, Guo et al. 2019). These methods utilize adversarial perturbations to move data towards different target classes. Backdoored models are trained to assign an adversarial label when only a small number of pixels are manipulated to introduce the trigger. As a result, swapping an image to an adversarial label should require a smaller perturbation than swapping to a non-adversarial label. The backdoor trigger is thus possibly recovered by computing adversarial perturbations for the target labels, and then selecting the smallest perturbation out of all labels.

Neural Cleanse (Wang et al. 2019), the first approach to use this observation, is able to detect poisoned models without access to the poisoned dataset. This method does require a number of clean image samples and full access to the trained model parameters with which it can perform gradient descent to find potential triggers. DeepInspect (Chen et al. 2019) improves this methodology in three ways. First, it simultaneously recovers potential triggers for multiple classes at once (and hence avoids the computational cost of constructing a potential trigger for each class individually). Second, it relies on model inversion (Fredrikson et al. 2015) to recover a substitute training dataset, thereby not requiring any clean data. And third, it trains a conditional GAN (Goodfellow et al. 2014) to estimate the probability density function of potential triggers for any target class. Another trigger reconstruction defense called TABOR (Guo et al. 2019) further improves upon Neural Cleanse by enhancing the fidelity of the reconstructed backdoor triggers via heuristic regularization methods. Most recently, Wang et al. (2020) study the data-limited (one shot per class) and data-free cases. In the data-limited case, they reconstruct a universal adversarial perturbation (i.e. trigger) and the image-wise perturbations for each label, the similarity of which is then used for backdoor detection. If a model is backdoored, then the universal perturbation and the image-wise one for the backdoor target label may share strong similarities due to the existence of a backdoor shortcut. In the data-free case, they first generate perturbed images from random seed images by maximizing neuron activations. Then, they detect if a model is backdoored by investigating the magnitude of the change in logit outputs with respect to random images and perturbed images.

4.2.2 Trigger-agnostic Detection

Different from the detection pipelines discussed above, MNTD (Xu et al. 2021) predicts whether a model is backdoored by examining its behavior on carefully crafted inputs. MNTD first generates a battery of benign and backdoored models. Then, a query set of images is generated and pushed through the battery of networks to create outputs. Finally, a binary meta-classifier is trained to examine these outputs and determine whether a model is backdoored. The query set is then jointly optimized with the parameters of the meta-classifier to obtain a high accuracy meta-classifier. Interestingly, this approach appears to detect attacks on architectures outside of the ensemble used to train the meta-classifier (Xu et al. 2021). Huang et al. (2020) define a "one-pixel" signature of a network, which is the collection of single-pixel adversarial perturbations that most effectively impact the label of a collection of images. They train a meta-classifier on these signatures to classify backdoored vs clean models. Kolouri et al. (2020) present a method for examining how networks respond to trigger-like patterns. A set of "universal litmus patterns" are pushed through a network, and a meta-classifier is trained on the resulting logits to determine whether the network is backdoored (Kolouri et al. 2020). Importantly, this method seems to generalizes well across architectures and backdoor attacks.

4.3 Repairing Poisoned Models after Training

While detection is useful for defending against data poisoning attacks, the methods described above only indicate whether or not an attack has occurred. Another class of methods removes backdoors from an already trained model without re-training the model from scratch. We describe methods that rely on (approximate) knowledge of the trigger and also methods that do not require such knowledge.

4.3.1 Patching Known Triggers

One line of defense strategies relies on trigger reconstruction methods to recover an approximation of the injected trigger as seen in Section 4.2.1. Once the trigger is identified, there are multiple ways of rendering it inactive. Neural Cleanse (Wang et al. 2019) shows that it is possible to identify which neurons are strongly activated by the presence of the trigger and use them to detect inputs containing the trigger during testing. Similarly, they remove the influence of these neurons by pruning them. Additionally, Neural Cleanse fine-tunes the model to *unlearn* the trigger by adding it to clean samples and training with correct labels. Rather than reconstructing a single trigger, the authors of Chen et al. (2019), Qiao et al. (2019), and Zhu et al. (2020) model a distribution of possible triggers using a GAN, which is then sampled to train an immunized model.

4.3.2 Trigger-agnostic Backdoor Removal

Another way to remove backdoor behavior is to modify the model, only keeping the parts necessary for the intended tasks. Since the backdoor is not active during forward passes on clean data, the backdoor behavior can be removed during this process. Liu et al. (2018) attempt such a defense by pruning neurons that are dormant—i.e., they are not activated on clean inputs. Specifically, their defense tests the poisoned model with clean inputs, records the average activation of each neuron, and iteratively prunes neurons in increasing order of average activation. However, this pruning defense cannot remove the backdoor without significantly degrading performance (Liu et al. 2018).

To overcome the performance loss of pruning defenses alone, several works propose fine-tuning the model on a clean dataset (Liu et al. 2018, Chen et al. 2019, Liu et al. 2020). Since the dataset does not include the backdoor trigger, the backdoor behavior may eventually be forgotten after updating the parameters during fine-tuning. Combining pruning with fine-tuning can indeed remove backdoors while preserving the overall model accuracy, even when an adversary crafts pruning-aware attacks (Liu et al. 2018). However, if the dataset used for fine-tuning is small, model performance may suffer significantly (Chen et al. 2019).

To better preserve the model's accuracy on clean data, the watermark removal framework REfiT (Chen et al. 2019) leverages elastic weight consolidation (Kirkpatrick et al. 2017). This defensive training process slows down the learning of model weights that are relevant to the main prediction task while updating other weights that are likely responsible for memorizing watermarks. Similarly, WILD (Liu et al. 2020) includes a feature distribution alignment scheme to achieve a similar goal.

4.4 Preventing Poisoning during Training

The methods described above aim to either detect or fix an already poisoned model. Here, we describe training-time strategies to avoid backdoor injection in the first place.

4.4.1 Randomized Smoothing

Randomized smoothing (Lecuyer et al. 2019, Cohen et al. 2019) was originally proposed to defend against evasion attacks (Biggio et al. 2013). Starting with a base model, a smoothed version of that model is defined by replacing the model prediction on each data point by the majority prediction in its neighborhood. The outputs of the smoothed model can be computed efficiently, while at the same time certifying its robustness to input perturbations (Cohen et al. 2019).

In the context of data poisoning, the goal is to protect the model against perturbations to the training set. Thus, the goal of *certifiable robustness* is for each test point, to return a prediction as well as a certificate that the prediction would not change had some quantity of training data been modified. To do so, one can view the entire training-plus-single-prediction pipeline as a function which can be robustified against input perturbations (Weber et al. 2020, Rosenfeld et al. 2020). Weber et al. (2020) apply this defense to backdoor attacks, where backdoor pixel perturbations are in the continuous space. On the other hand, Rosenfeld et al. (2020) use this defense against label flipping attacks where label perturbations are in the discrete space.

4.4.2 Majority Vote Mechanisms

A number of approaches utilize majority vote mechanisms to ignore poisoned samples. The underlying assumption is that the number of poisoned samples injected by the attacker is small compared to the size of the overall training dataset. Therefore, the poison samples will not significantly influence the majority vote when voters each use only a subset of the data. For example, Deep Partition Aggregation (Levine and Feizi 2020) learns multiple base classifiers by partitioning the training set into disjoint subsets. Similarly, Jia et al. (2020) train multiple base models on random subsamples of the training dataset. The base models are then combined via majority vote to produce an aggregate model, the robustness of which can be confirmed empirically and certified theoretically.Jia et al. (2020) predict the label of a test example via majority vote among the labels of its k nearest neighbors or all of its neighbors within radius r in the training dataset.

4.4.3   Differential Privacy

Differential Privacy (DP) (Dwork et al. 2006) was originally designed to protect the privacy of individuals contributing data. The core idea is that if the output of the algorithm remains essentially unchanged when one individual input point is added or subtracted, the privacy of each individual is preserved. From the perspective of data poisoning, differential privacy ensures that model predictions do not depend too much on individual data points. Thus, models will not be disproportionately affected by poisoned samples. Ma et al. (2019) study defenses based on DP against data poisoning from the practical and theoretical perspectives. Hong et al. (2020) empirically show that the off-the-shelf mechanism DP-SGD (Abadi et al. 2016), which clips and noises gradients during training, can serve as a defense. They point out that the main artifacts of gradients computed in the presence of poisoning are that their ℓ_2-norms have higher magnitudes and their orientation differs from clean gradients. Since DP-SGD bounds gradient magnitudes by clipping and minimizes the difference in orientation by random noise addition, it is successful in defending against poisoning attacks (Hong et al. 2020).

4.4.4   Input Preprocessing

Additionally, some works propose modifying the model input, during training or testing, to prevent the model from recognizing the backdoor trigger (Liu et al. 2017, Borgnia et al. 2020). Liu et al. (2017) utilize an autoencoder (Vincent et al. 2008) trained on clean data to preprocess the input. Since the input is not perfectly reconstructed (especially given that the autoencoder is not particularly sensitive to the trigger), the model is unlikely to recognize the trigger. Borgnia et al. (2020) propose using strong data augmentations during training, such as *mixup* (Zhang et al. 2017), CutMix (Yun et al. 2019), and MaxUp (Gong et al. 2020). Dramatic data augmentations sufficiently disrupt triggers and perturbations to the training data, foiling the attack. This approach is highly effective against both training-only and backdoor attacks and has the added benefit that it does not degrade model performance (Borgnia et al. 2020).

4.5   Defenses for Federated Learning

In Federated Learning (FL), a global model is trained by utilizing local data from many clients, providing a venue for new poisoning attacks from malicious clients. Since this setting allows for fundamentally different attacks compared to other learning settings (cf. Section 2.7), a number of application-specific defenses have been developed for FL. These include robust federated aggregation algorithms, robust federated training protocols, and post-training measures.

4.5.1   Robust Federated Aggregation

Robust federated aggregation algorithms attempt to nullify the effects of attacks while aggregating client updates. These methods can be broadly classified into two types; one type identifies and down-weights the malicious updates, while a second type does not attempt to identify malicious clients and instead computes aggregates in a way which is resistant to poisons. A prototypical idea for this second method estimates a true "center" of the received model updates rather than taking a weighted average.

Fung et al. (2018) identify sybils-based attacks, including label flipping and backdoors, as group actions. Sybils share a common adversarial objective whose updates are more similar to

each other than honest clients. They propose FoolsGold, which calculates the cosine similarity of the gradient updates from clients, reduces aggregation weights of clients that contribute similar gradient updates, thus promoting contribution diversity. Another avenue for defense in the FL setting is learning-based robust aggregation. Specifically, Li et al. (2020) utilize a variational autoencoder (VAE) (Kingma and Welling 2013) to detect and remove malicious model updates in aggregation, where the VAE is trained on clean model updates. The encoder projects model updates into low-dimensional embeddings in latent space, and the decoder reconstructs the sanitized model updates and generates a reconstruction error. The idea is that the low-dimensional embeddings retain essential features, so malicious updates are sanitized and trigger much higher reconstruction errors while benign updates are unaffected. Updates with higher reconstruction errors are deemed malicious and are excluded from aggregation. This method assumes that a clean dataset is available to train the detection model.

Another approach involves Byzantine-robust aggregation techniques which resist manipulation, even without identifying malicious clients. Two such algorithms, called Krum and Multi-Krum (Blanchard et al. 2017), select representative gradient updates which are close to their nearest neighbor gradients. Another algorithm called Bulyan (Mhamdi et al. 2018) first uses another aggregation rule such as Krum to iteratively select benign candidates and then aggregates these candidates by a variant of the trimmed mean (Yin et al. 2018).

Another class of approaches employs the coordinate-wise median gradient (Yin et al. 2018), geometric median of means (Chen et al. 2017), and approximate geometric median (Pillutla et al. 2019) since median-based computations are more resistant to outliers than mean-based aggregation. These methods are effective in robust distributed learning where the data of each user comes from the same distribution. However, they are less effective in FL where local data may be collected in a non-identically distributed manner across clients. Also, these methods are shown, both theoretically and empirically, to be less effective in the high-dimensional regime (Mhamdi et al. 2018). Another Byzantine-robust method called RSA (Li et al. 2019) penalizes parameter updates which move far away from the previous parameter vector and provides theoretical robustness guarantees. Unlike earlier methods, RSA does not assume that all workers see i.i.d. data from the same distribution (Li et al. 2019). Alternatively, Fu et al. (2019) estimate a regression line by a repeated median estimator (Siegel 1982) for each parameter dimension of the model updates, then dynamically assign aggregation weights to clients based on the residual of their model updates to that regression line.

4.5.2 Robust Federated Training

In addition to robust federated aggregation, several FL protocols mitigate poisoning attacks during training. Sun et al. (2019) show that clipping the norm of model updates and adding Gaussian noise can mitigate backdoor attacks that are based on the model replacement paradigm (Bagdasaryan et al. 2020, Bhagoji et al. 2019). This work highlights the success of this method on the realistic federated EMNIST dataset (Cohen et al. 2017, Caldas et al. 2018).

Andreina et al. (2020) leverage two specific features of federated learning to defend against backdoor attacks. Specifically, they utilize global models produced in the previous rounds and the fact that the attacker does not have access to a substantial amount of training data. They propose BaFFLe (Andreina et al. 2020), which incorporates an additional validation phase to each round of FL. That is, a set of randomly chosen clients validate the current global model by computing a validation function on their private data and report whether the current global model is poisoned.

The server decides to accept or reject the global model based on the feedback from validating clients. Specifically, the validation function compares the class-specific misclassification rates of the current global model with those of the accepted global models in the previous rounds and raises a warning when the misclassification rates differ significantly, which may indicate backdoor poisoning.

4.5.3 Post-Training Defenses

Other defense strategies focus on restoring the poisoned global model after training. Wu et al. (2020) extend pruning and fine-tuning methods (Liu et al. 2018) to the FL setting to repair backdoored global models. Their method requires clients to rank the dormant level of neurons in the neural network using their local data, since the server itself cannot access clean training data. They then select and remove the most redundant neurons via majority vote (Wu et al. 2020).

4.6 Open Problems

- **Defenses beyond image classification**: Although data poisoning and backdoor attacks have been applied in a variety of domains, image classification remains to be the major focus of research for defenses. It is thus crucial that these defenses are applied to other domains in order to understanding potential for real-world use, as well as any shortcomings.

- **Navigating trade-offs between accuracy, security, and data privacy:** Modern large-scale ML systems strive to achieve high accuracy while maintaining user privacy. However, these goals seem to be at odds in the presense of data poisoning. In fact, most FL defenses rely on direct access to model updates, which can reveal information about user data (Zhu et al. 2019, Geiping et al. 2020). Achieving security against poisoning while maintaining accuracy and privacy appears to be elusive given our current methods.

- **Can defenses be bypassed without access to training?** Tan and Shokri (2019) show that one can bypass certain outlier-based defenses by enforcing that the internal representations of a model on poison examples during training are similar to those corresponding to clean examples. The open question is whether these defenses can be bypassed *without access to the training protocol*.

- **Efficient and practical defenses**: Many approaches to identifying poisoned models require producing a set of auxiliary clean and poisoned models to train a detector (Xu et al. 2021, Huang et al. 2020, Kolouri et al. 2020), but this process is computational expensive. Moreover, generating additional models for trigger-agnostic methods or reconstructing possible triggers in trigger reconstruction methods (Wang et al. 2019, Guo et al. 2019) requires a clean dataset, which may not be feasible in practice. Therefore, designing efficient and practical defense methods with less data and computation requirements is essential for practical application.

- **Differential privacy and data poisoning:** Hong et al. (2020) and Jagielski et al. (2020) show that there remains a massive gap between the theoretical worst-case lower bounds provided by DP mechanisms and the empirical performance of the defenses against data poisoning. It is however unclear if this gap is due to existing attacks being insufficient or due to the theoretical bounds being unnecessarily pessimistic.

- **Certified defenses against poisoning attacks:** Certified defenses against poisoning attacks are still far from producing meaningful guarantees in realistic, large-scale settings. Moreover, they are particularly hard to study in a federated learning setting. Instead of analyzing the influence of training datasets on model predictions in an end-to-end manner like in the centralized setting (Weber et al. 2020, Rosenfeld et al. 2020), one needs to consider how the local training datasets influence the local updates, and how the performance of the global model is influenced by these local updates through aggregation.

- **Detection of inconspicuous poison examples:** Defense strategies rely on poison examples or backdoor model behavior being noticeably irregular in the context of the ambient dataset. Detecting malicious behavior when it does not appear anomalous is a much harder task, and existing methods often fail. Similarly, anomaly detection is ineffective in federated learning, where each client may have a dramatically different underlying data distribution. Picking out malicious clients from benign, yet atypical ones is an important open problem.

5   Conclusion

The expansion of the power and scale of machine learning models has been accompanied by a corresponding expansion of their vulnerability to attacks. In light of the rapid surge in work on data poisoning and defenses against it, we provide a birds-eye perspective by systematically dissecting the wide range of research directions within this space. The open problems we enumerate reflect the interests and experience of the authors and are not an exhaustive list of outstanding research problems. Moving forward, we anticipate work not only on these open problems but also on datasets and benchmarks for comparing existing methods since controlled comparisons are currently lacking in the data poisoning and backdoor literature. We hope that the overhead perspective we offer helps to illuminate both urgent security needs within industry and also a need to understand security vulnerabilities so that the community can move towards closing them.

Acknowledgements

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