Towards Privacy and Security of Deep Learning Systems: A Survey

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Abstract—Deep learning has gained tremendous success and great popularity in the past few years. However, recent research found that it is suffering several inherent weaknesses, which can threaten the security and privacy of the stackholders. Deep learning’s wide use further magnifies the caused consequences. To this end, lots of research has been conducted with the purpose of exhaustively identifying intrinsic weaknesses and subsequently proposing feasible mitigation. Yet few is clear about how these weaknesses are incurred and how effective are these attack approaches in assaulting deep learning. In order to unveil the security weaknesses and aid in the development of a robust deep learning system, we are devoted to undertaking a comprehensive investigation on attacks towards deep learning, and extensively evaluating these attacks in multiple views. In particular, we focus on four types of attacks associated with security and privacy of deep learning: model extraction attack, model inversion attack, poisoning attack and adversarial attack. For each type of attack, we construct its essential workflow as well as adversary capabilities and attack goals. Many pivot metrics are devised for evaluating the attack approaches, by which we perform a quantitative and qualitative analysis. From the analysis, we have identified significant and indispensable factors in an attack vector, \textit{e.g.}, how to reduce queries to target models, what distance used for measuring perturbation. We spotlight on 17 findings covering these approaches’ merits and demerits, success probability, deployment complexity and prospects. Moreover, we discuss other potential security weaknesses and possible mitigation which can inspire relevant researchers in this area.

Index Terms—deep learning, poisoning attack, adversarial attack, model extraction attack, model inversion attack

1 INTRODUCTION

Deep learning has gained a tremendous success and becomes the most significant driving force for artificial intelligence (AI). It fuels multiple areas including image classification, speech recognition, natural language processing, and malware detection. Due to the great advances in computing power and the dramatic increase in data volume, deep learning has exhibited superior potential in these scenarios, comparing to traditional techniques. Deep learning excels in feature learning, deepening the understanding of one object, and unparalleled prediction ability. In image recognition, convolutional neural networks (CNNs) can classify different unknown images for us, and some even perform better than humans. In natural language processing, recurrent neural networks (RNNs) or long-short-term memory networks (LSTMs) can help us translate and summarize text information. Other fields including autonomous driving, speech recognition, and malware detection all have widespread application of deep learning. Internet of things (IoT) and intelligent home system have also arisen in recent years. As such, we are stepping into the era of intelligence.

However, deep learning-based intelligent systems around us are suffering from a number of security problems. Machine learning models could be stolen through APIs [160]. Intelligent voice systems may execute unexpected commands [182]. 3D-printing objects could fool real-world image classifiers [20]. Moreover, to ensure safety, technologies such as autonomous driving need lots of security testing before it can be widely used [157] [185]. In the past few years, the security of deep learning has drawn the attention of many relevant researchers and practitioners. They are exploring and studying the potential attacks as well as corresponding defense techniques against deep learning systems. Szegedy \textit{et al.} [154] pioneer in exploring the stability of neural networks, and uncover their fragile properties in front of \textit{imperceptible perturbations}. Since then, adversarial attack has swiftly grown into a buzzing term in both artificial intelligence and security. Many efforts have been dedicated to disclosing the vulnerabilities in varying deep learning models (\textit{e.g.}, CNN [129] [114] [113], LSTM [54] [39] [131], reinforcement learning (RL) [74], generative adversarial network (GAN) [91] [138]), and meanwhile testing the safety and robustness for deep learning systems [90] [106] [124] [153] [62] [177]. On the other hand, the wide commercial deployment of deep learning systems raises the interest of proprietary asset protection such as the training data [117] [134] [186] [11] and model parameters [84] [96] [72] [88]. It has started a war where privacy hunters exert corporate espionage to collect privacy from the rivals and the corresponding defenders conduct extensive measures to counteract the attacks.

Prior works have been conducted to survey security and privacy issues in machine learning and deep learning [14] [25] [129] [22]. They enumerate and analyze attacks as well as defenses that are relevant to both training phase and prediction phase. However, these works mainly evaluate the attacks either in limited domains (\textit{e.g.}, computer vision) or perspectives (\textit{e.g.}, adversarial attack). Few studies can provide a systematical evaluation of these attacks in their entire life cycles, which include the general workflow, adversary model, and comprehensive comparisons between...
In this study, we first introduce the background of deep learning, and summarize relevant risks and commercial deep learning systems deployed in the cloud for public. For each type of attacks, we systematically study its capabilities, workflow and attack targets. More specifically, if one attacker is confronting a commercial deep learning system, what action it can perform in order to achieve the target. How the system is subverted step by step in the investigated approaches, and what influences the attack will make to both users and the system owner. In addition, we develop a number of metrics to evaluate these approaches such as reducing query strategies, precision of recovered training data, and distance with perturbed images. Based on a quantitative and qualitative analysis, we conclude many insights covering the popularity of specific attack techniques, merits and demerits of these approaches, future trend and so forth. **Takeaways.** According to our investigation, we have drawn a number of insightful findings for future research. In particular, we find that in a black-box setting, attackers have to interact by querying certain inputs from target deep learning systems. How to reduce the number of queries for avoiding the awareness of security detectors is the significant consideration for attackers. But there is few research on query reduction to date. It is doomed to be a crowded research area in the near future considering commercial deep learning systems have been equipped with more protection techniques for prohibitive queries (cf. Section 4). Substitute model is commonly seen across different attacks against deep learning systems, and becomes a prerequisite for attacks. It behaves similarly with the target model, and exhibits approximating properties. Due to the transferability, the successful attacks against the substitute model are likely effective in the target model. As a sequence, model extraction, model inversion and adversarial attack can all benefit from the substitute model. Additionally, it converts the black-box problem to a white-box one, which lowers the difficulties of attacks (cf. Section 4). Because of uncertainty of training data, data synthesis is a common practice to represent similar training data. Either generated by following the distribution or generative adversarial network, synthesized data can provide sufficient samples for training a substitute model (cf. Section 5). A more advanced way for poisoning purpose is to implant a backdoor in data and then attackers can manipulate the predictions results with crafted input (cf. Section 6). However, this technique is still far away from the mature and remains a promising area. Most of adversarial attacks have put their main efforts on addressing optimization objectives, i.e., maximizing prediction errors but minimizing “distance” with the original input (cf. Section 7). A few studies also explore their practicality and effectiveness in the physical space. In addition, the “distance” with the original input are measured in varying fashions and still need to be improved for better estimation and new applications. Moreover, we have discussed more security issues for modern deep learning systems in Section 8, such as ethical considerations and system security. Challenges of physical attacks are also presented in this paper. We have investigated some works on deep learning defenses and summarized them in terms of attacks.

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Fig. 2: Deep learning systems and the encountered attacks

Table 1: Notations used in this paper

| Notation | Explanation |
|----------|-------------|
| $D$      | dataset     |
| $x = \{x^1, \ldots, x^n\}$ | inputs in $D$ |
| $y = \{y^1, \ldots, y^n\}$ | predicted labels of $x$ |
| $y_t = \{y^1_t, \ldots, y^n_t\}$ | true labels of $x$ |
| $||x - y||^2_2$ | the Euclidean distance for $x$ and $y$ |
| $F$      | model function |
| $Z$      | output of second-to-last layer |
| $L$      | loss function |
| $w$      | weights of parameters |
| $b$      | bias of parameters |
| $\lambda$ | hyperparameters |
| $\delta$ | perturbation to input $x$ |

| 2 RELATED WORK |

There is a line of works that survey and evaluate attacks toward machine learning or deep learning.

Barreno et al. conduct a survey of machine learning security and present a taxonomy of attacks against machine learning systems [25]. They experiment on a popular statistical spam filter to illustrate their effectiveness. Attacks are dissected in terms of three dimensions, including workable manners, influence to input and generality. Amodei et al. [18] introduce five possible research problems related to accident risk and discuss probable approaches, with an example of cleaning robot, according to how it works. Papernot et al. [130] study the security and privacy of machine learning systematically. They summarize some attack and defense methods, and propose a threat model for machine learning. It introduces attack methods in training and inferring process, black-box and white-box model. However, methods they summarized in each attack are not comprehensive enough. Besides, they don’t involve much about defenses or the most widely used deep learning models.

Bae et al. [22] review the attack and defense methods under security and privacy AI concept. They inspect evasion and poisoning attacks, in black-box and white-box. In addition, their study focuses on privacy with no mention of other attack types.

Liu et al. [103] aim to provide a comprehensive literature review in two phases of machine learning, i.e., the training phase and the testing/inferring phase. As for the corresponding defenses, they sum up with four categories. In addition, this survey focuses more on data distribution drifting caused by adversarial samples and sensitive information violation problems in statistical machine learning algorithms.

Akhtar et al. [14] first conduct a comprehensive study on adversarial attacks on deep learning in computer vision. They summarize 12 attack methods for classification, and study attacks on models or algorithms such as autoencoders, generative model, RNNs and so on. They also study attacks in the real world and summarize defenses. However, they only study the computer vision part of adversarial attack.

3 OVERVIEW

3.1 Deep Learning System

Deep learning is inspired by biological nervous systems and composed of thousands of neurons to transfer information. Figure 2 demonstrates a classic deep learning model. Typically, it exhibits to the public an overall process including: 1) Model Training, where it converts a large volume of data into a data model, and 2) Model Prediction, where the model can...
be used for prediction as per input data. Prediction tasks are widely used in different fields. For instance, image classification, speech recognition, natural language processing and malware detection are all pertinent applications for deep learning.

To formalize the process of deep learning systems, we present some notations in Table 1. Given a learning task, the training data can be represented as \( x = \{x^1, x^2, \ldots, x^n\} \in D \). Let \( F \) be the deep learning model and it computes the corresponding outcomes \( y \) based on the given input \( x \), i.e., \( y = F(x) \). \( y \) is the true label of input \( x \). Within the course of model training, there is a loss function \( \mathcal{L} \) to measure the prediction error between predicted result and true label, and the training process intends to gain a minimal error value via fine-tuning parameters. The loss function can be computed as \( \mathcal{L} = \sum_{i=1}^{n} ||y^i - y^i||^2 \). So the process of model training can be formalized as [136]:

\[
\arg \min_{F} \sum_{1 \leq i \leq n} ||y^i - y^i||^2
\] (1)

3.2 Risks in Deep Learning

One deep learning system involves several pivotal assets that are confidential and significant for the owner. As per the phases in Figure 2, risks stem from three types of concerned assets in deep learning systems: 1) training dataset. 2) trained model including structure, algorithms and parameters. 3) inputs and results of predictions.

1 Training dataset. High-quality training data is significant and vital for a better performance of the deep learning model. As a deep learning system has to absorb plenty of data to form a qualified model, mislabelled or inferior data can hinder this formation and affect the model’s quality. These kinds of data can be intentionally appended to the benign by attackers, which is referred to as poisoning attack (cf. Section 6). On the other hand, the collection of training data takes lots of human resources and time costs. Industry giants such as Google have far more data than other companies. They are more inclined to share their state-of-the-art algorithms [83] [46], but they barely share data. Therefore, training data is crucial and considerably valuable for a company, and its leakage means big loss of assets. However, recent research found there is an inverse flow from prediction results to training data [161]. It leads that one attacker can infer out the confidential information in training data, merely relying on authorized access to the victim system. It is literally noted as model inversion attack whose goal is to uncover the composition of the training data or its specific properties (cf. Section 5).

2 Trained model. The trained model is a kind of data model, which is an abstract representation of its training data. Modern deep learning systems have to cope with a large volume of data in the training phase, which has a rigorous demand for high performance computing and mass storage. Therefore, the trained model is regarded as the core competitiveness for a deep learning system, endowed with commercial value and creative achievements. Once it is cloned, leaked or extracted, the interests of model owners will be seriously damaged. More specifically, attackers have started to steal model parameters [160], functionality [122] or decision boundaries [128], which are collectively known as model extraction attack (cf. Section 4).

3 Inputs and results of predictions. As for prediction data and results, curious service providers may retain user’s prediction data and results to extract sensitive information. These data may also be attacked by miscreants who intend to utilize these data to make their own profits. On the other hand, attackers may submit carefully modified input to fool models, which is dubbed adversarial example [154]. An adversarial example is crafted by inserting slight perturbations into the original normal sample which are not easy to perceive. This is recognized as adversarial attack or evasion attack (cf. Section 7).

3.3 Commercial Off-The-Shelf

Machine learning as a Service (MLaaS) has gained the momentum in recent years [99], and lets its clients benefit from machine learning without establishing their own predictive models. To ease the usage, the MLaaS suppliers make a number of APIs for clients to accomplish their own predictive tasks, e.g., classifying an image, recognizing a slice of audio or identifying the intent of a passage. Certainly, these services are the core competence which also charge clients for their queries. Table 2 shows representative COTS as well as their functionalities, outputs to the clients, and usage charges. Taking Amazon Image Recognition for example, it can recognize the person in a profile photo and tell his/her gender, age range, emotions. Amazon charges this service with 1,300 USD per one million queries.

3.4 Dataset

Here we present common datasets used in our paper. In image field, there are MNIST [95], CIFAR-10 [93], ImageNet [2], GTSRB [5], GSS [4], IJB-A [7] and so on. In text field, reviews from IMDB [8] are usually used. In speech field, corpora such as Mozilla Common Voice [10] are used. In malware field, datasets include DREBIN [1], Microsoft Kaggle [9], and millions of files or programs they found.

4 MODEL EXTRACTION ATTACK: YOUR MODEL IS MINE

4.1 Introduction

Model extraction attack attempts to duplicate a machine learning model through the provided APIs, without prior knowledge of training data and algorithms [160]. To formalize, given a specifically selected input \( X \), one attacker queries the target model \( F \) and obtains the corresponding prediction results \( Y \). Then the attacker can infer or even extract the entire in-use model \( F \). With regard to an artificial neural network \( y = wx + b \), model extraction attack can somehow approximate the values of \( w \) and \( b \). Model extraction attacks cannot only destroy the confidentiality of model, thus damaging the interests of its owners, but also construct a near-equivalent white-box model for further attacks such as adversarial attack [128].

Adversary Model. This attack is mostly carried out under a black-box model and attackers only have access to prediction APIs. Their capabilities are limited in three ways:
model knowledge, dataset access, and query frequency. In particular, attackers have no idea about model architectures, hyperparameters, training process of the victim’s model. They cannot obtain natural data with the same distribution of the target’s training data. In addition, attackers may be blocked by the target if submitting queries too frequently.

Workflow. Figure 3 shows a typical workflow of this attack. First, attackers submit inputs to the target model and get prediction values. Then they use input-output pairs and different approaches to extract the confidential data. More specifically, confidential data includes parameters [160], hyperparameters [165], architectures [119], decision boundaries [128] [84], and functionality [122] [45] of the model.

### 4.2 Approaches

There are basically three types of approaches to extract models:

- **Equation Solving (ES).** For a classification model computing class probabilities as a continuous function, it can be denoted as \( F(x) = \sigma(w \cdot x + b) \) [160]. Hence, given sufficient samples \((x, F(x))\), attackers can recover the parameters (e.g., \(w, b\)) by solving the equation \( w \cdot x + b = \sigma^{-1}(F(x)) \).

- **Training Metamodel (MM).** Metamodel is a classifier for classification models [119]. By querying a classification model on the outputs \( Y \) for certain inputs \( X \), attackers train a meta-model \( F^m \), mapping \( Y \) to \( X \), i.e., \( X = F^m(Y) \). The trained model can further predict model attributes from the query outputs \( Y \).

- **Training Substitute Model (SM).** Substitute model is a simulative model mimicking behaviors of the original model. With sufficient querying inputs \( X \) and corresponding outputs \( Y \), attackers train the model \( F^s \) where \( Y = F^s(X) \). As a result, the attributes of the substitute model can be near-equivalent to those of the original.

Stealing different information corresponds to different methods. In terms of time, equation solving is earlier than training meta- and substitute model. It can restore precise parameters but is only suitable for small scale models. Due to the increase of model size, it is common to train a substitute model to simulate the original model’s decision boundaries or classification functionalities. However, precise parameters seem less important. Metamodel [119] is an inverse training with substitute model, as it takes the query outputs as input and predicts the query inputs as well as model attributes. Besides, it can be also used to explore more informative inputs that help infer more internal information of model.

### 4.3 Extracted Information

#### 4.3.1 Parameters & Hyperparameter

Parameters are weight values (\( w \)) of layer to layer, and bias values (\( b \)) of each layer. Hyperparameters refer to parameters during training, including dropout rate, learning rate, mini-batch size, parameters in objective functions to balance loss function and regularization terms, and so on. In the early work, Tramèr et al. [160] tried equation solving to recover parameters in machine learning models, such as logistic regression, SVM, and MLP. They built equations about the model by querying APIs, and obtained parameters by solving equations. However, it needs plenty of queries and is not applicable to DNN. Wang et al. [165] tried to steal hyperparameter-\( \lambda \) on the premise of known model algorithm and training data. \( \lambda \) is used to balance loss functions and regularization terms. They assumed that the gradient of the objective function is \( \bar{0} \) and thus got many linear equations through many queries. They estimated the hyperparameters through linear least square method.

#### 4.3.2 Architectures

Architectures include that how many layers in the model, how many neurons in each layer, how are they connected, what activation functions are used, and so on. Recent papers usually train classifiers to predict attributes. Joon et al. [119] trained Metamodel, a supervised classifier of classifiers, to steal model attributes (architecture, operation time, and training data size). They submitted query inputs via APIs, and took corresponding outputs as inputs of metamodel, then trained metamodel to predict model attributes as outputs.

#### 4.3.3 Decision Boundaries

Decision boundaries are the classification boundary between any two classes. In [128] [84] [127], they steal decision boundaries and generate transferable adversarial samples to attack black model. Papernot et al. [128] used Jacobian-based Dataset Augmentation (JbDA) to produce synthetic

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**Table 2:** Commercial MLaaS systems and the provided functionalities, output for clients and charges per 1M queries

| System                | Functionality                  | Output                               | Cost/M-times |
|-----------------------|--------------------------------|--------------------------------------|--------------|
| Alibaba Image Recognition | Image marking          | label, confidence                    | 2500 CNY     |
|                       | scene recognition         | label, confidence                    | 1500 CNY     |
|                       | porn identification       | label, suggestion                    | 1620 CNY     |
| Amazon Image Recognition | Object & Scene Recognition | label, boundingbox, confidence       | 1300 USD     |
|                       | face recognition          | AgeRange, boundingbox, emotions, eyeglasses, gender, pose, etc | 1300 USD     |
| Google Vision API     | label description         | description, score                   | 1500 USD     |

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**Fig. 3:** Workflow of model extraction attack
samples, which moved to the nearest boundary between current class and all other classes. This technology aims not to maximize the accuracy of substitute models, but ensures that samples arrive at decision boundaries with small queries. Juuti et al. [84] extended JbDA to Jb-topk, where samples move to the nearest k boundaries between current class and any other class. They produced transferable targeted adversarial samples rather than untargeted [128]. In terms of model knowledge, Papernot et al. [127] found that model architecture knowledge was unnecessary because a simple model could be extracted by more complex model, such as DNN.

4.3.4 Functionalities

Similar functionalities refer to replicating the original model as much as possible on classification results. The primary goal is to construct a predictive model that have closest input-output pairs with the original. In [122] [45], they try to improve classification accuracy of substitute model. Silva et al. [45] used problem domain dataset, non-problem domain dataset, and their mixture to train a model respectively. They found model trained with non-problem domain dataset also did well in accuracy. Besides, Orekondy et al. [122] assumed attackers had no semantic knowledge over model outputs. They chose very large datasets and selected suitable samples one by one to query the black-box model. Reinforcement learning approach was introduced to improve query efficiency and reduce query counts.

4.4 Analysis

Model extraction attack is an emerging field of attack. In this study, we totally survey 8 related papers and classify them by target information as shown in Table 3. We sort them by the stolen information and evaluate them on multiple aspects including employed approaches, strategies for reducing queries, recovery rate for applicable models. Recovery rate means how many percent of information can be stolen, and is computed by differing the inferred data with that of the original model. However, the attacks on boundary decision cannot be directly measured in this way. Thus, we use the misclassification rate of generated adversarial examples as an alternative, since it reveals the similarity between the simulative model and the original model to some extent. Based on the statistics, we draw the following conclusions.

Finding 1. Training substitute model is by no doubt the dominant method in model extraction attacks with manifold advantages.

Finding 2. To learn a substitute model of deep learning models demands more queries than to infer parameters or hyperparmaeters in simple machine learning models.

Finding 3. Reducing queries, which can save monetary costs for a pay-per-query MLaaS commercial model and also be resistant to attack detection, has become an intriguing research direction in recent years.

The requirement of query reduction arises due to the high expense of queries and query amount limitation. In our investigated papers, [119] trains a metamodel–KENNEN-IO for optimizing the query inputs. [128], leverage reservoir sampling to select representative samples for querying, and [122] proposes two sampling strategies, i.e., random and adaptive to reduce queries. Moreover, active learning [97], natural evolutionary strategies [78], optimization-based approaches [44] [140] have been adopted for query reduction.

Finding 4. Model extraction attack is evolving from a puzzle solving game to a simulation game with cost-profit tradeoffs.

Table 3: Evaluation on model extraction attacks as per stolen information.

| Information | Paper | Approach | Reducing Query | Recovery Rate (%) for Models |
|-------------|-------|----------|----------------|-------------------------------|
| Parameter   | Tramer et al. [160] | ES | - | SVM: 99, DT: 99, LR: 99, KNN: 99, CNN: 99, DNN: 99 |
| Hyper-par   | Wang et al. [165] | ES | - | SVM: 99, DT: 99, LR: 99, KNN: 99, CNN: 99, DNN: 99 |
| Arch.       | Joon et al. [119] | MM | KENNEN-IO | SVM: -, DT: -, LR: -, KNN: -, CNN: -, DNN: 88 |
| Decision.   | Papernot et al. [128] | SM | reservoir sampling [163] | SVM: -, DT: -, LR: -, KNN: -, CNN: -, DNN: 84 |
| Decision.   | Papernot et al. [127] | SM | reservoir sampling [163] | SVM: 83, DT: 61, LR: 89, KNN: 85, CNN: 89, DNN: 89 |
| Decision.   | PRADA [84] | SM | - | SVM: -, DT: -, LR: -, KNN: -, CNN: -, DNN: 67 |
| Func.       | Silva et al. [45] | SM | random, adaptive sampling | SVM: -, DT: -, LR: -, KNN: -, CNN: -, DNN: 98 |
| Func.       | Orekondy et al. [122] | SM | - | SVM: -, DT: -, LR: -, KNN: -, CNN: -, DNN: 98 |
infer how many layers or neurons in the neural networks become impossible and unaffordably costly. Therefore, it makes a remarkable dent in attackers’ interest of solving model attributes. On the other hand, inferring decision boundary and model functionality emerge as new circumvention. Treating the target model as a black box, attackers observes the response by feeding it with crafted inputs, and finally construct a close approximation. Although the substitute model is likely simpler and underperforms in some cases, its prediction capabilities still make considerable profits for attackers.

5 Model Inversion Attack: Your Model Reveals Your Information

5.1 Introduction

In a typical model training process, lots of information is extracted and abstracted from the training data to the product model. However, there also exists one inverse information flow which allows attackers infer the training data from the model since neural networks may remember too much information of the training data [148]. Model inversion attack is just to leverage this information flow and restore the feed data or data properties such as faces in face recognition systems through model prediction or its confidence coefficient.

Additionally, model inversion attack can be further refined into membership inference attack (MIA) and property inference attack (PIA). In MIA, the attacker can determine whether a specific record is included or not in the training data. In PIA, the attacker can speculate whether there is a certain statistical property in the training dataset. Adversary Model. Model inversion attack can be executed in both black-box or white-box settings. In a white-box attack, the parameters and architecture of the target model are known by attackers. Hence, they can easily obtain a substitute model that behaves similarly, even without querying the model. In a black-box attack, attacker’s capabilities are limited in model architectures, statistics and distribution of training data and so on. Attackers cannot obtain complete training set information. However, in either setting, attackers can make queries with specific inputs and get corresponding outputs as well as class probabilities and confidence values.

Workflow. Figure 4 shows a workflow of model inversion attack which is suitable for both MIA and PIA. Here we take MIA as an example. MIA can be accomplished in varying ways: by querying the target model to get input-output pairs, attackers can merely exercise Step 4 with heuristic methods to determine the membership of a record [137] [19] (Approach 2); Due to the limitation of queries and model attributes, some studies introduce shadow models to provide training data for the attack model [147] [143], which necessitates shadow model training (Step 3). Attack model’s training data is obtained by query inputs and response [137] [19] (Approach 2); Alternatively, attackers can train an attack model for determination, which necessitates an attack model training process (Step 3). Attack model’s training data is obtained by query inputs and response [137] [19] (Approach 2); Due to the limitation of queries and model attributes, some studies introduce shadow models to provide training data for the attack model [147] [143], which necessitates shadow model training (Step 3). Moreover, data synthesis (Step 1) is proposed to provide more training data for a sufficient training (Approach 3).

5.2 Membership Inference Attack

Truex et al. [161] presented a generally systematic formulation of MIA. Given the instance $x$ and black-box access to the classification model $F_t$ trained on the dataset $D$, can an adversary infer whether the instance $x$ is included in $D$ when training $F_t$ with a high degree of confidence?

Most of MIAs proceed in accordance with the workflow in Figure 4. More specifically, to infer whether one data item or property exists in the training set, the attacker may prepare the initial data and make transformations to the data. Subsequently, it devises a number of principles for determining the correctness of its guessing. We details these components as follows.

5.2.1 Data Synthesis

Initial data has to be collected as prerequisites for determining the membership. According to our investigation, an approximated set of training data is desired to imply membership. This set can be obtained either by:

- **Generate samples manually.** This method needs some prior knowledge to generate data. For instance, Shokri [147] produced datasets similar to the target training dataset and used the same MLaaS to train several shadow models. These datasets were produced by model-based synthesis, statistics-based synthesis, noisy real data and other methods. If the attacker has access to part of dataset. Then he can generate noisy real data by flipping a few randomly selected features on real data. These data make up the noisy dataset. If the attacker has some statistical information about dataset, such as marginal distributions of different features. Then he can generate statistics-based synthesis using this knowledge. If the attacker has no knowledge above, he can also generate model-based synthesis by searching for possible data records. The records that search algorithm needs to find are correctly classified by target model with high confidence.

In [143], they proposed a data transferring attack without any query to target model. They chose different datasets to train the shadow model. The shadow model was used to capture membership status of data points in datasets.
• Generate samples by model. This method aims to produce training records by training generated models such as GAN. Generated samples are similar to that from the target training dataset. Improving the similarity ratio will make this method more useful.

Both [102] and [67] attacked generated models. Liu et al. [102] presented a new white-box method for single membership attacks and co-membership attacks. The basic idea was to train a generated model with the target model, which took the output of the target model as input, and took the similar input of the target model as output. After training, the attack model could generate data that is similar to the target training dataset. Considering about the difficult implementation of CNN in [147]. Hitaj et al. [69] proposed a more general MIA method. They performed a white-box attack in the scenario of collaborative deep learning models. They constructed a generator for target classification model, and used them to form a GAN. After training, GAN could generate data similar to the target training set. However, this method was limited in that all samples belonging to the same classification need to be visually similar, and it could not generate an actual target training pattern or distinguish them under the same class.

5.2.2 Shadow Model Training

Attacker have sometimes to transform the initial data for further determination. In particular, shadow model is proposed to imitate target model’s behavior by training on a similar dataset [147]. The dataset takes records by data synthesis as inputs, and their labels as outputs. Shadow model is trained on such dataset. It can provide class probability vector and classification result of a record. Shokri et al. [147] designed, implemented and evaluated the first MIA attack method for a black-box model by API calls in machine learning. They produced datasets similar to the target training dataset and used the same MLaaS to train several shadow models. These datasets were produced by model-based synthesis, statistics-based synthesis, noisy real data and other methods. Shadow models were used to provide training set (class labels, prediction probabilities and whether data record belongs to shadow training set) for the attack model. Salem et al. [143] relaxed the constraints in [147] (need to train shadow models on the same MLaaS, and the same distribution between datasets of shadow models and target model), and used only one shadow model without the knowledge of target model structure and training dataset distribution. Here, the shadow model just tried to capture the membership status of records in a different dataset.

5.2.3 Attack Model Training

The attack model is a binary classifier. Its input is the class probabilities and label of the record to be judged, and output is yes (means the record belongs to the dataset of target model) or no. Training dataset is usually required to train the attack model. The problem is that the output label of whether a record belongs to the dataset of target model cannot be obtained. So here attackers often generate substituted dataset by data synthesis. The input of this training is generated either by the shadow model [147] or the target model [137] [111]. The training process is to select some records from both inside and outside the substituted dataset, and obtain the class probability vector through target model or shadow model. The vector and the label of record are taken as input, and whether this record belongs to substituted dataset is taken as output. Then training and learning attack model.

5.2.4 Membership Determination

Given one input, this component is responsible for determining whether the query input is a member of the training set of the target system. To accomplish the goal, the contemporary approaches can be categorized into three classes:

• Attack model-based Method. In inference phase, attackers first put record to be judged into the target model, and get its class probability vector, then put the vector and label of record into the attack model, and get the membership of this record. Pyrgelis et al. [137] implemented MIA for aggregating location data. The main idea was to use priori position information and attack through distinguishability game process with a distinguishing function. They trained a classifier (attack model) as distinguishing function to determine whether data is in target dataset.

• Heuristic Method. This method uses prediction probability, instead of an attack model, to determine the membership. Intuitively, the maximum value in class probabilities of a record in the target dataset is usually greater than the record not in it. But they require some preconditions and auxiliary information to obtain reliable probability vectors or binary results, which is a limitation to apply to more general scenarios. How to lower attack cost and reduce auxiliary information can be considered in the future study. Fredrikson et al. [52] tried to construct the probability of whether a certain data appears in the target training dataset, according to the probability and auxiliary information, such as error statistics or marginal priors of training data. Then they searched for input data which maximized the probability, and the obtained data was similar to data in target training dataset. The third attack method in Salem et al. [143] only required the probability vector of outputs from the target model, and used statistical measurement method to compare whether the maximum classification probability exceeds a certain value.

Long et al. [104] put forward Generalized MIA method, which was easier to attack non-overfitted data, different from [147]. They trained a number of reference models similar to the target model, and chose vulnerable data according to the output of reference models before Softmax, then compared outputs between the target model and reference models to calculate the probability of data belonging to target training dataset. Reference models in this paper were used to mimic the target model, like shadow models. But they did not need an attack model. Haynes et al. [67] proposed a method of attacking generated models. The idea was that attackers determined which dataset from attackers belonged to target training set, according to the probability vector output by classifier. Higher probability was more likely from target training set (they selected the upper n sizes). In white-box, the
classifier was constructed by that of target model. In black-box, they used obtained data by querying target model to reproduce classifier with GAN.

5.3 Property Inference Attack

Property inference attack (PIA) mainly deduces properties in the training dataset. For instance, how many people have long hair or wear dresses in a generic gender classifier. Is there enough women or minorities in dataset of common classifiers. The approach is largely same to a membership inference attack. In this section, we only remark main differences between model inversion attacks.

Data Synthesis. In PIA, training datasets are classified by including or not including a specific attribute [19].

Shadow Model Training. In PIA, shadow models are trained by training sets with or without a certain property. In [19] [53], they used several training datasets with or without a certain property, then built corresponding shadow models to provide training data for meta-classifier.

Attack Model Training. Here, attack model is usually also a binary classifier. Atieniese et al. [19] proposed a white-box PIA method by training a meta-classifier. It took model features as input, and output whether the corresponding dataset contained a certain property. However, this approach did not work well on DNNs. To address this, Ganju et al. [53] mainly studied how to extract feature values of DNNs. The part of meta-classifier was similar to [19]. Melis et al. [111] trained a binary classifier to judge dataset properties in collaborative learning, which took updated gradient values as input. Here the model is continuously updated, so attacker could analyze updated information at each stage to infer properties.

5.4 Analysis

As shown in Table 4, we have totally surveyed 13 model/property inversion attack papers.

Finding 5. Shadow model has a number of advantages over other methods in model inversion attack.

Shadow models (4/13) are used in both MIA (2/13) [147] [143] and PIA (2/13) [19] [53]. It is superior than other methods in manifolds: 1) requiring no addition auxiliary information [52], which is underlied by the assumption that a higher confidence of prediction indicates the presence of data records of a higher probability. 2) providing true information as training dataset for attack model. For a model $F$ and its training dataset $D$, training attack model needs information of label $x$, $F(x)$, and whether $x \in D$. If using a shadow model, shadow model $F$ and its dataset $D$ are known. All information is from shadow model and corresponding dataset. If using the target model, $F$ is the target model and $D$ is the training dataset. However, attackers do not know $D$. So information whether $x \in D$ need to be replaced by whether $x \in D'$, where $D'$ is similar to $D$.

Finding 6. Data synthesis is a common practice to conduct model inversion attack, compared to direct querying.

Data synthesis could generate data similar to target dataset conveniently [147] [52] [69] [102], without querying too many times. The synthesized data, which could be generated either by the statistical distribution of known training data, or a generative adversarial network, can effectively sample the original data. Hence, it is employed to train a shadow model, a substitute for the target. It avoids too many queries to the target model and thereby lowers the perception by security mechanisms.

Finding 7. MIA is essentially a process that explicitly expresses the logical relations contained in the trained model.

This kind of attacks requires many datasets and much time, but the obtained information is really limited (only 1 bit [19] [53]). So the development of model inversion attack is to obtain more overall information. For example, what is the relationship between different training datasets. What's more, another development is to increase the amount of the obtained information, for example, how to get details in a single record.

Finding 8. Research about membership inference (10/13) is more than property inference (4/13).

This is because membership inference now has a more general adaptation scenario, and it emerges earlier. Furthermore, MIA can get more information than PIA in one-time attack (just like training an attack model). A trained attack model can be applied to many records in MIA, but only a few properties in PIA. In [19], attackers want to know if their speech classifier was trained only with voices from people who speak Indian English. In [53], they try to find if some classifiers have enough women or minorities in training dataset. In [33], they are interested in the global distribution of skin color. In [111], they want to know the proportion between black and asian people.

Finding 9. Studies about heuristic methods (6/13) and attack model (7/13) nearly share on a fifty-fifty basis.

In heuristic methods, using probabilities is easy to implement, but barely works (0.5 precision and 0.54 recall) on MNIST dataset [143]. Obtaining similar datasets usually needs to train a generative model [67] [102] [69]. In attack model methods, attackers need to train an attack model [137] [19]. Shadow models [147] [143] [19] are proposed to provide datasets for the attack model, but increase training costs.

6 Poisoning Attack: Create a Backdoor in Your Model

Poisoning attack seeks to downgrade deep learning systems’ predictions by polluting training data. Since it happens before the training phase, the caused contamination is usually inextricable by tuning the involved parameters or adopting alternative models.

6.1 Introduction

In the early age of machine learning, poisoning attack had been proposed as a non-trivial threat to the mainstream algorithms. For instance, Bayes classifiers [118], Support Vector Machine (SVM) [28] [31] [174] [173] [34], Hierarchical Clustering [29], Logistic Regression [110] are all suffering
to making wrong predictions. This is likely caused by the model could not well represent the correct data and prone by deviating its decision boundary. As a result, the poisoned data. One intuitive goal is to destroy the model’s availability over the training dataset. In particular, it discriminates how much new poisoned data attackers can insert, and whether the degradation from data poisoning. Along with the broad use of deep learning, attackers have moved their attention to deep learning instead. Attackers can implement this attack with full knowledge (white-box) and limited knowledge (black-box). Knowledge mainly means the understanding of training process, including training algorithms, model architectures, and so on. Capabilities of attackers refer to controlling over the training dataset. In particular, it discriminates how much new poisoned data attackers can insert, and whether they can alter labels in the original dataset and so on. Attack Goal. There are two main purposes for poisoning the data. One intuitive goal is to destroy the model’s availability by deviating its decision boundary. As a result, the poisoned model could not well represent the correct data and prone to making wrong predictions. This is likely caused by mislabeled data (cf. Section 6.2.1), whose labels are intentionally tampered by attackers, e.g., one photo with a cat in it is labeled as dog. The other purpose is to create a backdoor in the target model by inserting confused data (cf. Section 6.2.2). The model may behave normally at most of the time, but arouse wrong predictions with crafted data. With the pre-implanted backdoor and trigger data, one attacker can manipulate prediction results and launch further attacks.

Workflow. Figure 5 shows a common workflow of poisoning attack. Basically, this attack is accomplished by two methods: mislabel original data, and craft confused data. The poisoned data then enters into the original data and subverts the training process, leading to greatly degraded prediction capability or a backdoor implanted into the model. More specifically, mislabeled data is yielded by selecting certain records of interest and flipping their labels. Confused data is crafted by embedding special features that can be learnt by the model which are actually not the essence of target objects. These special features can serve as a trigger, incurring an wrong classification.

6.2 Poisoning Approach
6.2.1 Mislabeled Data
Learning model usually experiences training under labeled data in advance. Attackers may get access to a dataset, and change a correct label to wrong. Mislabeled data could push decision boundary of classifier significantly to incorrect zones, thus reducing its classification accuracy. Muñoz-González et al. [115] undertook a poisoning attack towards multi-class problem based on back-gradient optimization. It calculated gradient by automatic differentiation and reversed the learning process to reduce attack complexity. This attack is resultful for spam filtering, malware detection and handwritten digit recognition.

Xiao et al. [174] adjusted a training dataset to attack SVM by flipping labels of records. They proposed an optimized framework for finding the label flips which maximizes classification errors, and thus reducing the accuracy of classifier successfully. Biggio et al. [29] used obfuscation attack to maximally worsen clustering results, where they relied on heuristic algorithms to find the optimal attack strategy. Alfeld et al. [17] added optimal special records into training dataset to drive predictions in a certain direction. They presented a framework to encode an attacker’s desires and constraints under linear autoregressive models. Jagielski et al. [79] could manipulate datasets and algorithms to influence linear regression models. They also introduced a fast
TABLE 5: Evaluation on poisoning attack. The data denotes an attacker needs to contaminate how many percent of training data “Poison Percent” and achieves how many “Success Rate” under specific “Dataset”. “Model” indicates the attacked model. “Timeliness” denotes whether the poison attack is in an online or offline setting. “Damage” means how many predictions can be impacted. Attackers may possess two different “Knowledge”, either black-box or white-box, and make poisoned model predict as expected, i.e., “Targeted”, or not. “structured data” is the same as Table 4. “LR” is linear regression. “OLR” is online logistic regression. “SLHC” is single-linkage hierarchical clustering.

| Paper                        | Success Rate | Dataset          | Poison Percent | Model | Timeliness | Damage | Knowledge | Targeted | Application |
|------------------------------|--------------|------------------|----------------|-------|------------|--------|-----------|----------|-------------|
| Xiao et al. [172]            | 20%          | 11944 files      | 5%             | LASSO | offline    | -      | Black     | No       | malware     |
| Muñoz-González et al. [115]  | 25%          | MNIST            | 15%            | CNN   | offline    | 30% error | Black     | No       | image, malware|
| Jagielski et al. [79]        | 75%          | Health care dataset | 20%         | LASSO | offline    | 75% error | Black     | No       | structured data |
| Alfeld et al. [17]           | -            | -                | -              | LR    | offline    | -      | White     | Yes      | -           |
| Shafahi et al. [144]         | 60%          | CIFAR-10         | 5%             | DNN   | offline    | 20% error | White     | Yes      | image       |
| Wang et al. [171]            | 90%          | MNIST            | 100%           | OLR   | online     | -      | White     | Both     | image       |
| Biggio et al. [29]           | -            | MNIST            | 1%             | SLHC  | offline    | -      | White     | Yes      | image, malware|

Finding 11. A few (2/7) papers use confused data with the purpose of implanting a backdoor into the model.

Finding 12. Poisoning attacks essentially seek for a globally or locally distributional disturbance over training data.

It is well-known that the performance of learning is largely dependent on the quality of training data. Quality data is commonly acknowledged as being comprehensive, unbiased, and representative. In the process of data poisoning, wrongly labeled or biased data is deliberately crafted and added into training data, degrading the overall quality.

7 Adversarial Attack: Utilize the Weakness of Your Model

Similar to poisoning attack, adversarial attack also makes a model classify a malicious sample wrongly. Their difference is that poisoning attack inserts malicious samples into the training data, directly contaminating model, while adversarial attack leverages adversarial examples to exploit the weaknesses of the model and gets a wrong prediction result.

statistical attack which only required limited knowledge of training process.

The major research focuses on an offline environment where the classifier is trained on fixed inputs. However, training often happens as data arrives sequentially in a stream, i.e., in an online setting. Wang et al. [171] conducted poisoning attacks for online learning. They formalized the problem into semi-online and fully-online, with three attack algorithms of incremental, interval and teach-and-reinforce.

6.2.2 Confused Data

Learning algorithms elicit representative features from a large amount of information for learning and training. However, if attackers submit crafted data with special features, the classifier may learn fooled features. For example, marking figures with number “6” as a turn left sign and putting this instance is added to poisoned instances to allow overlap of some indivisible features.

6.3 Analysis

We investigated 7 papers on poisoning attack in total and evaluate them over 9 metrics in Table 5. Based on the analysis, we conclude the following findings.

Finding 10. Most attacks (6/7) are under an offline setting, and only one [171] implements an online attack via online gradient descent.
7.1 Introduction
Adversarial attack adds unperceived perturbations to normal samples during the prediction process, and then produces adversarial examples (AEs). This is an exploratory attack and violates the availability of a model. It can be used in many fields, e.g., image, speech, text, and malware, particularly widespread in image classification. They can deceive the trained model but look nothing unusual to humans. That is to say, AEs need to both fool the classifier and be imperceptible to humans. For an image, the added perturbation is usually tuned by minimizing the distance between the original and adversarial examples. For a piece of speech or text, the perturbation should not change the original meaning or context.

Workflow. Figure 6 depicts the general workflow for an adversarial attack. In white-box setting, attackers could directly calculate gradients [58] [16] [47] or solve optimization functions [38] [42] [68] to find perturbations on original samples (Step 1). Then they could train a substitute model to perform a white-box attack [127] [128] (Step 2.1), or estimate gradients (Step 2). In black-box setting, attackers obtain information by querying the target model many times (Step 1). They then could train a substitute model to perform a black-box attack [127] [128] (Step 2.1), or estimate gradients to search for AEs [77] (Step 2.2).

In addition to deceiving the classification model, AEs should carry minimal perturbations that evade the awareness of human. Generally, the distance between normal and adversarial sample can be measured by $L_p$ Distance (or Minkowski Distance), e.g., $L_0$, $L_1$, $L_2$ and $L_{\infty}$.

$$L_p(x, y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{\frac{1}{p}}$$

$$x = \{x^1, x^2, ..., x^n\}, \quad y = \{y^1, y^2, ..., y^n\}$$

7.2 Approach
Since the main development of adversarial attack is in the field of image classification [154] [58] [38], we will introduce more related work on image using CNN, and supplement research on other fields or other models at the end of this section.

7.2.1 White-box attack in image classification
First, we define that $F : \mathbb{R}^n \rightarrow \{1 \ldots k\}$ is the classifier of model to map image value vectors to a class label. $Z(\cdot)$ is the output of second-to-last layer, usually indicates class probability. $Z(\cdot)_t$ is the probability of $t$-th class. $Loss$ function describes the loss of input and output. $\delta$ is the perturbation. $||\delta||_p$ is the $p$-norm of $\delta$. $x \in \{x^1, x^2, ..., x^n\}$ is the original sample, $x^i$ is the pixel or element in sample where $x^i \in x, 1 \leq i \leq n$. $x_i$ is sample of the $i$-th iteration, usually $x_0 = x$.

The process of finding perturbations essentially needs to solve the following optimization problems (the first equation is non-targeted attack, the second equation is targeted attack, $T$ is targeted class label):

$$\arg \min_{\delta} ||\delta||_p, s.t. F(x + \delta) \neq F(x)$$

$$\arg \min_{\delta} ||\delta||_p, s.t. F(x + \delta) = T$$

Methods of finding perturbations can be roughly divided into calculating gradients and solving optimization function. Szegedy et al. [154] first proposed an optimization function to find AEs and solved it with L-BFGS. FGSM [58], BIM [16], MI-FGSM [47] are a series of methods to find perturbations by directly calculating gradients. Deepfool [114] and NewtonFool [81] approximate the nearest classification boundary by Taylor expansion. Instead of perturbing a whole image, JSMA [129] finds a few pixels to perturb through calculating partial derivative. C&W [38], EAD [42], OptMargin [68] are a series of methods to find perturbations by optimizing the objective function.

L-BFGS attack. Szegedy et al. [154] tries to find $\delta$ that satisfies $F(x + \delta) = l$, so to minimize perturbation and $Loss$ function, using Box-constrained L-BFGS to solve this constraint optimization problem. In Equation 4, $c (> 0)$ is a hyperparameter and obviously, $Loss(x, F(x)) = 0$.

$$\min_{\delta} c \cdot ||\delta||_2 + Loss(x + \delta, l)$$

$$s.t. \quad x + \delta \in [0, 1]^n$$

(4)

FGSM attack. Goodfellow et al. [58] attacked the classifier based on the gradient of input. $l_z$ is the true label of $x$. The direction of perturbation is determined by the computed gradient using back-propagation. Each pixel goes $\varepsilon$ size in gradient direction.

$$\delta = \varepsilon \cdot sign(\nabla_x Loss(x, l_z))$$

(5)

BIM attack. BIM (or I-FGSM) [16] iteratively changes the step for new inputs as Equation 6. $l_x$ is the true label of $x$. $Clip_{x,\mu}(\cdot)$ function performs clamping on image per-pixel.

$$x_0 = x$$

$$x_{i+1} = Clip_{x,\mu}(x_i + \alpha \cdot sign(\nabla_x Loss(x_i, l_x)))$$

(6)

MI-FGSM attack. MI-FGSM [47] adds momentum based on I-FGSM [16]. Momentum is used to escape from poor local maximum and iterations are used to stabilize optimization. In Equation 7 $y$ is the target class to be misclassified as:

$$x_{i+1} = Clip_{x,\mu}(x_i + \alpha \cdot \frac{g_{i+1}}{\|g_{i+1}\|_2})$$

$$g_{i+1} = \mu \cdot g_i + \frac{\nabla_x Loss(x_i, y)}{\|\nabla_x Loss(x_i, y)\|_1}$$

(7)

JSMA attack. JSMA [129] modifies a few pixels at every iteration. In each iteration, shown in Equation 8, $\alpha_{pq}$ represents the impact on target classification of pixels $p, q,$ and
\( \beta_{pq} \) represents the impact on all other outputs. Larger values in this map mean greater possibility to fool the network. They pick \((p^*, q^*)\) to attack.

\[
\alpha_{pq} = \sum_{i \in \{p,q\}} \frac{\partial Z(x)_i}{\partial x^i}
\]

\[
\beta_{pq} = \left( \sum_{i \in \{p,q\}} \sum_j \frac{\partial Z(x)_j}{\partial x^i} - \alpha_{pq} \right)
\]

\[
(p^*, q^*) = \arg \max_{(p,q)} (\alpha_{pq} - \beta_{pq}) \cdot (\alpha_{pq} > 0) \cdot (\beta_{pq} < 0)
\]

**NewtonFool attack.** NewtonFool [81] uses softmax output \( Z(x) \). In Equation 9, \( x_0 \) is the original sample and \( l = F(x_0) \). \( \delta_i = x_{i+1} - x_i \) is the perturbation at iteration \( i \). They tried to find small \( \delta \) so that \( Z(x_0 + \delta) \approx l \) \( \approx 0 \). Starting with \( x_0 \), they approximated \( Z(x_i)_l \) using a linear function step by step as follows.

\[
Z(x_{i+1}) \approx Z(x_i)_l + \nabla Z(x_i)_l \cdot (x_{i+1} - x_i), \ i = 0, 1, 2, \ldots
\]

**C&W attack.** C&W [38] tries to find small \( \delta \) in \( L_0 \), \( L_2 \), and \( L_\infty \) norms. Different from L-BFGS, C&W optimizes following goals,

\[
\min_{\delta} \| \delta \|_p + c \cdot f(x + \delta) \\
\text{s.t. } x + \delta \in [0, 1]^n
\]

\( c \) is a hyperparameter and \( f(\cdot) \) is defined as:

\[
f(x + \delta) = \max(\max_i \{ Z(x + \delta)_i : i \neq t \} - Z(x + \delta)_t, -K)
\]

\( f(\cdot) \) is an artificially defined function, the above is just one case. Here, \( f(\cdot) \leq 0 \) if and only if classification result is adversarial targeted label \( t \). \( K \) guarantees \( x + \delta \) will be classified as \( t \) with high confidence.

**EAD attack.** EAD [42] combines \( L_1 \) and \( L_2 \) penalty functions. In Equation 12, \( f(x + \delta) \) is the same as C&W and \( t \) is the targeted label. Obviously, C&W attack becomes a special EAD case when \( \beta = 0 \) [42].

\[
\min_{\delta} c \cdot f(x + \delta) + \beta \| \delta \|_1 + \| \delta \|_2^2 \\
\text{s.t. } x + \delta \in [0, 1]^n
\]

**OptMargin attack.** OptMargin [68] is an extension of C&W \( L_2 \) attack by adding many objective functions around \( x \). In Equation 13, \( x_0 \) is the original example. \( x = x_0 + \delta \) is adversarial. \( y \) is the true label of \( x_0 \). \( v_i \) are perturbations applied to \( x \). OptMargin guarantees not only \( x \) fools network, but also its neighbors \( x + v_i \).

\[
\min_{\delta} \| \delta \|_2^2 + c \cdot (f_1(x) + \cdots + f_m(x)) \\
\text{s.t. } x + \delta \in [0, 1]^n
\]

\[
f_i(x) = \max \{ Z(x + v_i)_y - \max_j \{ Z(x + v_i)_j : j \neq y \}, -K \}
\]

**UAP attack.** UAP [113] is universal perturbations which suit almost all samples of a certain dataset. In Equation 14, \( \mu \) is the dataset that contains all samples. \( P \) represents probability, and generally \( 0 < \zeta << 1 \). The purpose is to seek \( \delta \) which could fool \( F(\cdot) \) on almost any sample from \( \mu \).

\[
F(x + \delta) \neq F(x), \text{ for most } x \sim \mu \\
\text{s.t. } \| \delta \|_p \leq \xi \\
\mathcal{P}_{x \sim \mu} (F(x + \delta) \neq F(x)) \geq 1 - \zeta
\]

### 7.2.2 Black-box attack in image classification

Finding small perturbations often requires white-box models to calculate gradients. However, this method does not work in a black-box setting due to some constraints including gradients. Therefore, researchers propose several methods to overcome these constraints.

**Step 2.1. Training substitute model.** As mentioned in Section 4, stealing decision boundaries in model extraction attack and training substitute model can facilitate black-box adversarial attacks [128] [127] [84]. Papernot et al. [128] proposed a method based on an alternative training algorithm using synthetic data generation in black-box settings.

Training substitute model needs that AEs can transfer from the substitute model to the target model. Gradient Aligned Adversarial Subspace [159] estimated previously unknown dimensions of the input space. They found that a large part of the subspace is shared for two different models, thus achieving transferability. Further, they determined sufficient conditions for the transferability of model-agnostic perturbations.

**Step 2.2. Estimating gradients.** This method needs many queries to estimate gradients and then search for AEs. Narodytska et al. [116] used a technique based on local search to construct the numerical approximation of network gradients, and then constructed perturbations in an image. Moreover, Ilyas et al. [77] introduced a more rigorous and practical black-box threat model. They applied a natural evolution strategy to estimate gradients and perform black-box attacks, using 2~3 orders of magnitude less queries.

### 7.2.3 Attack in other fields

Except for the image classification, adversarial attacks are also used in other fields, such as speech recognition [57] [182], text processing [54], malware detection [75] [131] [133] [92] and so on.

In the speech field, Yuan et al. [182] embedded voice commands into songs, and thereby attacked speech recognition systems, not being detected by humans. DeepSearch [39] could convert any given waveform into any desired target phrase through adding small perturbations on speech-to-text neural networks.

In the text processing field, DeepWordBug [54] generated adversarial text sequences in black-box settings. They adopted different score functions to better mutate words. They minimized edit distance between the original and modified texts, and reduced text classification accuracy from 90% to 30~60%.

In the malware field, Rigaki et al. [138] used GANs to avoid malware detection by modifying network behavior to imitate traffic of legitimate applications. They can adjust command and control channels to simulate Facebook chat network traffic by modifying the source code of malware.
Hu et al. [70] [71] and Rosenberg et al. [141] proposed methods to generate adversarial malware examples in black-box to attack detection models. Dujaili et al. [15] proposed SLEIPNIR for adversarial attack on binary encoded encoded malware detection.

7.2.4 Attack against other models

There is further research in addition to DNN, such as generative model, reinforcement learning and some machine learning algorithms. Mei et al. [110] identified the optimal training set attack for SVM, logistic regression, and linear regression. They proved the optimal attack can be described as a bilevel optimization problem, which can be solved by gradient methods. Huang et al. [74] demonstrated that adversarial attack policies are also effective in reinforcement learning, such as A3C, TRPO, DQN. Kos et al. [91] attempted to produce AEs using deep generative models such as variational autoencoder. Their methods include a classifier-based attack, and an attack on latent space.

7.3 Analysis

In Table 6, we have measured 33 papers on adversarial attack in total, and identified the following interesting observations.

Finding 13. Only a few attacks could be implemented in the physical world.

Real-world attacks are scarce in image field (2/20) according to our research. AEs in the digital space may fail to fool classifiers in the physical space because physical attacks need to consider more environmental factors. For example, when an adversarial image is snapshot by a camera, it is affected by photographing viewpoints, environmental lighting, and camera noise. So camera may not be able to catch those tiny perturbations. There are also some studies about physical world attack [16] [20]. These images usually need larger and obvious changes.

Except for image classification, AEs in speech also need to consider physical channel because of the noise. However, this problem does not exist in text or malware field, so we give them all “Yes” in “Real-world”.

Finding 14. A bit more works focus on untargeted attacks (57.6%) which are easier to achieve but less severe than targeted attacks.

Untargeted attacks aim at inducing wrong predictions, and thus more flexible in finding perturbations which only need smaller modifications. Therefore, it can achieve success more easily. Targeted attacks have to make the model predict what as expected. Therefore, much more perturbations need to be created for accomplishing the target. However, they are usually more harmful and practical in reality. For example, attackers may disguise themselves as authenticated users in a face recognition system, in order to gain the access to privileged resources.

Finding 15. Philosophy of distance selection.

Distance metrics is an important factor to find minimum perturbations, which mostly use $L$-distance currently. In Table 6, 60.1% attacks use $L_2$ distance, 36.4% use $L_\infty$ distance, 18.2% use $L_1$ distance and 18.2% use $L_0$ distance. Considering image classification only, 70% attacks use $L_2$ distance, 45% use $L_\infty$ distance, 10% use $L_1$ distance and 20% use $L_0$ distance.

$L_0$ distance reflects the number of changed elements, but it is unable to limit the variation of each element. It suits the scenes that only care about the number of perturbation pixels, but not variation size. $L_1$ distance is the absolute values summation of every element in perturbations, equivalent to Manhattan distance in 2D space. It limits the sum of all variations, but does not limit large perturbation of individual elements. $L_\infty$ distance does not care about how many elements have been changed, but only cares about the maximum of perturbations, equivalent to Chebyshev distance in 2D space. $L_2$ distance is an Euclidean distance that considers all pixel perturbation, which is a more balanced and the most widespread metric. It takes into account both the largest perturbation and the number of changed elements.

Finding 16. Different positions should have different weights for perturbation.

In the current measurement methods, the perturbations of different elements are considered to have the same weight. However, in face images, the same perturbations applied on the important part of face such as nose, eyes and mouth, will be easier to identify than that applied on the background. Similarly, in audio analysis, perturbations are difficult to be noticed in a chaotic scene, but are easily perceived in a quiet scene. According to above analysis, we can consider to adopt different weights on different elements when measuring distance. The important part has a larger weight, so it can only make smaller perturbations, while the unimportant part has a smaller weight, which can introduce larger perturbations.

Finding 17. More advanced measurements for human perception are desired.

The original goal of AEs is to make the model classify samples wrongly while make humans be unaware of the differences. However, it is difficult to measure humans’ perception of these perturbations. Intuitively, small $L_p$ distance implies a low probability of being detected by humans. While recent work found that $L_p$ distance is neither necessary nor sufficient for perceptual similarity [145]. That is, perturbations with large $L_p$ values may also look similar to humans, such as overall translation and rotation of images, and small $L_p$ perturbations do not mean imperceptible. Therefore, we should break the constraint of $L_p$ distance. How to search for AEs systematically without $L_p$ limitation, and how to propose new measurements that could be necessary or sufficient for perceptual similarity, will be a trend of adversarial attack in the near future.

8 DISCUSSION

In this section, we summarize 7 observations according to the survey as follows.
TABLE 6: Evaluation on adversarial attacks. This table presents “Success Rate” of these attacks in specific “Dataset” with varying target “System” and “Model”. “Distance” implies how these works measure the distance between samples. “Real-world” is used to distinguish the works that are also suitable for physical adversarial attacks. “Knowledge” is valued either black-box or white-box. “Iterative” illustrates whether the optimization steps are iterative. “Targeted” differs whether an attack is a targeted attack or not. “Application” covers the practical areas.

| Paper                  | Success Rate | Dataset         | System         | Distance | Model | Real-world | Knowledge | Iterative | Targeted | Application |
|------------------------|--------------|-----------------|----------------|----------|-------|------------|-----------|-----------|----------|-------------|
| L-BFGS [154]           | 20%          | MNIST           | FC10(1)        | L∞        | DNN   | No         | White     | Yes       | No       | image       |
| FGSM [38]              | 54.6%        | MNIST           | a shallow softmax network | L∞ | DNN   | No         | White     | No        | No       | image       |
| BIM [16]               | 24%          | ImageNet        | Inception v3   | L∞        | CNN   | Yes        | White     | No        | Yes       | image       |
| MI-FGSM [47]           | 37.6%        | ImageNet        | Inception v3   | L∞        | CNN   | No         | White     | Yes       | Yes       | image       |
| JSMA [129]             | 97.05%       | MNIST           | LeNet          | L0        | CNN   | No         | White     | Yes       | Yes       | image       |
| C&W [38]               | 100%         | ImageNet        | Inception v3   | L0, L1, L∞ | CNN   | No         | White     | Yes       | Yes       | image       |
| EAD [42]               | 100%         | ImageNet        | Inception v3   | L1, L2, L∞ | CNN   | No         | White     | Yes       | Yes       | image       |
| OptMargin [68]         | 100%         | CIFAR-10        | ResNet         | L0, L1, L∞ | CNN   | No         | White     | No        | No        | image       |
| Guo et al. [69]        | 95.5%        | ImageNet        | ResNet-50      | L0        | CNN   | No         | Both      | Yes       | No        | image       |
| Deepfool [114]         | 68.7%        | ILSVRC2012      | GoogLeNet      | L2        | CNN   | No         | White     | No        | No        | image       |
| NewtonFool [81]        | 81.63%       | GTSRB           | CNN(3Conv+1FC) | L2       | CNN   | No         | White     | No        | No        | image       |
| UAP [113]              | 90.7%        | ILSVRC2012      | VGG-16         | L0, L∞    | CNN   | No         | White     | Yes       | Yes       | image       |
| UAN [66]               | 91.8%        | ImageNet        | ResNet-152     | L0, L∞    | CNN   | No         | White     | Yes       | Yes       | image       |
| ATN [25]               | 89.2%        | MNIST           | CNN(3Conv+1FC) | L2       | CNN   | No         | White     | Yes       | Yes       | image       |
| Athalye et al. [20]    | 83.4%        | 3D-printed turtle | Inception-v3   | L2       | CNN   | Yes        | White     | No        | Yes       | image       |
| Ilyas et al. [77]      | 99.2%        | ImageNet        | Inception-v3   | -         | CNN   | No         | Black     | No        | Both      | image       |
| Namdicky et al. [118]  | 97.51%       | CIFAR-10        | VGG            | L0        | CNN   | No         | Black     | No        | No        | image       |
| Kon et al. [89]        | 78%          | MNIST           | VAE-GAN        | L2        | GAN   | No         | White     | No        | No        | image       |
| Met et al. [120]       | -            | -               | -              | L2        | SVM   | No         | Black     | Yes       | No        | image       |
| Huang et al. [74]      | -            | -               | -              | L1, L2, L∞| No     | Both       | No        | No        | No        | image       |
| Papernot et al. [152]  | 100%         | Reviews         | LSTM           | L2        | RNN   | Yes        | White     | No        | No        | text        |
| DeepWordBug [54]       | 51.80%       | IMDb Review     | LSTM           | L0        | RNN   | Yes        | Black     | Yes       | Yes       | text        |
| DeepSpeech [39]        | 100%         | Mozilla Common Voice | LSTM        | L0        | RNN   | No         | White     | No        | No        | speech      |
| Gang et al. [67]       | 72%          | IEMOCAP         | LSTM           | L0        | RNN   | Yes        | White     | No        | No        | speech      |
| CommanderSong [182]    | 96%          | Fisher          | Aspire Chain Model | L1   | RNN   | Yes        | White     | No        | No        | speech      |
| Rosenberg et al. [141] | 99.99%       | 500000 files   | LSTM           | L2        | RNN   | Yes        | Black     | No        | Yes       | malware     |
| MNIST [75]             | 97%          | 45000000 files  | DNN(4 Hidden layers) | L2    | DNN   | Yes        | Black     | No        | No        | malware     |
| SLEEPNR [15]           | 99.7%        | 50000 PEs       | DNN            | L0, L∞    | DNN   | Yes        | Black     | No        | No        | malware     |
| Rigaki et al. [138]    | 63%          | -               | GAN            | L0        | GAN   | Yes        | Black     | No        | No        | malware     |
| Pascanu et al. [133]   | 69%          | DREBIN          | DNN            | L1        | DNN   | Yes        | Black     | No        | No        | malware     |
| Kreuk et al. [92]      | 88%          | Microsoft Kaggle 2015 | CNN          | L0, L∞    | CNN   | Yes        | White     | No        | Yes       | malware     |
| Hu et al. [70]         | 90.05%       | 180 programs    | BiLSTM         | L1        | RNN   | Yes        | Black     | Yes       | No        | malware     |
| Hu et al. [71]         | 99.80%       | 180000 programs | MalGAN         | L1        | GAN   | Yes        | Black     | No        | No        | malware     |

8.1 Regulations on privacy protection

As shown in Section 4 and 5, both the enterprises and users are suffering from the risk of privacy. In addition to removing privacy in the data, governments and related organizations can issue laws and regulations against privacy violations in the course of data use and transmission. In particular, it is recommended that: 1) introducing regulatory authorities to monitor these deep learning systems and strictly supervise the use of data. The involved systems are only allowed to extract features and predict results within the permitted range. The private information is forbidden for being extracted and inferred without authorization. 2) establishing and improving relevant laws and regulations (e.g., GDPR [3]), for supervising the process of data collection, use, storage and deletion. 3) adding digital watermarks into the data for leak source tracking [21]. The watermarks helps to fast find out the rule breakers that are liable for exposing privacy.

8.2 Secure implementation of deep learning systems

Most of the research on deep learning security is concentrat-
vulnerabilities in future.

8.3 How far away from a complete black-box attack?
Black-box attacks are relatively more destructive as they do not require much information about the target which lowers the cost of attack. Many works are claiming they are performing black-box attacks towards deep learning systems [147] [143] [79]. But it is not clear that whether they are feasible on a large number of models and systems, and what is the gap between these works with the real world attack.

According to the surveyed results, we find that many black-box attacks still assume that some information is accessible. For example, [160] has to know what exact model is running as well as its model structure before successfully stealing out the model parameters. [147] conducts a membership inference attack built on the fact that the statistics of training data is publicly known and similar data with the same distribution can be easily synthesized. However, these conditions may be difficult to satisfy the real world, and a complete black-box attack is rarely seen in the recent research.

Another difficulty of a complete black-box attack stems from the protection measures performed by deep learning systems: 1) query limit. Commercial deep learning systems usually set a limit for service requests that prevents substitute model training. In [84], PRADA can detect model extraction attacks based on characteristic distribution of queries. 2) uncharted defense deployment. Besides not fully tangible model, a black-box attacker also cannot infer how the defense is deployed and configured at the backend. These defenses may block a malicious request [112] [107], create misleading results [84] and dynamically change or enhance their abilities [165] [160]. Due to the extreme imbalance of knowledge between attackers and defenders, all of the above measures can avoid black-box attacks efficiently and effectively.

8.4 Relationship between interpretability and security
The development of interpretability can help us better understand the underlying principles of all these attacks. Since the neural network was born, it has the problem of low interpretability. A small change of model parameters may affect the prediction results drastically. People also cannot directly understand how neural network operates. Recently, interpretability has become an urgent field in deep learning. In May of 2018, GDPR is announced to protect the privacy of personal data and it requires interpretability when using AI algorithms [3]. How to deeply understand the neural network itself, and explain how the output is affected by the input are all problems that need to be solved urgently.

Interpretability mainly refers to the ability to explain the logic behind every decision/judgment made by AI and how to trust these decisions [162]. It mainly includes rationality, traceability, and understandability [86]. Rationality means being able to understand the reasoning behind each prediction. Traceability refers to the ability to track predictive processes, which can be derived from the logic of mathematical algorithms [87] [169]. Understandability refers to a complete understanding of the model on which decisions are based.

At present, some work is about security and robustness proof, usually against adversarial attack [169]. Deeper work requires to explain the reasons for prediction results, making training and prediction processes are no longer in black-box.

Kantchevan et al. [86] suggested that system designers need to broaden the classification goal into an explanatory goal and deepen interaction with human operators to address the challenge of adversarial drift. Reluplex [87] can prove in which situations, small perturbations to inputs cannot cause misclassification. The main idea is the lazy handling of ReLU constraints. It temporarily ignores ReLU constraints and tries to solve the linear part of problems. As a development, Wang et al. [169] presented ReluVal to do formal security analysis of neural networks using symbolic intervals. They proposed a new direction for formally checking security properties without Satisfiability Modulo Theory. They leveraged symbolic interval algorithm to compute rigorous bounds on DNN outputs through minimizing over-estimations. AI² [55] attempts to do abstract interpretation in AI systems, and tries to prove the security and robustness of neural networks. They constructed almost all perturbations, made them propagate automatically, and captured the behavior of convolutional layers, max pooling layers and fully connected layers. They also solved the state space explosion problem. DeepStellar [48] characterizes RNN internal behaviors by modeling a RNN as an abstract state transition system. They design two trace similarity metrics to analyze RNNs quantitatively and also detect AEs with very small perturbations.

The interpretability cannot only bring security, but also uncover the mystery of neural network and make us understand its working mechanism easily. However, this is also beneficial to attackers. They can exclude the range of input proved secure, thus reducing the retrieval space and finding AEs more efficiently. They can also construct targeted attacks through an in-depth understanding on models. In spite of this, this field should not be stagnant. Because a black-box model does not guarantee security [148]. Therefore, with the improvement of interpretability, deep learning security may rise in a zigzag way.

The development of interpretability is also conductive to solving the hysteresis of defensive methods. Since we have not yet achieved a deep understanding of DNN (it is not clear why a record is predicted to the result, and how different data affect model parameters), finding vulnerabilities for attack is easier than preventing in advance. So there is a certain lag in deep learning security. If we can understand models thoroughly, it is believed that defense will precede or synchronize with attack [87] [169] [55].

8.5 Discrimination in AI
AI system may seem rational, neutral and unbiased, but actually, AI and algorithmic decisions can lead to unfair and discrimination [30]. For example, amazon’s AI hiring tool taught itself that male candidates were preferable [63]. There are also discrimination in crime prevention, online shops [30], bank loan [6], and so on. There are two main reasons causing AI discrimination [6]: 1) Imbalanced training data; 2)Training data reflects past discrimination.

In order to solve this problem and make AI system better benefit humans, what we need to do is: 1) balancing dataset,
by adding/removing data about under/over represented subsets. 2) modifying data or trained model where training data reflects past discrimination [6]; 3) importing testing techniques to test the fairness of models, such as symbolic execution and local interpretability [12]; 4) enacting non-discrimination law, and data protection law, such as GDPR [3].

8.6 Corresponding defense methods

There is a line of approaches for preventing the aforementioned attacks.

MEA defense. Blurring the prediction results is an effective way to prevent model stealing, for instance, rounding parameters [165] [160], adding noise into class probabilities [96] [84]. On the other hand, detecting and prevent abnormal queries can also resolve MEA. Kesarwani et al. [88] recorded all requests made by clients and calculated the explored feature space to detect attack. PRADA [84] detected attack based on sudden changes in the distribution of samples submitted by a given customer.

MIA defense. To defend with model inversion attacks, researchers propose the following approaches:

- **Differential privacy (DP)**, which is a cryptographic scheme designed to maximize the accuracy of data queries while minimizing the opportunity to identify their records when querying from a statistical database [50]. Individual features are removed to preserve user privacy. It is first proposed in [49] and prove to be effective in privacy preservation in database. DP can be applied to prediction outputs [41] [64] [166] [184] [76], loss function [89] [155], and gradients [149] [26] [155] [11] [184] [187].

- **Homomorphic encryption (HE)**, which is an encryption function and enables the following two operations are value-equivalent [139]: exercising arithmetic operations $\oplus$ on the ring of plain text and encrypting the result, encrypting operators first and then carry on the same arithmetic operations, i.e., $E_n(x) \oplus E_n(y) = E_n(x + y)$. In this way, clients can encrypt their data and then send it to MLaaS. The server returns encrypted predictions without learning anything about the plain data. In the meantime, the clients have no idea about the model attributes [56] [101] [85] [82].

- **Secure multi-party computation (SMC)**, stemming from Yao’s Millionaires’ problem [180] and enabling a safe calculation of contract functions without trusted third parties. In the context of deep learning, it extends to that multiple parties collectively train a model and preserve their own data [164] [146] [134] [135]. As such, the training data cannot be easily inferred by attackers residing at either computing servers or the client side.

- **Training reconstitution.** Cao et al. [37] put forward machine unlearning, which makes ML models completely forget a piece of training data and recover the effects to models and features. Ohrimenko et al. [120] proposed a data-oblivious machine learning algorithm. Osia et al. [123] broke down large, complex deep models to enable scalable and privacy-preserving analytics by removing sensitive information with a feature extractor.

PA defense. Poisoning attack can be mitigated through two aspect: protecting data, including avoiding data tampering, denial and falsification, and detecting poisonous data [170] [105] [65]. In particular, Olufowobi et al. [121] described the context of creation or modification of data points to enhance trustworthiness and dependability of the data. Chakarov et al. [40] evaluated the effect of individual data points on the performance of trained model. Baracaldo et al. [24] used source information of training data points and the transformation context to identify poisonous data; protecting algorithm, which adjusts training algorithms, e.g., robust PCA [35], robust linear regression [43] [100], and robust logistic regression [51].

AA defense. As adversarial attack draws the major attention, defensive work is more comprehensive and ample accordingly. The mainstream defense approaches is as follows:

- **Adversarial training.** This method selects AEs as part of the training dataset to make trained model learn characteristics of AEs [73] [94]. Furthermore, Ensemble Adversarial Training [158] contained each turbine input transferred from other pre-trained models.

- **Region-based method.** Understanding properties of adversarial regions and using more robust region-based classification could also defend adversarial attack. Cao et al. [36] developed DNNs using region-based classification instead of point-based. They predicted label through randomly selecting several points from the hypercube centered at the testing sample. In [125], the classifier mapped normal samples to the neighborhood of low-dimensional manifolds in the final-layer hidden space. Local Intrinsic Dimensionality [107] characterized dimensional properties of adversarial regions and evaluated the spatial fill capability. Background Class [109] added a large and diverse class of background images into datasets.

- **Transformation.** Transforming inputs can defend adversarial attack to a large extent. Song et al. [150] found that AEs mainly lay in the low probability regions of the training regions. So they purified an AE by moving it back towards the distribution adaptively. Guo et al. [61] explored model-agnostic defenses on image-classification systems by image transformations. Xie et al. [176] used randomization at inference time, including random resizing and padding. Tian et al. [156] considered that AEs are more sensitive to certain image transformation operations, such as rotation and shifting, than normal images. Wang et al. [168] [167] thought AEs are more sensitive to random perturbations than normal. Buckman et al. [32] used thermometer code and one-hot code discretization to increase the robustness of network to AEs.

- **Gradient regularization/masking.** This method hides gradients or reduces the sensitivity of models. Madry et al. [108] realized it by optimizing a saddle point formulation, which included solving an inner maximization solved and an outer minimization. Ross et al. [142] trained differentiable models that penalized the degree to infinitesimal changes in inputs.

- **Distillation.** Paperot et al. [126] proposed Defensive Distillation, which could successfully mitigate AEs constructed by FGSM and JSMA. Paperot et al. [132] also used the knowledge extracted in distillation to reduce the magnitude of network gradient.

- **Data preprocessing.** Liang et al. [98] introduced scalar quan-
zation and smooth spatial filtering to reduce the effect of perturbations. Zantedeschi et al. [183] used bounded ReLU activation function for hedging forward propagation of adversarial perturbation. Xu et al. [179] proposed feature squeezing methods, including reducing the depth of color bit on each pixel and spatial smoothing.

- **Defense network**: Some studies use networks to automatically fight against AEs. Gu et al. [59] used deep contractive network with contractive autoencoders and denoising autoencoders, which can remove amounts of adversarial noise. Akhtar et al. [15] proposed a perturbation rectifying network as pre-input layers to defend against UAPs. MagNet [112] used detector networks to detect AEs which are far from the boundary of manifold, and used a reformer to reform AEs which are close to the boundary.

### 8.7 Future direction of attack and defense

It is an endless war between attackers and defenders, and neither of them can win an absolute victory. But both sides can research new techniques and applications to gain advantages. From the attacker’s point of view, one effective way is to explore new attack surfaces, find out new attack scenarios, seek for new attack purposes and broaden the scope of attack effects. In particular, main attack surfaces on deep learning systems include malformed operational input, malformed training data and malformed models [175].

In adversary attack, \( L_p \)-distance is not an ideal measurement. Some images with big perturbations are still indistinguishable for humans. However, unlike \( L_p \)-distance, there is no standard measure for large \( L_p \) perturbations. This will be a hot point for adversarial learning in future. In model extraction attack, stealing functionality of complex models needs massive queries. How to come up with a better method to reduce the number of queries in order of magnitude will be the focus of this field.

The balance of attack cost and benefit is also an important factor. Some attacks, even can achieve fruitful targets, have to perform costly computation or resources [160]. For example, in [147], the attacker has to train a number of shadow models that simulate the target model, and then undertake membership inference. They need 156 queries to produce a data point on average.

Attack cost and attack benefit are a trade-off process [110]. Generally, the cost of attack contains time, computation resources, acquired knowledge, and monetary expense. The benefit from an attack include economic payback, rivals’ failure and so forth. In this study, we will not give a uniform formula to quantify the cost and benefit as the importance of each element is varying in different scenarios. Nevertheless, it is usually modeled as an optimization problem where the cost is minimized while the benefit is maximized, like a min-max game [117].

As for defenders, a combination of multiple defense techniques is a good choice to reduce the risk of being attacked. But the combination may incur additional overhead on the system that should be solved in design. For example, in [101] [85], they adopted a mixed protocol combining HE and MPC, which improved performance but with high bandwidth.

### 9 Conclusion

In this paper, we conduct a comprehensive and extensive investigation on attacks towards deep learning systems. Different from other surveys, we dissect an attack in a systematic way, where interested readers can clearly understand how these attacks happen step by step. We have compared the investigated works on their attack vectors and proposed a number of metrics to compare their performance. Based on the comparison, we then proceed to distill a number of insights, disclosing advantages and disadvantages of attack methods, limitations and trends. The discussion covering the difficulties of these attacks in the physical world, security concerns in other aspects and potential mitigation for these attacks provide a platform that future research can be based.

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