A Survey of Privacy Attacks in Machine Learning

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As machine learning becomes more widely used, the need to study its implications in security and privacy becomes more urgent. Research on the security aspects of machine learning, such as adversarial attacks, has received a lot of focus and publicity, but privacy related attacks have received less attention from the research community. Although there is a growing body of work in the area, there is yet no extensive analysis of privacy related attacks. To contribute into this research line we analyzed more than 40 papers related to privacy attacks against machine learning that have been published during the past seven years. Based on this analysis, an attack taxonomy is proposed together with a threat model that allows the categorization of the different attacks based on the adversarial knowledge and the assets under attack. In addition, a detailed analysis of the different attacks is presented, including the models under attack and the datasets used, as well as the common elements and main differences between the approaches under the defined threat model. Finally, we explore the potential reasons for privacy leaks and present an overview of the most common proposed defenses.

CCS Concepts: • Computing methodologies → Machine learning; • Security and privacy;

Additional Key Words and Phrases: privacy, machine learning, membership inference, property inference, model extraction, reconstruction

1 INTRODUCTION

Fueled by large amounts of available data and hardware advances, machine learning has experienced tremendous growth, both in terms of academic research and of real world applications. At the same time, the impact of machine learning in security, privacy, and fairness is receiving increasing attention. In terms of privacy, our personal data are being harvested by almost every online service and are used to train models that power machine learning based applications. When these applications are presented as black-box models, it is expected that they should not reveal information about the data used for their training. If a model was trained using sensitive data such as location, health records, or identity information, then an attack that allows an adversary to extract this information is highly undesirable. At the same time, if private data have been used without their owners' consent, the same type of attack could be used as a way to determine unauthorized use and thus work in favor of the user's privacy.

The security of machine learning and the impacts of adversarial attacks in the performance of the models have been widely studied in the community, with several surveys highlighting the major advances in the area [6, 57, 75, 98]. Some of these surveys also provide a partial coverage on the topic of privacy attacks, but there is no overall survey that considers privacy attacks against machine learning models as its main focus. This paper is, as far as we know, the *first comprehensive survey* of privacy-related attacks against machine learning. This survey focuses on leaks of information from the training data and also leaks of information about the models themselves. In this sense, an attack that extracts information about the model structure is, strictly speaking, an attack against model confidentiality. The decision to include model extraction attacks was made because (i) these attacks are an important part of the threat model presented in Section 3 and (ii) because in the existing literature, attacks against model confidentiality are usually grouped together with privacy attacks [6, 75]. In addition, Veale et al. [93] made the argument that privacy attacks such as membership inference (Section 4.1) increase the risk of machine learning models being classified as

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personal data under the General Data Protection Regulation (GDPR) because they can render a person identifiable. Although models are currently not covered by the GDPR, if they are potentially considered as personal data, then attacks against them may fall on the same scope as attacks against personal data. This may be further complicated by the fact that model extraction attacks can be used as a stepping stone for other privacy based attacks.

This survey present and summarize research about privacy-based attacks on machine learning that has been published in top tier conferences and journals during 2014-2020 in the areas of security, privacy, and machine learning. An initial set of papers was selected in Google Scholar using keyword searches related to "privacy", "machine learning" and the names of attacks themselves. After the initial set of papers was selected, backward searches based on their references as well as forward searches based on papers that cited them, were used to generated the final list.

The main contributions of this paper are:

- The first comprehensive study of attacks against privacy and confidentiality of machine learning systems.
- A threat model and a taxonomy of attacks against machine learning privacy (Sections 3 and 4).
- An in-depth comparison of similarities and differences of the design of the attacks (Section 5).
- A discussion on the probable causes of the privacy leaks in machine learning systems (Section 6).
- An overview of the different defensive measures tested to protect against the attacks (Section 7).

2 MACHINE LEARNING

Machine learning (ML) is a field that studies the problem of learning from data without being explicitly programmed. This section provides a very high level overview of machine learning in order to facilitate the discussion in the subsequent chapters and to introduce the relevant notation. Several textbooks such as [7, 24, 64, 81] provide a more thorough coverage of the topic.

2.1 Types of Machine Learning

At a very high level ML is usually split into three major areas: *supervised*, *unsupervised* and *reinforcement* learning. Deep Learning is a subset of ML that focuses on deep neural network (DNN) models. It has grown in popularity during the past decade and has applications in all ML areas.

- 2.1.1 Supervised Learning. In a supervised learning setting, a model f with parameters θ is a mapping function between inputs \mathbf{x} and outputs $\mathbf{y} = f(\mathbf{x}; \theta)$, where \mathbf{x} is a vector of attributes or features with dimensionality n and the output or response can assume different dimensions depending on the learning task. A training set \mathcal{D} used for training the model is a set of data points $\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^m$, where m is the number of the input-output pairs. The most common supervised learning tasks are classification and regression. The vast majority of the attack papers presented in this work are focused in supervised learning.
- 2.1.2 Unsupervised Learning. In unsupervised learning there are no labels y. The training set D consists only of the inputs \mathbf{x}_i . Unsupervised algorithms aim to find structure or patterns in the data without having access to labels. Usual tasks in unsupervised learning are clustering, feature learning and dimensionality reduction. Generative tasks that aim to learn how to generate samples from the underlying data distribution, such as Generative Adversarial Networks (GANs) [25] and Variational Autoencoders (VAEs) [48] are also considered a part of unsupervised learning.

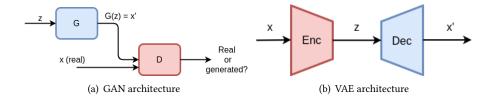


Fig. 1. GAN and VAE architectures. The GAN consists of a Generator (G) and a Discriminator (D). Similarly, the VAE consists of a Encoder (Enc) and an Decoder (Dec). Attacks against GANs and VAEs take into account varying levels of knowledge about G and Dec as well as possible although unlikely access to D and Enc.

Generative Adversarial Networks consist of two neural networks, a generator and a discriminator. The generator \mathcal{G} maps a latent variable z typically sampled from a Gaussian or Uniform distribution, to the output x. The discriminator \mathcal{D} is trying to learn the difference between the generated output and the real data. The generic architecture of GANs is depicted in Figure 1(a). The training between the two components is adversarial in nature and in its initial formulation it was expressed as a zero-sum game [25]. Since its inception, several hundreds of papers have been published proposing formulations that improve not only the quality of generated data, but also address problems in GAN training such as mode collapse.

Variational Autoencoders consist also of two components, an encoder $\mathcal{E}nc$ and a decoder $\mathcal{D}ec$. The encoder maps the input x to a latent variable zs while the decoder takes z as input and tries to reconstruct x. VAEs are constructed and trained in such a way so that the latent variable z is sampled from a known distribution, typically a Gaussian [48]. The VAE architecture is depicted in Figure 1(b).

Attacks against unsupervised learning are until now focused mostly on GANs and VAEs.

2.1.3 Reinforcement Learning. Reinforcement learning concerns itself with agents that make observations of the environment and use these to take actions with the goal of maximizing a reward signal. In the most general formulation the set of actions is not predefined and the rewards are not necessarily immediate but can occur after a sequence of actions [90]. At the moment, no privacy related attacks against reinforcement learning have been reported but it has been used to mount model extraction attacks [72].

2.2 Training and Inference

Training of supervised ML models usually follows the Empirical Risk Minimization (ERM) approach, where the objective is to find the parameters θ^* that minimize the *risk* or *objective function*, which is calculated as an average over the training dataset:

$$\mathcal{J}(\mathcal{D};\theta) = \frac{1}{m} \sum_{i=1}^{m} l(f(x_i;\theta), y_i)$$
 (1)

where $l(\cdot)$ is a loss function such as cross entropy loss and m is the number of data points in the dataset \mathcal{D} .

The idea behind ERM is that the training dataset is a subset drawn from the unknown true data distribution for the learning task. Since we have no knowledge of the true data distribution we cannot minimize the true objective function but instead we minimize the estimated objective over the data samples that we have. In some cases a regularization term is added to the objective function in order to reduce overfitting and stabilize the training process.

The training process usually involves an iterative optimization algorithm such as gradient descent which aims to minimize the objective function by following the path induced by its gradients. When the dataset is large, as is often the case with deep neural networks, taking one gradient step becomes too costly. In that case, a variant of gradient descent which involves steps taken over smaller batches of data is preferred. This optimization method is called Stochastic Gradient Descent (SGD):

$$\theta_{t+1} = \theta_t - \eta \mathbf{g} \tag{2}$$

$$\mathbf{g} = \frac{1}{m'} \nabla_{\theta} \sum_{i=1}^{m'} l(f(\mathbf{x}_i; \theta), \mathbf{y}_i)$$
(3)

where η is the learning rate and the gradient g of the loss function with respect to parameters θ is calculated over the batch of data that has size m'.

Once models are trained, they can be used to make inferences or predictions over previously unseen data. At this stage, the assumption is that the model parameters are fixed.

3 THREAT MODEL

In order to understand and defend against attacks to machine learning from a privacy perspective, it is useful to have a general model of the environment, the different actors, and the assets to protect.

From a threat model perspective, the assets that are sensitive and are potentially under attack, are the training dataset \mathcal{D} and the model itself; its parameters θ , its hyper-parameters, and architecture. The actors identified in this threat model are

- (1) The **data owners** whose data may be sensitive.
- (2) The **model owners** which may or may not own the data and may or may not want to share information about their models.
- (3) The **model consumers** that use the services that the model owner exposes, usually via some sort of programming or user interface.
- (4) The **adversary** may also have access to these interfaces as a normal consumer does. If the model owner allows, they may have access to the model itself.

Figure 2 depicts the assets and the identified actors under the threat model, as well as the information flow and possible actions. This threat model is a logical model and it does not preclude the possibility that some of these assets may be collocated or spread in multiple locations.

Since the interest of this survey is in the privacy attacks based on unintentional information leakage with regards to the data or the machine learning model, there is no coverage of *security-based* attacks, such as model poisoning or evasion attacks, or attacks against the infrastructure that hosts the data, the models or the provided services.

The different attack surfaces against machine learning models can be modelled in terms of adversarial knowledge. The range of knowledge varies from limited e.g., having access to a machine learning API, to having knowledge of the full model parameters and training settings. In between these two extremes there is a range of possibilities such as partial knowledge of the model architecture, its hyper-parameters or training setup. The knowledge of the adversary can also be considered from a dataset point of view. In the majority of the works reviewed, the authors assume the adversary has no knowledge of the training data samples, but some knowledge of the underlying data distribution.

From a taxonomy point of view, the attacks where the adversary has no knowledge of the model parameters, architecture or training data are called **black-box** attacks. An example of a black-box system is Machine Learning as a Service (MLaaS) where the users usually provide some input and receive either a prediction vector or a class label from a pre-trained model hosted in the cloud. Most

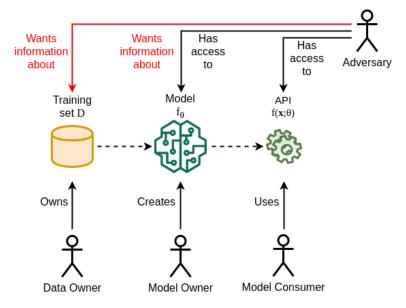


Fig. 2. Threat Model of privacy and confidentiality attacks against machine learning systems. The human figure represents actors and the symbols represent the assets. Dashed lines represent data and information flow, while full lines represent possible actions. In red are the adversarial actions available under the threat model.

black-box papers assume the existence of a prediction vector. In a similar fashion, **white-box** are the types of attacks where the adversary has either complete access to the target model parameters or their loss gradients during training. This is the case for example, in most distributed modes of training. In between the two extremes, there are also attacks that make stronger assumptions than the black-box ones, but do not assume full access to the model parameters. We refer to these attacks as **partial white-box** attacks. It is important to add here, that the majority of works assumes full knowledge of the expected input, although some form of preprocessing might be required.

The time of the attack is another parameter to consider from a taxonomy point of view. The majority of the works in the area are dealing with attacks during **inference**, however most white-box attacks assume access to the model parameters and gradients during **training**. Attacks during the training phase of the model open up the possibilities for different types of adversarial behavior. A **passive** or *honest-but-curious* attacker does not interfere with the training process and they are only trying to infer knowledge during or after the training. If the adversary interferes with the training in any way, they are considered an **active** attacker.

4 TAXONOMY OF THREATS

In privacy related attacks an adversary's goal is related to gaining knowledge that was not intended to be shared, such as knowledge about the training data \mathcal{D} or information about the model, or even extracting information about properties of the data such as unintentionally encoded biases. In our taxonomy, the attacks studied are categorized into four types: **membership inference**, **reconstruction**, **property inference**, and **model extraction**.

4.1 Membership Inference Attacks

Membership inference tries to determine whether an input sample x was used as part of the training set \mathcal{D} . This is the most popular category of attacks and was first introduced by Shokri et al. [85]. The attack assumes only knowledge of the model's prediction vector (black-box) and was carried against supervised machine learning models. White-box attacks are also a threat especially in a collaborative setting, where an adversary can mount both passive and active attacks. Access to model parameters and gradients allows for more effective white-box membership inference attacks in terms of attack accuracy [66].

Apart from supervised models, generative models such as GANs and VAEs are also susceptible to membership inference attacks [11, 30, 34]. The goal of the attack in this case is to retrieve information about the training data using varying degrees of knowledge of the data generating elements.

Finally, while we are mostly focused on these attacks from a negative perspective, they can also be used from a positive viewpoint. One such example is the ability to audit black-box models in order to see if data have been used without the data owner's authorization [35, 86].

4.2 Reconstruction Attacks

Reconstruction attacks try to recreate one or more training samples and / or their respective training labels. The reconstruction can be partial or full. Previous work have also used the terms **attribute inference** or **model inversion** to describe attacks that, given output labels and partial knowledge of some features, try to recover sensitive features or the full data sample. For the purpose of this survey, all these attacks are considered as part of the larger set of reconstruction attacks. The term **attribute inference** has been used in other parts of the privacy related literature to describe attacks that infer sensitive "attributes" of a targeted user by leveraging publicly accessible data [23, 41]. These attacks are not part of this review as they are mounted against the individual's data directly and not against ML models.

A major distinction between the works of this category is between those that create an actual reconstruction of the data [31, 100, 104, 109, 110] and the ones that create class representatives or probable values of sensitive features that do not necessarily belong to the training dataset [20, 33, 36, 104]. In classification models, the latter case is limited to scenarios were classes are made up of one type of object, e.g., faces of the same person. While this limits the applicability of the attack, it can still be an interesting scenario in some cases.

4.3 Property Inference Attacks

The ability to extract dataset properties which were not explicitly encoded as features or were not correlated to the learning task, is called **property inference**. An example of property inference is the extraction of information about the ratio of women and men in a patient dataset when this information was not an encoded attribute or a label of the dataset. Or having a neural network that performs gender classification and can be used to infer if people wear glasses or not. In some settings this type of leak can have privacy implications. These types of properties can also be used to get more insight about the training data, which can lead to adversaries using this information to create similar models [2] or even have security implications when the learned property can be used to detect vulnerabilities of a system [21].

Property inference aims to extract information that was learned from the model unintentionally and that is not related to the training task. Even well generalized models may learn properties that are relevant to the whole input data distribution and sometimes this is unavoidable or even necessary for the learning process. What is more interesting from an adversarial perspective are

properties that may be inferred from the specific subset of data that was used for training, or eventually about a specific individual.

Property inference attacks so far target either class wide properties [2, 21] or the emergence of properties within a batch of data [61]. The latter attack was performed against collaborative training of a model.

4.4 Model Extraction Attacks

Model extraction is a class of black-box attacks where the adversary tries to extract information and potentially fully reconstruct a model or create a substitute model \hat{f} that behaves very similarly to the model under attack f. When it comes to substitute models the focus is on creating models that either match the accuracy of f in some test set that is drawn from the input data distribution related to the learning task [49, 63, 72, 91] or to create a model \hat{f} that matches f at a set of input points that are not necessarily related to the learning task [13, 39, 44, 91]. Jagielski et al. [39] referred to the former attack as **task accuracy** extraction and the latter as **fidelity** extraction. In task accuracy extraction the adversary is interested in creating a substitute that learns the same task as the target model equally well or better. In the latter case the adversary aims to create a substitute that replicates the decision boundary of f as faithfully as possible. This type of attack can be later used as a stepping stone before mounting other types of attacks such as adversarial attacks [44, 74] or membership inference attacks [66]. In both cases, it is assumed that the adversary wants to be as efficient as possible, i.e., to use as few queries as possible. Knowledge of the target model architecture is assumed in some works but it is not strictly necessary if the adversary selects a substitute model that has the same or higher complexity than the model under attacks [44, 49, 72].

Apart from creating substitute models there are also approaches that focus on recovering information from the target model such as hyper-parameters in the objective function [97] or information about various neural network architectural properties such as activation types, optimisation algorithm, number of layers, etc [71].

5 DESIGN OF THE ATTACKS

To study the design of these attacks, more than 40 papers were analyzed in relation to privacy attacks against machine learning. This section describes in some detail the techniques used in most of these attacks by tracing the most common design elements as well as essential differences between the various techniques. The papers are discussed in three sections: attacks on centralized supervised learning, attacks on distributed modes of learning, and attacks on generative models.

5.1 Attacks Against Centralized Supervised Learning

5.1.1 Shadow training. A common design pattern for a lot of supervised learning attacks is the use of **shadow models** and **meta-models** or **attack-models** [2, 21, 35, 40, 71, 77–79, 85, 92]. The general shadow training architecture is depicted in Figure 3. The main intuition behind this design is that models behave differently when they see data that do not belong to the training dataset. This difference is captured in the model outputs as well as in their internal representations. In most designs there is a target model and a target dataset. The adversary is trying to infer either membership or properties of the training data. They train a number of shadow models using shadow datasets $\mathcal{D}_{shadow} = \{\mathbf{x}_{shadow,i}, \mathbf{y}_{shadow,i}\}_{i=1}^n$ that usually are assumed to come from the same distribution as the target dataset. After the shadow models' training, the adversary constructs an attack dataset $\mathcal{D}_{attack} = \{f_i(\mathbf{x}_{shadow,i}), \mathbf{y}_{shadow,i}\}_{i=1}^n$, where f_i is the respective shadow model. The attack dataset is used to train the meta-model which essentially performs inference based on

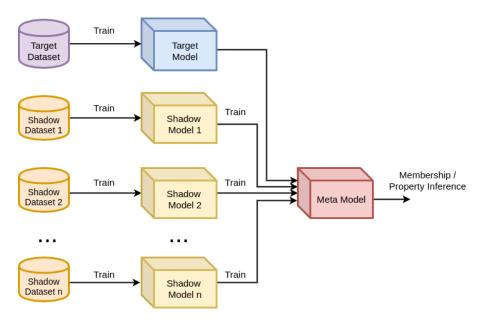


Fig. 3. Shadow training architecture. At first, a number of shadow models are trained with their respective shadow datasets in order to emulate the behavior of the target model. At the second stage, a meta-model is being trained from the outputs of the shadow models and the known labels of the shadow datasets. The meta-model is used to infer membership or properties of data or the model given the output of the target model.

the outputs of the shadow models. Once the meta-model is trained it is used for testing using the outputs of the target model.

5.1.2 Membership inference attacks. In membership inference black-box attacks the output of the shadow models is usually a prediction vector [40, 77, 79, 85, 92]. The labels used for the attack dataset come from the test and training splits of the shadow data, where data points that belong to the test set are labelled as non-members of the training set. The meta-model is trained to recognize patterns in the prediction vector output of the target model. These patterns allow the meta-model to infer whether a data point belongs to the training dataset or not. The number of shadow models affects the attack accuracy but it also incurs cost to the attackers. Salem et al. [79] showed that membership inference attacks are possible with as little as one shadow model.

Shadow training can be further reduced to a threshold-based attack, where instead of training a meta-model, one can calculate a suitable threshold function that indicates whether a sample is a member of the training set. The threshold can be learned from multiple shadow models [78] or even without using any shadow models [106]. Sablayrolles et al. [78] showed that a Bayes optimal membership inference attack depends only on the loss and their attack outperformed previous attacks such as [85, 106]. In terms of attack accuracy, they reported up to 90.8% attack accuracy against large neural network models such as VGG16 which were performing classification on the Imagenet dataset.

In addition to relaxations on the number of shadow models, attacks have been shown to be transferable i.e., an attack to one target model transfers to another target if the training dataset was the same [92].

Shadow model training requires a shadow dataset. One of the main assumptions of membership inference attacks against supervised learning models is that the adversary has no or limited knowledge of the training samples used. However the adversary knows something about the underlying data distribution of the training data. If the adversary does not have access to a suitable dataset, they can try to generate one [85, 92]. Access to statistics about the probability distribution of several features allows an attacker to create the shadow dataset using sampling techniques. If a statistics based generation is not possible, a query based approach using the target models' prediction vectors is possible. If the adversary manages to find input data that generate predictions with a high confidence, then no prior knowledge of the data distribution is required for a successful attack [85]. Salem et al. [79] went so far as to show that it is not even necessary to train the shadow models using data from the same distribution as the target, making the attack more realistic since it does not assume any knowledge of the training data.

The previous discussion is mostly relevant to supervised classification or regression tasks. The efficacy of membership inference attacks against sequence-to-sequence models training for machine translation was studied by [35]. The authors used shadow models that try to mimic the target model's behavior and then used a meta-model to infer membership. They found that sequence generation models are much harder to attack compared to other types of models such as image classification. However, membership of *out-of-domain* and out-of-vocabulary data was easier to infer.

5.1.3 Reconstruction attacks. The initial reconstruction attacks were based on the assumption that the adversary has access to the model f, the priors of the sensitive and non-sensitive features and the output of the model for a specific input x. The attack was based on estimating values of sensitive features given values of non-sensitive features and the output label [20]. This method used a maximum a posteriori (MAP) estimate of the attribute that maximizes the probability of observing the known parameters. Hidano et al. [33] used a similar attack but they made no assumption about knowledge of the non-sensitive attributes. In order for their attack to work, they assumed that the adversary can perform a *model poisoning* attack during training.

Both of the previous attacks worked against linear regression models, but as the number of features and their range increases, attack feasibility decreases. In order to overcome the limitations of the MAP attack, Fredrikson et al. [19] proposed another inversion attack which recovers features using target labels and optional auxiliary information. The attack was formulated as an optimization problem where the objective function is based on the observed model output and uses gradient descent in the input space in order to recover the input data point. The method was tested on image reconstruction. The result was a class representative image which in some cases was quite blurry even after denoising. A formalization of the model inversion attacks in [19, 20] was later proposed by Wu et al. [101].

Since the optimization problem in [19] is quite hard to solve, Zhang et al. [109] proposed to use a GAN in order to learn some auxiliary information of the training data and produce better results. The auxiliary information in this case is the presence of blurring or masks in the input images. The attack first uses the GAN in order to learn to generate realistic looking images from masked or blurry images using public data. The second step is a GAN inversion that calculates the latent vector \hat{z} which generates the most likely image:

$$\hat{z} = \arg\min_{z} L_{prior}(z) + \lambda L_{id}(z) \tag{4}$$

where the prior loss L_{prior} is ensuring the generation of realistic images and L_{id} ensures that the images have a high likelihood in the target network. The attack is quite successful, especially against masked images.

The only black-box reconstruction attack until now was proposed by Yang et al. [104]. This attack employs an additional classifier that performs an inversion from the output of the target model f(x) to a candidate output \hat{x} . The setup is similar to that of an autoencoder, only in this case the target network that plays the role of the encoder is a black-box and it is not trainable. The attack was tested in different types of target model outputs: the full prediction vector, a truncated vector and the target label only. When the full prediction vector is available the attack performs a good reconstruction, but with less available information, the produced data point looks more like a class representative.

- 5.1.4 Property inference attacks. In property inference the shadow datasets are labelled based on the properties that the adversary wants to infer, so the adversary needs access to data that have the property and data that do not have it. The meta-model is then trained to infer differences in the output vectors of the data that have the property versus the ones that they don't have it. In white-box attacks, the meta-model input can be other feature representations such as support vectors [2] or transformations of neural network layer outputs [21].
- 5.1.5 Model extraction attacks. When the adversary has access to the inputs and prediction outputs of a model, it is possible to view these pairs of inputs and outputs as a system of equations where the unknowns are the model parameters [91] or hyper-parameters of the objective function [97]. In the case of a linear binary classifier, the system of equations is linear and only d+1 queries are necessary to retrieve the model parameters, where d is the dimension of the parameter vector θ . In more complex cases, such as multi-class linear regression or multi-layer perceptrons the systems of equations are no longer linear. Optimization techniques such as BroydenâĂŞFletcherâĂŞGoldfar-bâĂŞShanno (BFGS) [70] or stochastic gradient descent are then used in order to approximate the model parameters [91].

Lack of prediction vectors or a high number of model parameters renders equation solving attacks inefficient. A strategy is required in order to select the inputs that will provide the most useful information for model extraction. From this perspective, model extraction is quite similar to *active learning* (AL) [10]. Active learning makes use of an external oracle that provides labels to input queries. The oracle can be a human expert or a system. The labels are then used to train or update the model. In the case of model extraction, the target model plays the role of the oracle.

Following the AL approach, several papers propose an adaptive training strategy. They start with some initial data points or *seeds* which they use to query the target model and retrieve labels or prediction vectors which they use to train the substitute model \hat{f} . For a number of subsequent rounds they extend their dataset with new synthetic data points based on some adaptive strategy that allows them to find points close to the decision boundary of the target model [10, 44, 74, 91]. Chandrasekaran et al. [10] provided a more query efficient method of extracting non-linear models such as kernel SVMs, with slightly lower accuracy than the method proposed by Tramer et al. [91], while the opposite was true for Decision Tree models.

Several other strategies for selecting the most suitable data for querying the target model use: (i) data that are not synthetic but belong to different domains such as images from different datasets [13, 72], (ii) semi-supervised learning techniques such as rotation loss [107] or Mix-Match [5] to augment the dataset [39] or (iii) randomly generated input data [44, 49, 91]. In terms of efficiency, unsupervised methods such as MixMatch require much fewer queries than fully supervised extraction methods in order to perform similarly or better in terms of task accuracy and fidelity, against models trained for classification using CIFAR-10 and SVHN datasets [39]. For larger models, trained for Imagenet classification, even querying a 10% of the Imagenet data, gives a comparable performance to the target model [39]. Against a deployed MLaaS service that provides

facial characteristics, Orekondy et al. [72] managed to create a substitute model that performs at 80% of the target in task accuracy, spending as little as \$30.

Some, mostly theoretical, work has demonstrated the ability to perform direct model extraction beyond linear models [39, 63]. Full model extraction was shown to be theoretically possible against two-layer fully connected neural networks with rectified linear unit (ReLU) activations by Milli et al. [63]. However, their assumption was that the attacker has access to the loss gradients with respect to the inputs. Jagielski et al. [39] managed to do a full extraction of a similar network without the need of gradients. Both approaches take into account that ReLUs transforms the neural network into a piece-wise linear function of the inputs. By probing the model with different inputs it is possible to identify where the linearity breaks and use this knowledge to calculate the network parameters. In a hybrid approach that uses both a learning strategy and direct extraction, Jagielski et al. [39], showed that they can extract a model trained on MNIST with almost 100% fidelity by using 2^{19.2} to 2^{22.2} queries against models that contain up to 400,000 parameters. However, this attack assumed access to the loss gradients similarly to [63].

Finally, apart from learning substitute models directly, there is also the possibility of extracting model information such as architecture, optimization methods and hyper-parameters using shadow models [71]. The majority of attacks were performed against neural networks trained on MNIST. Using the shadow models' prediction vectors as input, the meta-models managed to learn to distinguish whether a model has certain architectural properties. An additional attack by the same authors, proposed to generate adversarial samples which were created by models that have the property in question. The generated samples were created in a way that makes a classifier output a certain prediction if they have the attribute in question. The target model's prediction on this adversarial sample is then used to establish if the target model has a specific property. The combination of the two attacks, proved to be the most effective approach. Some properties such as activation functions, presence of dropout and max-pooling where the most successfully predicted.

5.2 Attacks Against Distributed Learning

In centralized modes of learning, attacks are focused on one machine learning model and its properties. The adversaries are assumed to be able to query the model or to have access to its parameters. Distributed modes of learning such as federated or collaborative learning, introduce different spatial models of adversaries. In a federated learning setting, the adversary can be collocated with the global model but it can also be a local attacker that **actively** or **passively** tries to attack (Figure 4). The presence of multiple actors allows also the possibility of *colluding* adversaries that join forces.

Federated learning (FL) is a form of decentralized training where the goal is to learn one **global** model from data stored in multiple remote devices / locations [52]. The main idea is that the data do not leave the remote devices. They are processed **locally** and only the intermediate updates are sent to the central server that hosts the global model. The most popular learning algorithm for FL is Federated Averaging [59], where each remote device, calculates one step of the gradient descent locally and then shares the updated model weights with the parameter server. The parameter server averages the weights of all the remote participants and updates the global model which is subsequently shared again with the remote devices:

$$\theta_{t+1} = \frac{1}{K} \sum_{k=1}^{K} \theta_t^{(k)} \tag{5}$$

where K is the number of remote participants and the parameters θ_t^k of participant k have been calculated locally based on Equations 2 and 3.

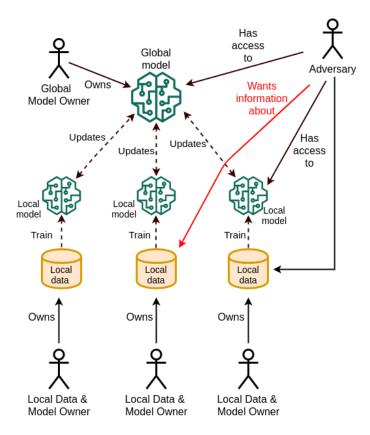


Fig. 4. Threat model in a distributed learning setting. Dashed lines represent data and information flows, while full lines represent possible actions. In red are the adversarial actions available under the threat model. In this setting the adversary can be placed either at the parameter server or locally. Model consumers are not depicted for reasons of simplicity. In a federated learning setting, local model owners are also model consumers.

Another approach that comes from the area of distributed computing is Downpour (or synchronized) SGD [14], which proposes to share the loss gradients of the distributed devices with the parameter server that aggregates them and then performs one step of gradient descent:

$$\theta_{t+1} = \theta_t - \eta \sum_{k=1}^{K} \frac{m^{(k)}}{M} g_t^{(k)}$$
(6)

where $\mathbf{g}_t^{(k)}$ is the gradient computed by participant k based on Equation 3 using their local data, $m^{(k)}$ is the number of data points in the remote participant and M is the total number of data points in the training data. After the calculation of Equation 6, the parameter server shares the updated model parameters θ_{t+1} with the remote participants.

Both Federated Averaging and Synchronous SGD can be problematic from a privacy perspective because, in essence, each remote device has access to the model parameters. The same applies to the parameter server that obtains the model parameters or their loss gradients from multiple devices.

5.2.1 Membership inference attacks. Nasr et al. [65] showed that a membership inference attack is more effective than the black-box one, under the assumption that the adversary has some auxiliary knowledge about the training data, i.e., has access to some data from the training dataset, either explicitly or because they are part of a larger set of data the adversary possesses. The adversary can use the model parameters and the loss gradients as inputs to another model which is trained to distinguish between members and non-members. The white-box attack accuracy against various neural network architectures was up to 75.1%, however, all models had a high generalization error.

In the active attack scenario, the attacker which is also a local participant, alters the gradient updates to perform a gradient ascent instead of descent for the data whose membership is under question. If some other participant uses the data for training, then their local SGD will significantly reduce the gradient of the loss and the change will be reflected in the updated model, allowing the adversary to extract membership information. Attacks from a local active participant reached attack accuracy of 76.3% and in general attack active attack accuracy was higher than the passive accuracy in all tested scenarios. However, as the number of participants increases, it has adverse effects in the attack accuracy which drops significantly after five or more participants. A global active attacker which is in a more favourable position, can isolate the model parameter updates they receive from each participant. Such an active attacker reached attack accuracy of 92.1%.

- 5.2.2 Property inference attacks. Passive property inference requires access to some data that possess the property and some that do not. The attack applies to both federated average and synchronized SGD settings, where each remote participant receives the parameter updates from the parameter server after each training round [61]. The initial dataset is of the form $\mathcal{D}' = \{(\mathbf{x}, \mathbf{y}, \mathbf{y}')\}$, where x and y are the data used for training the distributed model and y' are the property labels. Every time the local model is updated, the adversary calculates the loss gradients for two batches of data. One batch that has the property in question and one that does not. This allows the construction of a new dataset that consists of gradients and property labels $(\nabla L, y')$. Once enough labeled data have been gathered, a second model f' is trained to distinguish between loss gradients of data that have the property versus those that do not. This model is then used to infer whether subsequent model updates were made using data that have the property. The model updates are assumed to be done in batches of data. The attack reaches an attack area under the curve (AUC) score of 98% and becomes increasingly more successful as the number of epochs increases. Attack accuracy also increases as the fraction of data with the property in question, also increases, However, as the number of participants in the distributed model increases, the attack performance decreases significantly.
- 5.2.3 Reconstruction attacks. Some data reconstruction attacks in a federated learning setting make use of generative models and specifically GANs [36, 100]. When the adversary is one of the participants they can force the victims to release more information about the class they are interested in reconstructing [36]. This attack works as follows: The potential victim has data for a class "A" that the adversary wants to reconstruct. The adversary trains an additional GAN model. After each training round the adversary uses the target model parameters for the GAN discriminator, whose purpose is to decide whether the input data come from class "A" or are generated by the generator. The aim of the GAN is to create a generator that is able to generate faithful class "A" samples. In the next training step of the target model, the adversary generates some data using the GAN and labels them as class "B". This forces the target model to learn to discriminate between classes "A" and "B" which in turn improves the GAN training and its ability to generate class "A" representatives.

If the adversary has access to the central parameter server, they have direct access to model updates of each remote participant. This makes it possible to mount more successful reconstruction

attacks [100]. In this case the GAN discriminator is again using the shared model parameters and learns to distinguish between real and generated data, as well as the identity of the participant. Once the generator is trained, the reconstructed samples are created using an optimization method that minimizes the distance between the real model updates and the updates due to the generated data. Both GAN based methods assume access to some auxiliary data that belong to the victims. However, the former method generates only class representatives.

In a synchronized SGD setting, an adversary with access to the parameter server has access to the loss gradients of each participant during training. Using the loss gradients is enough to produce a high quality reconstruction of the training data samples, especially when the batch size is small [110]. The attack is utilizing a second "dummy" model. Starting with random dummy inputs x' and and labels y', the adversary tries to match the dummy model's loss gradients $\nabla_{\theta} \mathcal{J}'$ to the participant's loss gradients $\nabla_{\theta} \mathcal{J}$. This gradient matching is formulated as an optimization task that seeks to find the optimal x' and y' that minimize the gradients' distance:

$$x^*, y^* = \arg\min_{x', y'} \|\nabla_{\theta} \mathcal{J}'(\mathcal{D}'; \theta) - \nabla_{\theta} \mathcal{J}(\mathcal{D}; \theta)\|^2$$
(7)

The minimization problem in Equation 7 is solved using limited memory BFGS (L-BFGS) [53]. The size of the training batch is an important factor in the speed of convergence in this attack.

Data reconstruction attacks are also possible during the inference phase in a collaborative inference scenario [31]. This is a setup relevant to situations where remote or edge devices are connected to a central cloud server but they have limited resources. This scenario is typical with internet of things (IoT) devices. In collaborative inference the trained model is split into two or more parts. The edge devices keep the initial layers of the deep learning model and the centralized server keeps the final layers [29, 47]. The reason for the split is mainly to lower communication costs by sending intermediate model outputs instead of the input data.

When the local nodes process new data, they perform inference on these initial layers and then send their outputs to the centralized server. In this attack, the adversary is placed in the centralized server and their goal is to try to reconstruct the data used for inference. He et al. [31] cover a range of scenarios: (i) white-box, where the adversary has access to the initial layers and uses them to reconstruct the images, (ii) black-box where the adversary has no knowledge of the initial layers but can query them and thus re-create the missing layers and (iii) query-free where the adversary cannot query the remote participant and tries to create a substitute model that allows data reconstruction. The latter attack produces the worst results, as expected, since the adversary is the weakest. The split of the layers between edge device and centralized server is also affecting the quality of reconstruction. Fewer layers in the edge neural network allow for better reconstruction in the centralized server.

5.3 Attacks Against Generative Models

Previous sections dealt with attacks on discriminative learning and specifically on supervised learning. However, attacks on privacy may be relevant for generative models, too. An adversary may be interested in information about the training dataset used in a generative model or interested in the model itself. While there is prior research in many different types of generative models, there are two types that are currently the most popular; Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). Most research on attacking generative models has been focused on these two types of models so far.

Since generative models have more than one component (generator/discriminator, encoder/decoder), adversarial knowledge needs to take them into account. For these type of models, the taxonomy proposed by Chen et al. [11] is partially followed. We consider black-box access to the generator as

the ability to access generated samples and partial black-box access, the ability to provide inputs z and generate samples. Having access to the generator model and its parameters is considered a white-box attack. The ability to query the discriminator is also a white-box attack. This scenario, addressed by Hayes et al. [30] is considered unrealistic, since these component are not likely to be published. Similarly, the VAE white-box attack requires access to the full VAE model which is also not a realistic scenario [34]. However, it is important to understand what is possible and what is not and to establish an upper bound of potential leakage.

So far, the focus of privacy related attacks against GANs and VAEs has been membership inference [11, 30, 34]. The full white-box attacks with access to the GAN discriminator are based on the assumption that if the GAN "overfitted", then data points used for its training will receive higher confidence values as output in the discriminator [30]. In addition to the previous attack, Hayes et al. proposed a set of attacks in the partial black-box setting. These attacks are applicable to both GANs and VAEs or any generative model. If the adversary has no auxiliary data, they can attempt to train an auxiliary GAN whose discriminator distinguishes between data generated by the target generator and data generated by the auxiliary GAN. Once the auxiliary GAN is trained, its discriminator can be used for the white-box attack. The authors considered also scenarios where the adversary may have auxiliary information such as knowledge of training and test data. Using the auxiliary data they can train another GAN whose discriminator would be able to distinguish between members of the original training set and non-members.

An attack applicable to both GANs and VAEs in a partial black-box setting was proposed by Hilprecht et al. [34]. Assuming that an "overfitted" generator will have memorized the training data, a way to establish membership for a new data sample, is to measure how likely it is to be close to the training points generated by the generator or encoder using a metric such as Euclidean distance. The estimation of the probability of a data point being a member of the training set is performed using Monte Carlo integration while the Euclidean distance was measured based on the top 40 principal components derived by principal component analysis.

Another distance based attack over the nearest neighbors of a data point, was proposed by Chen et al. [11] for the full black-box model. In this case a data point ${\bf x}$ is a member of the training set if within its k-nearest neighbors there is at least one point that has a distance lower than a threshold ϵ . The authors proposed more complex attacks as the level of knowledge of the adversary increases, based on the idea that the reconstruction error between the real data point x and a sample generated by the generator given some input z should be smaller if the data point is coming from the training set. In both the partial black-box attack and the white-box attack with access to the generator, the authors propose to calculate the value of z which provides the smallest distance between a generated data point and the original one:

$$z^* = \arg\min_{z} \mathcal{L}(x, G(z))$$
 (8)

where \mathcal{L} is a distance metric. In the image generation domain \mathcal{L} calculated based on pixel-to-pixel similarity, a regularization term and the Learned Perceptual Image Patch Similarity (LPIPS) metric [108]. Once z^* is calculated, if the distance between x and $G(z^*)$ is below a certain threshold, the data point in question is assumed to belong to the training set \mathcal{D} . The white-box setting provides the best results because access to the model allows differentiation and the use of optimization methods such as L-BFGS.

A property of a successful generative model is to produce high quality samples that cover the data distribution as much as possible. One of the problems, especially with the training of GANs is that it is not that easy to measure the generated data quality and distribution support in conjunction with the training metrics. One of most popular metrics of the quality of a GAN generator is the

Frechet Inception Distance (FID) which scores both the quality and the diversity of the generated data. Unfortunately only [11] offers FID measurements for the models under test.

These are early stages of attacks against generative models. While the attacks are promising, they suffer as the size of the training set increases. The only attack that seems to withstand the increase of the dataset is the one that assumes access to the discriminator, which is the strongest possible adversary.

5.4 Design Summary

To summarize the attacks proposed against machine learning privacy, Table 1 presents the 40 papers analyzed in terms of adversarial knowledge, model under attack, attack type and timing of the attack.

In terms of model types, 92.5% of the papers dealt with attacks against neural networks, with linear models being the second most popular model to attack at 17.5% (some papers covered attacks against multiple model types). The concept of neural networks groups together both shallow and deep models, as well as multiple architectures, such as convolutional neural networks, recurrent neural networks, GANs, and VAEs.

The most popular attack types are membership inference and reconstruction attacks (35% of the papers, respectively) with model extraction the next most popular (27.5%). The majority of proposed attacks are mounted during the inference phase (87.5%). Attacks during training are mainly against distributed forms of learning. Black-box and white-box attacks were studied in 65% and 55% of the papers, respectively (some papers covered both settings). In the white-box category we also include partial white-box attacks.

While there is a diverse set of works presented, it is possible to discern some high-level patterns in the proposed attacking techniques. Figure 5 shows the number of papers in relation to the attacking technique and attack type. Most notably, nine papers used shadow training mainly for membership and property inference attacks. Active learning was quite popular in model extraction attacks with four papers, while four papers used GANs and another three used gradient matching techniques. It should be noted here, that the "Learning" technique includes a number of different approaches, spanning from using model parameters and gradients as inputs to classifiers [61, 65] to using input-output queries for substitute model creation [13, 39, 72] and learning classifiers from language models for reconstruction attacks [73]. In "Threshold" based attacks we categorized the attacks proposed in [106] and [78] and subsequent papers that used them for membership and property inference.

Some attacks may be applicable against multiple learning tasks and datasets, however, this is not the case universally. Dataset size and complexity might also be a factor for the success of certain attacks, especially since most of them are empirical. Table 2 is a summary of the datasets used in all attack papers along with the data types of their features, the learning task they were used for and the dataset size. The datasets were used during the training of the target models and in some cases as auxiliary information during the attacks. The table contains 49 unique datasets used across 40 papers, an indication of the variation of different approaches.

This high variation is both a blessing and a curse. On one hand it is highly desirable to use multiple types of datasets to test the different hypotheses and the majority of the reviewed research follows that approach. However, these many options make it harder to compare methods. As it is evident from Table 2, some of the datasets are quite popular. MNIST, CIFAR-10, CIFAR-100 and UCI Adult have been used by more than six papers while 24 datasets have been used by only one paper.

The number of model parameters varies based on the model, task and dataset used in the experiments. As it can be seen in Table 2, most datasets are not extremely large, hence the models under attack are not extremely large. Given that most papers deal with neural networks this might

Table 1. Summary of papers on privacy attacks on machine learning systems, including information of their assumptions about adversarial knowledge (black / white-box), the type of model(s) under attack, the attack type, and the timing of the attack (during training or during inference)

Reference	Year	Knowledge		Model Type				Attack Type			Timing				
		Black-box	White-box	Linear	Decision Trees	SVM	HMM	Neural network	GAN / VAE	Membership Inference	Reconstruction	Property Inference	Model Extraction	Training	Inference
Fredrikson et al. [20]	2014		•	•							•				•
Fredrikson et al. [19]	2015	•	•		•			•			•				•
Ateniese et al. [2]	2015		•			•	•					•			•
Tramer et al. [91]	2016	•	•	•	•	•		•					•		•
Wu et al. [101]	2016	•	•		•			•			•				•
Hidano et al. [33]	2017		•	•							•				•
Hitaj et al. [36]	2017		•					•			•			•	
Papernot et al. [74]	2017	•						•					•		•
Shokri et al. [85]	2017	•						•		•					•
Correia-Silva et al. [13]	2018	•						•					•		•
Ganju et al. [21]	2018		•					•				•			•
Oh et al. [71]	2018	•						•					•		•
Long et al. [55]	2018	•						•		•					•
Rahman et al. [77]	2018		•					•		•					•
Wang & Gong [97]	2018		•	•		•							•		•
Yeom et al. [106]	2018	•	0	•	•			•			•				•
Carlini et al. [8]	2019	•						•			•				•
Chen et al. [11]	2019	•	•						•	•					•
Hayes et al. [30]	2019	•	•						•	•					•
He et al. [31]	2019	•	•					•			•				•
Hilprecht et al. [34]	2019	•							•	•					•
Jayaraman & Evans [40]	2019	•	•					•		•	•				•
Juuti et al. [44]	2019	•						•					•		•
Milli et al. [63]	2019	•		•				•					•		•
Nasr et al. [66]	2019		•					•		•				•	
Melis et al. [61]	2019		•					•		•		•		•	
Orekondy et al. [72]	2019	•						•					•		•
Sablayrolles et al. [78]	2019		0					•		•					•
Salem et al. [79]	2019	•						•		•					•
Song L. et al. [88]	2019	•						•		•					•
Truex, et al. [92]	2019	•						•		•					•
Wang et al. [100]	2019		•					•			•			•	
Yang et al. [104]	2019	•						•			•				•
Zhu et al. [110]	2019		•					•			•			•	
Chandrasekaran et al. [10]	2020	•		•	•	•		•					•		•
Hishamoto et al. [35]	2020	•						•		•					•
Jagielski et al. [39]	2020	•						•					•		•
Krishna et al. [49]	2020	•						•					•		•
Pan et al. [73]	2020		•					•			•				•
Zhang et al. [109]	2020		•					•			•				•

indicate that most attacks focused on smaller datasets and models which might not be representative of realistic scenarios. However, privacy attacks do not necessarily have to target large models with extreme amounts of data and neural networks however popular, are not necessarily the most used models in the "real world".

Another dimension that could be interesting to analyze is the types of learning tasks that have been the target of attacks so far. Figure 6 presents information about the number of papers in

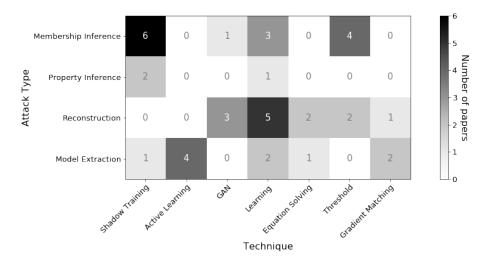


Fig. 5. Number of papers that used an attacking technique for each attack type. Darker gray means higher number of papers.

relation to the learning task and the attack type. By learning task we refer to the task in which the target model initially trained. As the figure clearly shows, the majority of the attacks are against models that were trained for classification tasks, both binary and multi-class. This is the case across all four attack types.

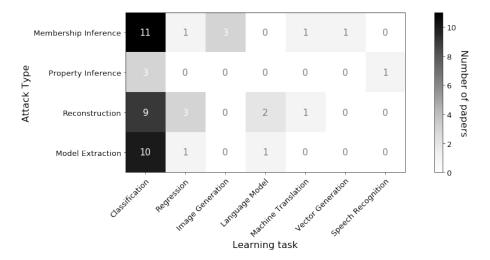


Fig. 6. Number of papers used against each learning task and attack type. Classification includes both binary and multi-class classification. Darker gray means higher number of papers. This figure shows in which attack types were still not studied for some learning tasks.

Table 2. Summary of datasets used in the papers about privacy attacks against machine learning systems. The size of the datasets is measured in number of samples unless otherwise indicated. A range in the size column indicates that different papers used different subsets of the dataset.

Name	Data Type	Learning Task	Reference(s)	Size (samples)	
538 Steak Survey[32]	mixed features	multi-class classification	[10, 19, 33, 91]	332	
AT&T Faces [3]	images	multi-class classification	[19, 36, 100]	400	
Bank Marketing [16]	mixed features	multi-class classification	[97]	45,210	
Bitcoin prices	time series	regression	[91]	1,076	
Breast Cancer [16]	numerical feat.	binary classification	[10, 55, 91]	699	
Caltech 256 [26]	images	multi-class classification	[72]	30,607	
Caltech birds [96]	images	multi-class classification	[72]	6,033	
CelebA [54]	images	binary classification	[11, 21, 104, 109]	20-202,599	
CIFAR-10 [50]	images	image generation, multi-class classifi- cation	[30, 31, 34, 39, 63, 77–79, 85, 88, 92, 104, 106]	60,000	
CIFAR-100 [50]	images	multi-class classification	[40, 66, 79, 85, 106, 110]	60,000	
CLiPS stylometry [94]	text	binary classification	[61]	1,412 reviews	
Chest X-ray [99]	images	multi-class classification	[109]	10,000	
Diabetes [16]	time series	binary class., regression	[10, 91, 97]	768	
Diabetic ret. [46]	images	image generation	[30, 72]	88,702	
Enron emails	text	char-level language model	[8]	-	
Eyedata [80]	numerical feat.	regression	[106]	120	
FaceScrub [69]	images	binary classification	[61, 104]	18,809-48,579	
Fashion-MNIST [102]	images	multi-class classification	[34, 39, 88]	60,000	
Foursquare [103]	mixed features	binary classification	[61, 79, 85]	528,878	
Geog. Orig. Music [16]	numerical feat.	regression	[97]	1,059	
German Credit [16]	mixed features	binary classification	[91]	1,000	
GSS marital survey [27]	mixed features	multi-class classification	[10, 19, 91]	16127	
GTSRB [89]	images	multi-class classification	[44, 74]	51839	
HW Perf. Counters	numerical feat.	binary classification	[21]	36,000	
Imagenet [15]	images	multi-class classification	[39, 71, 78]	14,000,000	
Instagram [4]	location data	vector generation	[11]	,,	
Iris [18]	numerical feat.	multi-class classification	[10, 91]	150	
IWPC [12]	mixed features	regression	[20, 106]	3497	
IWSLT Eng-Vietnamese	text	neural machine translation	[8]	5177	
LFW [37]	images	image generation	[30, 61, 110]	13233	
Madelon [16]	mixed features	multi-class classification	[97]	4,400	
MIMIC-III [43]	binary features	record generation	[11]	41,307	
Movielens 1M [28]	numerical feat.	regression	[33]	1,000,000	
Woviciens IVI [20]	numericai icat.	regression	[10, 21, 31, 34, 36, 39, 44, 55,	1,000,000	
MNIST [51]	images	multi-class classification	63, 71, 74, 77, 79, 85, 91, 92, 100, 104, 106, 109, 110]	70,000	
Mushrooms [16]	categorical feat.	binary classification	[10, 91]	8,124	
Netflix [67]	binary features	binary classification	[106]	2,416	
Netflows	network data	binary classification	[2]	-	
PTB [58]	text	char-level language model	[8]	5 MB	
PiPA [108]	images	binary classification	[61]	18,000	
Purchase-100 [45]	binary features	multi-class classification	[40, 66, 85, 92]	197,324	
SVHN [68]	images	multi-class classification	[39, 110]	60,000	
TED talks [38]	text	machine translation	[8]	100,000 pairs	
Texas-100 [9]	mixed features	multi-class classification	[66, 85]	67,330	
UJIndoor [16]	mixed features	regression	[97]	19,937	
UCI / Adult [16]	various	binary classification	[10, 21, 55, 79, 85, 91, 92]	48,842	
Voxforge [95]	audio	speech recognition	[2]	11,137 rec.	
Wikitext-103 [62]	text	word-level language model	[8, 49]	500 MB	
Yale-Face [22]	images	multi-class classification	[88]	2,414	
Yelp reviews [105]	text	binary classification	[61]	16-40,000	

6 WHY DO MACHINE LEARNING MODELS LEAK?

The connection between overfitting and black-box membership inference was initially investigated by Shokri etal. [85]. The authors showed experimentally that overfitting can lead to privacy leakage but also noted that it is not the only condition. This finding was later corroborated by Yeom et al. [106] where they showed that overfitting is a sufficient condition for performing membership

inference attacks but not a necessary one. Additionally, Long et al. [55] showed that even in well generalized models, it is possible to perform membership inference for a subset of the training data which they named *vulnerable records*.

Other factors, such as the model architecture, the model type, and the dataset structure, affect attack accuracy. Models with smaller generalization error on the same dataset were shown to leak more in some MLaaS cases [85]. This means that model type and complexity are an important factor in membership inference. Similarly, in the white-box setting, Nasr et al. [66] showed that two models with the same generalization error showed different degrees of leakage. More specifically the most complex model in terms of numbers of parameters exhibited higher attack accuracy, showing that model complexity is also an important factor.

Truex et al. [92] ran different types of experiments to establish the significance of model and data complexity. They found that certain model types such as Naive Bayes are less susceptible to membership inference attacks than decision trees or neural networks. They also found that the complexity of the data increases the potential of membership leaks. The higher number of classes led to highest attack accuracy [92].

Securing machine learning models against adversarial attacks can also have an adverse effect on the model's privacy as shown by Song et al. [88]. Current state of the art proposals for robust model training, such as projective gradient descent (PGD) adversarial training [56], increases the model's susceptibility to membership inference attacks. This is not unexpected since robust training methods (both empirical and provable defenses) tend to increase the generalization error. As previously discussed, the generalization error is related to the success of the attacks. Furthermore, the authors of [88] argue that robust training may lead to increased model sensitivity to the training data, which can also affect membership inference.

The generalization error is easily measurable in supervised learning under the assumption that the test data can capture the nuances of the real data distribution. In generative models and specifically in GANs this is not the case, hence the notion of overfitting is not directly applicable. All three papers that deal with membership inference attacks against GANs, mention overfitting as an important factor behind successful attacks [11, 30, 34]. In this case, overfitting means that the generator has memorized and replays part of the training data. This is further corroborated in the ablation study in [11], where their attacks are shown to be less successful as the training data size increases.

While black-box membership inference attacks are connected to overfitting this is not necessarily the case with other types of attacks. Model extraction is possible even when the models under attack have 98% or higher accuracy rate in the test set [71]. Property inference is also possible against well-generalized models [21, 61].

When it comes to reconstruction attacks, Yeom et al. [106] showed that a higher generalization error can lead to higher probability in inferring data attributes, but also that the influence of the target feature to the model is an important factor. However, they assume that the adversary has knowledge of the prior distribution of the target features and labels. Using weaker assumptions about the adversary's knowledge, Zhang et al. [109] showed theoretically and experimentally that a model that has high predictive power is more susceptible to reconstruction attacks. Finally, similarly to vulnerable records in membership inference, memorization and retrieval of data which are *out-of-distribution* was shown to be the case even for models that do not overfit [8].

7 DEFENDING MACHINE LEARNING PRIVACY

Leaking personal information such as medical records or credit card numbers is usually an undesirable situation. The purpose of studying attacks against machine learning models is to be able to explore the limitations and assumptions of machine learning and to anticipate the adversaries'

actions. Most of the analyzed papers propose and test mitigations to counter their attacks. One of the most popular proposed countermeasure is differential privacy (DP). This section presents a non exhaustive overview of differential privacy as it is used in privacy preserving machine learning (PPML), as well as other defensive measures proposed in the reviewed literature.

7.1 Differential Privacy

Differential privacy started as a privacy definition for data analysis and it is based on the idea of "learning nothing about an individual while learning useful information about a population" [17]. Its definition is based on the notion that if two databases differ only by one record and are used by the same algorithm (or mechanism), the output of that algorithm should be similar. More formally,

Definition 7.1 ((ϵ , δ)-Differential Privacy). A randomized mechanism \mathcal{M} with domain \mathcal{R} and output \mathcal{S} is (ϵ , δ)-differentially private if for any adjacent inputs $D, D' \in \mathcal{R}$ and for any subsets of outputs \mathcal{S} it holds that:

$$Pr[\mathcal{M}(D) \in \mathcal{S}] \le e^{\epsilon} Pr[\mathcal{M}(D') \in \mathcal{S}] + \delta$$
 (9)

where ϵ is the privacy budget and δ is the failure probability.

The original definition of DP did not include δ which was introduced as a relaxation that allows some outputs not to be bounded by e^{ϵ} .

The usual application of DP is to add Laplacian or Gaussian noise to the output of a query or function over the database. The amount of noise is relevant to the *sensitivity* which gives an upper bound on how much we must perturb the output of the mechanism in order to preserve privacy [17]:

Definition 7.2. l_1 (or l_2)-Sensitivity of a function f is defined as

$$\Delta f = \max_{D, D', ||D - D'|| = 1} ||f(D) - f(D')|| \tag{10}$$

where $\|.\|$ is the l_1 or the l_2 -norm and the max is calculated over all possible inputs D, D'.

From a machine learning perspective, D and D' are two datasets that differ by one training sample and the randomized mechanism \mathcal{M} is the machine learning training algorithm. In deep learning the noise is added at the gradient calculation step. Because it is necessary to bound the gradient norm, gradient clipping is also applied [1].

Differential privacy offers a trade-off between privacy protection and utility or model accuracy. Evaluations of differentially private machine learning models against membership inference attacks concluded that the models could offer privacy protection only when they considerably sacrifice their utility [40, 77]. Jayaraman et al. [40] evaluated several relaxations of DP in both logistic regression and neural network models against membership inference attacks. They showed that these relaxations have an impact to the utility-privacy trade off. While they reduce the required added noise they also increase the privacy leakage.

Distributed learning scenarios require additional considerations when it comes to differential privacy. In a centralized model the focus is on sample level DP, i.e., in protecting the privacy at the individual data point level. In a federated learning setting where we have multiple participants, we not only care about the individual training data points they use but we care about ensuring privacy at the participant level. A proposal which applies DP at the participant level was introduced by McMahan et al. [60] however it requires a large number of participants. When it was tested with a number as low as 30 the method was deemed unsuccessful [61].

7.2 Other Defensive Approaches

While differential privacy is one of the most popular countermeasures proposed in attack oriented papers, there are several other defences that have been explored.

- (1) **Regularization**. Most often in the form of dropout, regularization, is proposed by multiple papers with varying levels of success [8, 30, 61, 79, 85, 88]. Given that black-box membership inference attacks are connected to overfitting, it is a sensible approach against this type of attack.
- (2) **Prediction vector tampering**. As many models assume access to the prediction vector during inference, one of the countermeasures proposed was the restriction of the output to the top-k classes or predictions of a model [85]. However, this restriction, even to the strictest form (outputting only the class label) did not seem to fully mitigate membership inference attacks, since information leaks can still happen due to model misclassifications. The level of prediction vector truncation affects also reconstruction attacks, but it does not stop them completely [104]. Another option is to lower the precision of the prediction vector which leads to less information leakage [85]. Adding noise calculated using adversarial learning, also thwarts membership inference attacks [42].
- (3) **Model compression**. Setting all the loss gradients which are below a certain threshold to zero, was proposed as a defence against reconstruction attacks in deep learning. This technique proved quite effective with as little as 20% of the gradients set to zero and with negligible effects in model performance [110].
- (4) **Ensemble** methods, such as model stacking were tested in [79] and produced positive results against membership inference.
- (5) **Noisy data** addition. Randomly flipping labels on 5% of the training data had moderate success on preventing property inference attacks [21].
- (6) **Weight Quantization** or using **half-precision floating points** for neural network weights did not seem to deter the attacks in [8] and [110], respectively.
- (7) **Selective sharing** of gradients. In a distributed learning system that uses synchronized SGD, Shokri and Shmatikov proposed that the participants can partially share their gradients with the parameter server [83]. While this did not impact the model performance, it was later shown to be an inadequate measure [76].
- (8) **Protecting against DNN Model Stealing Attacks (PRADA)**. Detecting model stealing attacks based on the model queries that are used by the adversary was proposed by Juuti et al. [44]. The detection is based on the assumption that model queries that try to explore decision boundaries will have a different distribution than the normal ones. While the detection was successful, the authors noted that it is possible to be evaded if the adversary adapts their strategy.
- (9) **Membership inference**. The idea of using membership inference in order to defend against model extraction was studied by Krishna et al. [49]. It is based on the premise that using membership inference the model owner can distinguish between legitimate user queries and nonsensical ones whose only purpose is to extract the model. The authors note that this type of defence has limitations such as potentially flagging legitimate but out-of-distribution queries made by legitimate users, but more importantly that they can be evaded by adversaries that make adaptive queries.

8 DISCUSSION

Attacks against machine learning privacy have been increasingly brought to light. However, we are still at an exploratory stage. Many of the attacks are applicable only under specific sets of

assumptions or do not scale to larger training data sets, number of classes, number of participants, etc. The attacks will keep improving and in order to successfully defend against them, the community needs to answer fundamental questions about why they are possible in the first place. While progress has been made in the theoretical aspects of some of the attacks, there is still a long way to go when it comes to achieve better theoretical understanding of privacy leaks in machine learning.

As much as we need answers about why leaks happen at a theoretical level, we also need to know how well privacy attacks work against real deployed systems. Adversarial attacks against realistic systems brought to light the issue of additional constraints that need to be in place for the attacks to work. When creating glasses that can fool a face recognition system, Sharif et al. [82], had to pose constraints that had to do with physical realizations, e.g., that the color of the glasses should be printable. In privacy related attacks, the most realistic attacks come from the model extraction area, where attacks against MLaaS systems have been demonstrated in multiple papers. For the majority of other attacks, it is certainly an open question of how well they would perform against deployed models and what kind of additional requirements need to be in place for them to succeed.

At the same time, the main research focus up to now has been supervised learning. Even within supervised learning, there are areas and learning tasks that have been largely unexplored, such as recurrent models. In unsupervised learning, the focus is mainly in generative models and only just recently papers started exploring areas such as representation learning. Some attacks against image classifiers, do not transfer that well against natural language processing tasks [35] while others do, but may require different sets of assumptions and design considerations [73].

Beyond expanding the focus to different learning tasks there is the question of datasets. The impact of data complexity in the attack success has been demonstrated by several papers. Yet, currently, we lack a common approach as to which datasets are best suited to demonstrate privacy attacks, or constitute the minimum requirement for a successful attack. Several questions are worth considering: do we need standardized datasets and if yes how do we go about and create them? Are all data worth protecting and if some are more interesting than others, shouldn't we be testing attacks beyond popular image datasets?

Finally, as we strive to understand the privacy implications of machine learning, we also realize that several research areas are connected and affect each other. We know, for instance, that adversarial training adversely affects membership inference [84] and that model censoring can still leak private attributes [87]. Property inference attacks can deduce properties of the training dataset that were not specifically encoded or were not necessarily correlated to the learning task. This can be understood as a form of bias detection which means that relevant literature in the area of model fairness should be reviewed as potentially complementary. Looking at adjacent areas of machine learning research might help us improve our understanding of privacy attacks, too.

9 CONCLUSION

As machine learning becomes ubiquitous, the scientific community becomes increasingly interested in its impact and side-effects in terms of security, privacy, fairness, and explainability. This survey conducted a comprehensive study of the state-of-the-art privacy-related attacks to create a new threat model and taxonomy of the different types of attacks and their characteristics. An in-depth examination of the different types of attacks allowed us to perform a further analysis which revealed common design patterns and differences between them. Our analysis revealed a somewhat narrow focus of the research conducted so far. At the same time, a thorough theoretical understanding of the reasons behind privacy leaks is still under-developed and this affects both the proposed defensive measures and our understanding of the limitations of privacy attacks. While the community is still in exploratory mode in regards to privacy leaks of machine learning systems, we hope that

this survey will provide the necessary background to both the interested readers as well as the researchers that wish to continue working in this topic.

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