Abstract

We consider membership inference attacks, one of the main privacy issues in machine learning. These recently developed attacks have been proven successful in determining, with confidence better than a random guess, whether a given sample belongs to the dataset on which the attacked machine learning model was trained. Several approaches have been developed to mitigate this privacy leakage but the tradeoff performance implications of these defensive mechanisms (i.e., accuracy and utility of the defended machine learning model) are not well studied yet. We propose a novel approach of privacy leakage avoidance with switching ensembles (PASE), which both protects against current membership inference attacks and does that with very small accuracy penalty, while requiring acceptable increase in training and inference time. We test our PASE method, along with the the current state-of-the-art PATE approach, on three calibration image datasets and analyze their trade-offs.

1. Introduction

The spectacular successes of machine learning in recent years have also brought significant scrutiny in its high-profile security vulnerabilities. Although the focus has been mostly on adversarial attacks, which were successfully constructed for a variety of applications [3, 4, 18, 21, 22, 16, 23, 13, 25], another group of security issues was recently identified in machine learning concerning various forms of privacy attacks. It was shown that it is possible to extract information about the training data by analyzing or querying a machine learning model [1, 8, 7, 29, 2, 28].

In this paper, we focus on a type of attack commonly referred to as membership inference attack. A successful membership inference attack can determine, with better than random success rate, if a given sample belongs to the training set when given access to a machine learning model [27]. This type of attack was introduced in [27], and later [17] proposed a method of providing privacy guarantees while taking into account the accuracy of the defended classifier. The attack [27] leverages the differences in the target model’s predictions (confidence values) on the samples it was trained on versus the samples which were outside of training data for detecting if a sample was part of the training data. Even with such limited information, this attack can be effective and remains effective for a variety of privacy defense methods [27].

There have been many recent research advances in the area of membership inference attacks. While [27] makes several assumptions that weaken the scope of membership attacks such as knowledge of the type of model and knowledge of certain aspects of the training data, [24] is able to generate successful attacks with weaker assumptions. In [26], membership attacks exploit interpretable machine learning output to get extra information about the training data. Even unsupervised learning is susceptible as [9] has described successful membership attacks in case of generative adversarial networks. Perhaps the most interesting research has been applying differential privacy [6] as a way to guarantee a defense against membership attacks. The PATE algorithm [5, 20] uses a teacher-student framework to protect any machine learning algorithm from a broad range of privacy attacks, including membership attacks, with differential privacy guarantees.

However, a security solution (in this context, privacy protection) often entails some performance penalty (deteri-
oration of accuracy and / or utility of the defended system). For instance, for the case of preventing privacy leakage of machine learning models, an obvious approach is to restrict the classifier’s output to discrete labels without disclosing the associated confidence values. However, this approach significantly reduces the utility of machine learning model since the choice of the subsequent actions frequently depends on the level of confidence of the provided classification decision. A less obvious approach is to restrict the class of machine learning models to simple classifiers such as linear threshold functions as their output does not have local optima that can betray the identity of training data. However, the applicability of such classifiers to realistic, complex problems is severely limited. Finally, approaches involving strong differential privacy guarantees can negatively affect the utility / performance of the protected model. In the case of PATE [6], the algorithm depends on an ensemble of teachers where each teacher is based on a small subset of the original training data. This not only negatively affect the resulting accuracy, but also does that in the circumstances where the problem of privacy leakage is most serious. Specifically, our experiments suggest that the efficiency of privacy attacks increases with the decrease of the size of training dataset since that makes training data more “sparse” in the feature space, which exposes more data “individuality” that can then be then detected more easily by the attacker.

In this paper, we propose and investigate a novel framework of protecting machine learning models against membership attacks. Our framework is based on ensemble learning with the focus on maintaining utility and accuracy of the existing machine learning model that is being protected. For this framework, we modify the generally solid approach of constructing an ensemble of classifiers by replacing its final step of combining all their outputs (using, for instance, some weighted voting) with a switching decision that selects only one of the classifiers in the ensemble for providing the classification output for a given input. This modification allows us to train the classifiers of the ensemble on significantly larger subsets of the original dataset, thus incurring negligible performance penalty while maintaining the desired privacy protection of the training data identity. We describe the architecture of our proposed Privacy Leakage Avoidance with Switching Ensembles (PASE) method, discuss its properties and implementation details, and calibrate its performance (along with the state-of-the-art PATE approach [20]) on three popular image datasets (CIFAR-10 [12], MNIST [14], SVNH [19]) within the framework of the state-of-the-art membership inference attack proposed in [27].

2. Privacy Leakage Avoidance Method

The training phase of PASE consists of building a set (ensemble) of individual auxiliary classifiers, each trained on a large subset of the original training data, where these subsets are constructed in the same way as subsets for cross-validation; the accuracy of each classifier would thus be close to that of the baseline machine learning model that uses all the available data for its training. The inference phase of PASE is executed when a request for classification is received – in this case, we select the element of our constructed ensemble of classifiers that was not trained on this input or the element of the training data that is closest to that input and use it for classification of the provided input (hence the term “switching ensemble”).

More formally, Figure 1 shows that we generate $k$ different auxiliary classifiers (for illustration purposes, $k = 4$ in Figure 1), where each classifier is built using an auxiliary subset of the original training data $G$ (shown as blue circle in Figure 1), where these subsets (shown as three-quarters of $G$ in Figure 1) are created in the same way as in cross-validation procedure with $k = 4$ folds. Specifically, we randomly partition the set of training instances (elements of training data $G$) into $k$ approximately equally-sized groups $g_1, g_2, \ldots, g_k$. We then train $k$ classifiers $M_1, M_2, \ldots, M_k$, where each $M_j$ is trained on all these groups except group $g_j$, i.e., on $G \setminus g_j$. Our motivation here is to create a set of these multiple classifiers so that, at inference phase, we can select one of these classifiers that was not trained on the given test instance $x$ (shown as a green dot in Figure 1). In order to ensure that, before making the actual inference, we first select the element $y$ of the training data that is closest to test instance $x$ (for that, we use Facebook AI Similarity Search (FAISS) open source software [10]), and then select the classifier that was trained on a dataset that did not include $y$; in Figure 1, that is the classifier $M_2$.

In order to illustrate PASE operation geometrically, consider Figure 2. The upper third of Figure 2 shows the training dataset consisting of 15 data points labeled as positive and negative, so the machine learning task is to construct a
binary classifier. Using \( k = 3 \) in our PASE approach, the training dataset is partitioned into three disjoint auxiliary subsets shown in Figure 2 using black, blue and red colors. The middle third of Figure 2 shows \( k = 3 \) auxiliary training subsets, each of which containing all the original training data without one of the above subsets. Specifically, the leftmost training dataset does not include black subset, the middle training dataset does not include blue dataset, and the rightmost training dataset does not include red dataset. The auxiliary classifiers (black, blue, and red), trained on each of the three auxiliary training datasets, form PASE switching ensemble, which effectively partitions the space into multiple areas (similar to Voronoi diagram) shown in the bottom part of Figure 2. The switching mechanism of PASE then selects the appropriate classifier for any given query point: for instance, if the query point belongs to the area with black boundaries, the black classifier will be applied; if the query point belongs to the area with blue boundaries, the blue classifier will be applied, etc.

As follows from the description above, if PASE is queried with a data point \( y \) from training data, a classifier that was not trained on \( y \) will be selected to respond to the query. Moreover, as Figure 2 illustrates, this classifier will be selected even the queried data point is not \( y \) itself but rather a point that is “close” to \( y \) (i.e., located in the same area with \( y \)). That property is especially important for image applications since visual similarity to one of the elements of training data might be actually quite sufficient for the purpose of membership inference attack.

Due to the way PASE selects its classifiers for making an inference, it might seem that a membership inference attack against PASE would always label the data as being not in the training set, thus making the true negative value of that binary attack classifier (the membership attack system is essentially a binary classifier that decides, based on the query response from the attacked system, whether the given query was a part of training data or not) equal to 100%. That is actually incorrect, and the confusion matrix of a membership attack on a PASE-protected machine learning system exhibits a more nuanced and interesting behavior. Conceptually, the balance between false positives and false negatives of a membership attack on PASE mostly depends on the sparsity of the training data in the corresponding feature space.

Specifically, if data points are relatively “close” to each other (or, to put it differently, the images do not exhibit much individuality), the membership inference attack would tend to label any point as not belonging to the training set (which again does not cause privacy leakage for the training data points). These effects match the observations made in [27] regarding the overall efficiency of membership inference attacks: for instance, in CIFAR10 dataset [12], the privacy leakage for the class of cars is smaller than that of the class of cats, while privacy leakage in MNIST dataset [14] is even smaller (images of cats apparently have more “individuality” that those of cars, and MNIST images of heavily preprocessed handwritten digits have even less “individuality”). Nevertheless, for the purpose of protection against privacy leakage, this traditional tradeoff between false positives and false negatives eventually yields the accuracy of the membership inference attack (against PASE-protected system) being practically equal to 50% (i.e., the toss-up decision for the attacker), as illustrated in the next Section on several representative experiments.

In terms of practical implementation of the described PASE approach, the same type / architecture of machine learning model that has been already optimized for a given dataset can be used for training for each of the ensemble classifiers – there is no need to change that architecture with the reasonable risk of adversely affecting the overall performance. Depending on the number \( k \) of algorithms in the switching ensemble, the accuracy penalty of our PASE solution can be made negligibly small (of course, the training time will have to be proportionally increased), at least within the context of membership inference attack of the type [27].

Since PASE inference process includes the selection of the appropriate algorithm from the constructed switching ensemble, the inference would take more time than the standard machine learning model. However, in the experiments we have carried out so far (described in the next Section), we have not observed any practically meaningful delay in terms of PASE inference time.
To summarize, the proposed PASE approach

- prevents privacy leakage in the context of membership inference attacks of the type [27],
- does not cause any meaningful deterioration of accuracy / utility of the protected machine learning model,
- does not require any architecture changes of the machine learning model preferred for the given data

at the expense of practically acceptable

- increased training time,
- increased inference time,
- increased storage requirements for maintaining switching ensemble models and training data index.

The next Section illustrates these tradeoff properties and provides calibration results for a diverse set of image classification tasks.

Finally, note that PASE is designed for the type of current state-of-the-art membership inference attack introduced in [27]. The efficiency of such practical attacks has been demonstrated on a variety of diverse datasets, and their key enabler (confidence overfitting on some elements of the training data) for such privacy leakage is already well understood. Given PASE protection against such attacks, it is theoretically possible that an adversary might explore its architecture for launching the following “next level” attack: by using significant amount of probing the outputs of the machine learning model by feeding it various data points in the feature space, the attacker can reverse engineer the boundaries of the areas where PASE decision is switched from one classifier to another (illustrated in the bottom third of Figure 2) and then infer the identity of the data point(s) contained in these areas by some processing of these boundaries.

However, the practicality of such an attack is yet unclear: besides seemingly enormous amount of probing it would take to discover any meaningful portion of boundaries (that amount can be probably significantly reduced if the probing is carried out within a reasonably low-dimensional manifold containing the training data – for instance, as it has been done in the recently proposed model inversion attack [2], although current model inversion attacks produce just generalized class representations, which is very different from finer-granularity identities of training data points), the way of identifying the training data point from the discovered boundaries is unknown. The investigation of practicality and efficiency of such kinds of model inference attacks is thus a subject of future work. However, in the event that these attacks turn out to be implementable and efficient, the current PASE architecture can be then easily modified, for instance, by using the “moving target” approach, where \( k \) auxiliary subsets are periodically changed (and the corresponding \( k \) classifiers in the PASE ensemble are re-trained), thus completely invalidating the results of the previous probes by the attacker. The exact details of such modifications are also a subject of future work, to be carried out depending on the feasibility of the “next level” attack described above.

3. Experiments and Discussion

We have carried out several experiments for evaluating and comparing PASE and PATE [20] approaches in terms of the membership privacy attack [27] designed to determine whether a given data record was a member of the model’s training dataset. In our experiments, we used three datasets: CIFAR-10 dataset [12] contains 50,000 training images and 10,000 test images. MNIST dataset [14] contains 60,000 training images and 10,000 test images. SVHN dataset [19] contains 600,000 images.

We re-partitioned these standard datasets in the following way: (1) merged the training and test sets; (2) split the whole dataset into two disjoint parts, where the first part is for the baseline model, PASE model and PATE model, and the second part is for the membership attack model; (3) the dataset for each model is further split to training and test sets (for the training data of PATE model, we used 90% for the teacher model’s training and the remaining 10% – for the student model’s training).

We have used different classification models for different datasets to show the effects of the privacy preservation models. For each dataset, we have used the same classification model for the baseline (undefended) model, PASE model, PATE model and the shadow models of the membership inference. For MNIST, we used a 3-layer fully connected neural network (DNN - Dense layer Neural Network). For SVHN, we used a CNN model from the released PATE code which consists of 2 convolutional layers and some fully connected layers, pooling layers and normalization layers. For CIFAR-10, we used a VGG16 neural network architecture. Finally, for the attack model, we used a 3-layer fully connected neural network (DNN) similar to the one used for the MNIST dataset described above.

As [27] demonstrated, even small overfitting can be efficiently leveraged by an attacker towards making statistically meaningful membership inference. Since generalization performance of different machine learning algorithms vary, in order to demonstrate both the efficiency of membership inference attack on the unprotected machine learning model and the efficiency of corresponding membership privacy protection mechanisms, we need to choose a machine learning model that exhibits some overfitting while having good utility accuracy. For example, on the model architecture selection for the MNIST dataset, we used the
DNN model because the DNN model has good utility accuracy and noticeable overfitting. In one experiment of an undefended baseline model training on MNIST dataset with DNN model, the test accuracy was 97.06% and the training accuracy was 100%. The generalization error, i.e., the difference between training and testing accuracy, was thus 2.94% which indicates noticeable overfitting. We also tried the CNN model on MNISt dataset. The testing accuracy was very good (which was 99%) but the overfitting was small (the generalization error was 1%). Therefore, we did not use the CNN model for MNIST dataset to explore the effects of the privacy preservation models: there would not be much privacy leakage there, and thus there would not be much need for prevention of such privacy leakage.

Similarly, the generalization error of the baseline model with the VGG16 architecture on CIFAR-10 dataset was 25.9% and the generalization error of the baseline model with the CNN architecture on SVHN dataset was 3.4%. Note that the generalization errors were higher than typical models trained with full datasets. We did not use the full datasets for the training and testing of baseline models as well as of PASE and PATE models because we put aside part of the data for training the membership attack’s shadow models. Overfitting and generalization error usually increase with the decrease of the size of training data.

During the inference phase, one of our $k$ auxiliary PASE classifiers is selected to answer a test query. We assume that the samples in the PASE training data are unique. If the querying sample is in the training data, there will be only one classifier which is not trained with that querying sample and that classifier is chosen to answer that query. If the querying sample is not in the training data, none of the $k$ PASE classifiers are trained with that querying sample. In that case, we look for a sample in the training data which is most similar to the querying sample and choose the classifier which was not trained with that most similar sample to answer the query. Training data are randomly partitioned and similar training samples may end up in random different partitions. If there are samples in the training data that are not unique, we can either remove the duplicate samples or partition the training data in such a way that the same duplicate samples land in a same partition so that PASE switching mechanism will still work properly. In our experiments, we used the FAISS library [10] to build the search index for similarity search of test sample on training data. The index for fast searching can be precomputed and can be efficiently used for very large datasets. For the experimental results presented in this paper, we simply converted the training images from their original 2D matrix format to 1D vectors and then built the FAISS index using $L_2$ distance metric. Since image similarity search can also rely on various image feature descriptors / representations, we plan to explore, in our future work, alternative ways of building the search index by leveraging specialized feature descriptors and representations of the images, such as SIFT [15], image embedding using Convolutional Neural Networks [11], etc.

The results of our experiments are summarized in Table 1 - Table 4. For comparison purposes, the PATE results are produced without the random noise added for the PATE model’s student. Indeed, if it is added, the privacy attack accuracy does not change (it is already at the level of 50%), while the utility accuracy is reduced. A large number of teacher classifiers can then compensate the utility accuracy loss, but, for some datasets such as CIFAR10, a large number of teacher classifiers reduces the size of training data for each PATE teacher, which, in turn, reduces the teacher model’s accuracy, and, therefore, the student’s accuracy will be also reduced. The PASE models used ensemble of $k = 5$ classifiers. The attack models used 10 shadow models for training data generation. The other experiment parameters used for the results in tables were as follows.

CIFAR-10 dataset: 29,000 samples used for utility model training and test; the utility models used the VGG16 neural network; the PATE model used 20 teachers.

MNIST dataset: 30,000 samples used for utility model training and test; the utility models used the DNN neural network; the PATE model used 10 teachers.

SVHN dataset: 80,000 samples used for utility model training and test; the utility models used the CNN neural network; PATE model used 100 teachers.

| Dataset | Utility accuracy | | | |
|--------|------------------|---|---|---|
| CIFAR10 | 74.13% | 69.64% | 26.79% |
| MNIST | 97.06% | 96.53% | 88.87% |
| SVHN | 95.46% | 95.11% | 79.73% |

Table 1. Utility accuracy of baseline classification model, PASE and PATE privacy-preserving models.

| Dataset | Attack accuracy | | | |
|--------|-----------------|---|---|---|
| CIFAR10 | 68.70% | 50.17% | 50.20% |
| MNIST | 53.48% | 50.15% | 51.00% |
| SVHN | 52.15% | 49.87% | 50.22% |

Table 2. Membership inference attack accuracy of baseline classification model, PASE and PATE privacy-preserving models.

As Table 2 shows, both PATE and PASE approaches achieve their goal of eliminating privacy leakage (the success rate of membership inference attack is practically equal to the value 50% of the random choice), with PASE approach maintaining the accuracy of the defended model quite closely to the original baseline model as shown in Table 1. Note that it was achieved by using only $k = 5$
classifiers in PASE ensemble: a proportionally longer training time of a larger number of \( k \) classifiers would provide classification performance that is even closer to the baseline model, while retaining the same level of privacy protection.

| Dataset   | Training time (the ratio over baseline training time) |
|-----------|-------------------------------------------------------|
| CIFAR10   | 1 3.3 1.2 (10 teachers)                              |
| MNIST     | 1 3.2 1.4 (20 teachers)                              |
| SVHN      | 1 3.1 23.2 (100 teachers)                            |

Table 3. Training time of baseline classification model, PASE and PATE privacy-preserving models.

Table 3 shows the computing time used to train the models. The results are the ratios of the models’ training time over their corresponding baseline models’ training time. We used \( k = 5 \) in our experiments, and the total time to train the five PASE models is about 3.2 times larger than the time used to train one baseline model. Note that the training time of PATE models varies significantly since different numbers of teachers were used.

| Dataset   | Architecture | Baseline | PASE | PATE |
|-----------|--------------|----------|------|------|
| CIFAR10   | VGG16        | 0.35     | 0.94 | 0.30 |
| MNIST     | DNN          | 0.034    | 0.120| 0.028|
| SVHN      | CNN          | 0.107    | 0.416| 0.106|

Table 4. Inference time of baseline classification model, PASE and PATE privacy-preserving models.

Table 4 shows the inference time of the trained models on their corresponding test samples. PASE model’s inference time is expectedly longer (but still well within practical bounds) to that of the baseline model. This is mostly due to the time used to search for the most similar training sample in the FAISS index. The PATE model’s inference time is comparable to that of the baseline model. The VGG16 model, which was used for CIFAR10 dataset, is more complex than the CNN model which was used for the SVHN dataset; the CNN model is more complex than the DNN model, which was used for the MNIST dataset. As a result, the inference times of the CIFAR10 models were longer than those of the SVHN models, and the inference times of SVHN models were longer than those of the MNIST models.

4. Conclusions

We have proposed and tested a novel approach of preventing privacy leakage of machine learning models during membership inference attacks. We showed that our approach has good performance (both in terms of privacy leakage avoidance and small accuracy penalty) on several calibration image datasets.

In future work, we plan to explore various implementation options (such as selection of number and type of constituent auxiliary classifiers in the switching ensemble, choices in inference mechanism, etc.), build similarity search index with state of the art feature descriptors and explore the applicability of our approach to non-image datasets. We also plan to investigate the feasibility of “next level” model inversion attacks against PASE architecture (as described in the end of Section 2) and the corresponding modifications of PASE architecture that they might necessitate.

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References

[1] G. Ateniese, G. Felici, L. V. Mancini, A. Spognardi, A. Villani, and D. Vitali. Hacking smart machines with smarter ones: How to extract meaningful data from machine learning classifiers. CoRR, abs/1306.4447, 2013.

[2] S. Basu, R. Izmailov, and C. Mesterharm. Membership model inversion attacks for deep networks. ArXiv, abs/1910.04257, 2019.

[3] B. Biggio, I. Corona, D. Maiorca, B. Nelson, N. Šrndić, P. Laskov, G. Giacinto, and F. Roli. Evasion attacks against machine learning at test time. In H. Blockeel, K. Kersting, S. Nijssen, and F. Železný, editors, Machine Learning and Knowledge Discovery in Databases, pages 387–402, Berlin, Heidelberg, 2013. Springer Berlin Heidelberg.

[4] B. Biggio, G. Fumera, and F. Roli. Security evaluation of pattern classifiers under attack. IEEE Transactions on Knowledge and Data Engineering, 99:1, 01 2013.

[5] Q. Chen, C. Xiang, M. Xue, B. Li, N. Borisov, D. Kaafar, and H. Zhu. Differentially private data generative models. CoRR, abs/1812.02274, 2018.

[6] C. Dwork and A. Roth. The algorithmic foundations of differential privacy. Found. Trends Theor. Comput. Sci., 9(3–4):211–407, Aug. 2014.

[7] M. Fredrikson, S. Jha, and T. Ristenpart. Model inversion attacks that exploit confidence information and basic countermeasures. In Proceedings of the 22Nd ACM SIGSAC Conference on Computer and Communications Security, CCS ’15, pages 1322–1333, New York, NY, USA, 2015. ACM.

[8] M. Fredrikson, E. Lantz, S. Jha, S. Lin, D. Page, and T. Ristenpart. Privacy in pharmacogenetics: An end-to-end case study of personalized warfarin dosing. In 23rd USENIX Security Symposium (USENIX Security 14), pages 17–32, San Diego, CA, Aug. 2014. USENIX Association.

[9] J. Hayes, L. Melis, G. Danezis, and E. D. Cristofaro. LOGAN: evaluating privacy leakage of generative models using generative adversarial networks. CoRR, abs/1705.07663, 2017.

[10] J. Johnson, M. Douze, and H. Jégou. Billion-scale similarity search with gpus. arXiv preprint arXiv:1702.08734, 2017.

[11] D. Kiela and L. Bottou. Learning and transferring mid-level image representations using convolutional neural networks. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 36–45, 25–29 October 2014.

[12] A. Krizhevsky, V. Nair, and G. Hinton. Cifar-10 (canadian institute for advanced research).

[13] A. Kurakin, I. Goodfellow, and S. Bengio. Adversarial examples in the physical world. 07 2016.

[14] Y. LeCun and C. Cortes. MNIST handwritten digit database. 2010.

[15] D. G. Lowe. Distinctive image features from scale-invariant keypoints. In International Journal of Computer Vision, volume 60, pages 91–110, 25–29 October 2004.

[16] S.-M. Moosavi-Dezfooli, A. Fawzi, and P. Frossard. Deepfool: a simple and accurate method to fool deep neural networks. CVPR, 11 2016.

[17] M. Nasr, R. Shokri, and A. Houmansad. Machine learning with membership privacy using adversarial regularization. In Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security, CCS ’18, pages 634–646, New York, NY, USA, 2018. ACM.

[18] B. Nelson, B. Rubinstein, L. Huang, A. D. Joseph, S. J. Lee, S. Rao, and J. D. Tygar. Query strategies for evading convex-inducing classifiers. Journal of Machine Learning Research, 13, 07 2010.

[19] Y. Netzer, T. Wang, A. Coates, A. Bissacco, B. Wu, and A. Y. Ng. Reading digits in natural images with unsupervised feature learning. In NIPS Workshop on Deep Learning and Unsupervised Feature Learning 2011, 2011.

[20] N. Papernot, M. Abadi, U. Erlingsson, I. Goodfellow, and K. Talwar. Semi-supervised knowledge transfer for deep learning from private training data. In Proceedings of the International Conference on Learning Representations, 2017.

[21] N. Papernot, P. McDaniel, and I. Goodfellow. Transferability in machine learning: from phenomena to black-box attacks using adversarial samples. 05 2016.

[22] N. Papernot, P. McDaniel, I. Goodfellow, S. Jha, Z. B. Celik, and A. Swami. Practical black-box attacks against machine learning. pages 506–519, 04 2017.

[23] N. Papernot, P. McDaniel, S. Jha, M. Fredrikson, Z. B. Celik, and A. Swami. The limitations of deep learning in adversarial settings. pages 372–387, 03 2016.

[24] A. Salem, Y. Zhang, M. Humbert, M. Fritz, and M. Backes. MI-leaks: Model and data independent membership inference attacks and defenses on machine learning models. CoRR, abs/1806.01246, 2018.

[25] M. Sharif, S. Bhagavatula, L. Bauer, and M. Reiter. Accesorize to a crime: Real and stealthy attacks on state-of-the-art face recognition. pages 1528–1540, 10 2016.

[26] R. Shokri, M. Strobel, and Y. Zick. Privacy risks of explaining machine learning models. CoRR, abs/1907.00164, 2019.

[27] R. Shokri, M. Stronati, C. Song, and V. Shmatikov. Membership inference attacks against machine learning models. In 2017 IEEE Symposium on Security and Privacy, SP 2017, San Jose, CA, USA, May 22-26, 2017, pages 3–18.

[28] F. Tramèr, F. Zhang, A. Juels, M. K. Reiter, and T. Ristenpart. Stealing machine learning models via prediction apis. In 25th USENIX Security Symposium (USENIX Security 16), pages 601–618, Austin, TX, Aug. 2016. USENIX Association.

[29] X. Wu, M. Fredrikson, S. Jha, and J. F. Naughton. A methodology for formalizing model-inversion attacks. In CSF, pages 355–370. IEEE Computer Society, 2016.