Adversarial Attack Attribution:
Discovering Attributable Signals in Adversarial ML Attacks

Marissa Dotter, Sherry Xie, Keith Manville, Josh Harguess, Colin Busho, Mikel Rodriguez
The MITRE Corporation
{mdotter, stxie, kmanville, jharguess, cbusho, mikel}@mitre.org

Abstract
Machine Learning (ML) models are known to be vulnerable to adversarial inputs and researchers have demonstrated that even production systems, such as self-driving cars and ML-as-a-service offerings, are susceptible. These systems represent a target for bad actors. Their disruption can cause real physical and economic harm. When attacks on production ML systems occur, the ability to attribute the attack to the responsible threat group is a critical step in formulating a response and holding the attackers accountable. We pose the following question: can adversarially perturbed inputs be attributed to the particular methods used to generate the attack? In other words, is there a way to find a signal in these attacks that exposes the attack algorithm, model architecture, or hyperparameters used in the attack? We introduce the concept of adversarial attack attribution and create a simple supervised learning experimental framework to examine the feasibility of discovering attributable signals in adversarial attacks. We find that it is possible to differentiate attacks generated with different attack algorithms, models, and hyperparameters on both the CIFAR-10 and MNIST datasets.

Introduction
As we collectively begin to use machine learning (ML) in safety critical systems and as components in large commercial systems, potential attacks on these systems become much more than an intellectual curiosity. An adversary attacking a ML system could result in loss of life, disruption of service and economic damages, or theft of valuable intellectual property. Researchers have demonstrated proof-of-concept attacks on several commercial systems, including Tesla’s autopilot (Tencent Keen Security Lab 2019), Amazon Alexa’s speech recognition (Li et al. 2019), and Microsoft Azure (MITRE, Microsoft et al. 2020). It is only a matter of time before adversaries leverage these techniques to cause real harm. Attribution can potentially deter cyber attacks or hold attackers accountable by leading to political sanctions or legal proceedings (Roth 2020a,b). In the cybersecurity world, two of the key indicators that enable cyber attribution are tradecraft and malware (Office of the Director of National Intelligence 2018). Security analysts have identified that threat groups follow certain Tactics, Techniques and

Figure 1: Adversarial Attack Attribution Overview

Procedures (TTPs) and the attacks they use may leave behind particular identifying signals. TTPs and signatures can be used to help attribute an attack to a particular group. With that goal in mind, Figure 1 presents an overview of adversarial attack attribution. Attribution is a larger concept that plays a key role alongside intent, infrastructure, and other cyber indicators in revealing tradecraft. Identifying the types of adversarial attacks used could provide vital cyber threat information related to these indicators. Further analysis of these indicators could aid in the attribution of the attacks and hold bad actors accountable.

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is nascent, the Defense Advanced Research Projects Agency (DARPA), under the newly formed, Reverse Engineering of Deceptions (RED) effort (DARPA 2020) (accessed August 22, 2020), is also interested in developing “techniques that automatically reverse engineer the tool-chains behind attacks such as multimedia falsification, adversarial ML attacks, or other information deception attacks.”

Adversarial attack attribution research may help us understand the techniques used by bad actors in practice. The ability to recover the process used to generate an attack could lend insights leading to better defenses. This includes discovering the attack algorithm, model architecture, and hyperparameters used to create attacks as well as the methods that adversaries use to introduce attacks to a system. With the continual growth of the machine learning field, many publicly available tools, frameworks, and even models can be downloaded and modified for adversarial needs (Papernot et al. 2016a; Rauber, Brendel, and Bethge 2017). Attribution could further help determine the sophistication of the attacker, the resources they have available, and even characterize their methods from attacks that do not fit within these publicly available tools.

This paper seeks to understand if adversarial ML attacks are attributable to the methods used to generate them, and thus aid in attribution to a particular threat group. More specifically, from a data sample with an embedded attack, can we identify the attack algorithm, model, or attack hyperparameters used to generate the adversarial example? Our experimental setup covers a broad-range of attack algorithms, models, and individual attack hyperparameters to attempt to answer that question. By creating this experimental space we can begin to understand properties of attribution, where it succeeds in distinguishing attacks, and where it fails within our current approach. We can also work towards addressing the following questions:

1. Are there underlying signals embedded within adversarial perturbations that can be used to classify the adversarial attack algorithm that was used to create the adversarial dataset? We present our experiments on multiple attack algorithms, created using the same model architecture, and optimized to have minimal perceptible perturbations, which maximize the adversarial accuracy of the data. We find that attack algorithm attribution is possible, and there does exist an underlying signal that particular algorithms leave behind that a classifier can discover.

2. Are there underlying signals that can distinguish the model that was used to create the adversarial dataset? We train models with various architectures and use them to generate attacks. We find that particular models do leave behind underlying signals indicating that a classifier can uncover attribution of not only the attack algorithms, but also the architecture used to generate the attack.

3. Are there underlying signals that can be used to distinguish the individual attack algorithm hyperparameters that were used to create the adversarial dataset? We create variations of adversarial datasets with different attack algorithm hyperparameters and $L_p$ norm constraints to study the task of hyperparameter attribution. Our attribution framework can in some cases distinguish these hyperparam-

Figure 2: An image from un-targeted attacks (top row) and the underlying perturbations (bottom row) on a CIFAR-10 image using the AlexNet CNN to create the attacks.

eters, indicating that even subtle changes in the optimization of an attack algorithm can be discovered.

The paper is organized as follows. We first summarize related work in adversarial machine learning as well as work in cyber attack attribution. Our methodology and experimental design for adversarial attack attribution follow. We then present the results of our experiments with a discussion of the results. Finally, we conclude the paper with our final thoughts and considerations for future work.

Related Work

This work relates quite closely to the literature of adversarial attacks and defenses in the context of real-world cyber attacks. We briefly introduce several well-known attacks (Akhtar and Mian 2018) and defenses (Chakraborty et al. 2018), touch on related work in fingerprinting GANs, and finally discuss cyber attribution.

Adversarial Attacks: (Szegedy et al. 2013) is one of the earliest demonstrations of adversarial attacks on deep learning models. In that work, the authors added small perturbations to images that could fool deep learning models into highly confident misclassifications. In (Goodfellow, Shlens, and Szegedy 2014), the authors present a simple, yet effective method of creating adversarial examples called the fast gradient sign method (FGSM). DeepFool (Moosavi-Dezfooli, Fawzi, and Frossard 2016) efficiently finds the minimal perturbation needed to fool a deep learning model. It does this by projecting the input onto the closest hyperplane and minimally perturbing the input until it is misclassified resulting in extremely small perturbations. Carlini & Wagner (Carlini and Wagner 2017) introduced a powerful optimization-based adversarial attack that has been shown to be effective even against defended models.

Adversarial Defenses: As research into attack types and variations grow, so do the defenses against those attacks. The earliest and most common approach to defense is adversarial training (Goodfellow, Shlens, and Szegedy 2014), which injects adversarial examples into the training set to increase model robustness. Using the fact that methods such as FGSM rely on the model’s gradient for the attack, gradient hiding defenses have been developed (Tramèr et al. 2017). Network distillation methods, which is a way to transfer knowledge from larger networks to smaller ones, (Papernot et al. 2016a) Rauber, Brendel, and Bethge 2017). Attribution could further help determine the sophistication of the attacker, the resources they have available, and even characterize their methods from attacks that do not fit within these publicly available tools.
Adversarial Detection: Much of the defensive literature has aimed to create models that are robust to adversarial attacks. However, some works try to explicitly detect adversarial inputs (Pang et al. 2018; Grosse et al. 2017; Weilin Xu 2018; Yang et al. 2020) so their predictions can be flagged as unreliable. Adversarial attribution can be seen as a fine-grained detection task. In this work, we operate under the assumption that an input has already been identified as adversarial.

GAN Attribution: In Yu, Davis, and Fritz (2019), the authors explore whether Generative Adversarial Networks have unique “fingerprints” that are discoverable in generated images. They find that images are attributable to a particular GAN. The authors also find that fingerprinting can help defend against attacks. Our work poses similar questions for adversarial examples. We explore attribution of not only the model, but the attack algorithm and its hyperparameters.

Cybersecurity: This work is directly related to the ongoing work of attribution of a particular cybersecurity attack or set of attacks to a bad actor or group of bad actors. An extensive summary of various techniques to perform attribution of cyber attacks, as well as an introduction of a taxonomy of attribution techniques, is presented in Wheeler and Larsen 2003. In Rid and Buchanan 2015, the authors introduce the ‘Q Model’ designed to explain, guide, and improve the making of attribution of cyber attacks. An Enhanced Cyber Attack Attribution Framework is introduced in Pitropakis et al. 2018 to detect and defend against Advanced Persistent Threats (APTs) and ultimately attribute the attack to malicious parties behind the campaign. The authors of Guitton and Korzak 2013 argue that the level of “sophistication” of a cyber-attack is not necessarily an indication for attribution of an attack to a particular actor, as is often argued and assumed in cyber attack attribution. A framework for cyber attack attribution based on threat intelligence is introduced in Qiang et al. 2016 which uses the ‘local advantage model’ to analyze the process of cyber attacks. In Edwards et al. 2017, the authors use a game-theoretic approach resulting in a ‘blame game’ to analyze policy-relevant questions, including the attribution of cyber attacks. In terms of real-world incidents within adversarial ML, MITRE, Microsoft and several other organizations have joined together to create the Adversarial ML Threat Matrix (MITRE, Microsoft et al. 2020) that will allow security analysts to work with threat models in a similar way to how these analysts confront cybersecurity attacks.

Methodology
In this work we pose the problem of adversarial attribution as a simple supervised learning problem as described by Figure 3. We assume knowledge of the possible attack on the target ML system and the ability to generate attacked versions of the test data. We also assume that the data has already been identified as adversarial, therefore the identification of individual adversarial attacks is outside of the scope of this paper and considered future work. The focus of this work is solely on the attribution of these attacks. We say an attack is attributable if a classifier can be trained to distinguish between different attacks. We consider attacks that utilize different attack algorithms, models, and hyperparameters to generate datasets for our attribution experiments. A summary of the datasets created is in Table 1. No comparisons to other algorithms are shown since we believe this is the first work of its kind at this time.

For our experiments we train baseline models AlexNet (Krizhevsky, Sutskever, and Hinton 2012), VGG16 (Simonyan and Zisserman 2014), and ResNet50 (He et al. 2016) on the CIFAR-10 (Krizhevsky, Hinton et al. 2009) and MNIST (LeCun, Cortes, and Burges 2010) datasets. These models are trained with randomly initialized weights without pre-training or transfer-learned weights/layers, which limits extraneous variables presented to our attribution classifier. The three attacks used to create adversarial datasets from the CIFAR-10 and MNIST datasets were the Fast Gradient Sign Method (FGSM) (Goodfellow, Shlens, and Szegedy 2014), DeepFool (Moosavi-Dezfooli, Fawzi, and Frossard 2016), and Carlini & Wagner (C&W) (Carlini and Wagner 2017). These attacks were chosen due to their simplicity and effectiveness, as well as to include optimized and non-optimized attacks for comparison. These attack algorithms were all implemented and modified from the Cleverhans library (Papernot et al. 2016a). An example of each adversarial attack and the underlying perturbation is shown in Figure 2 on the CIFAR-10 dataset. We also consider attack hyperparameters including $L_2$ and $L_{\infty}$ norms. We optimized each attack algorithm as an un-targeted attack meaning that the attack algorithm aims to mis-classify each sample without targeting a specific class. The adversarial datasets were created combinatorially through parameter choices as shown in Table 1.

Only adversarial datasets that effectively fool the original architecture are retained for our attribution experiments. If the attack is not effective, it would not be of concern in a real-world setting. This helped ensure that our datasets were close to a real-world attack while remaining in this experimental framework.

After creating the adversarial datasets across the different optimization parameters, we train a Convolutional Neural Network (CNN) with a standard cross-entropy loss for a binary or multi-class classification problem. The model we
chose for these classification tasks had an architecture consisting of six convolutional layers and two fully connected layers followed by a softmax output as seen in Figure 3. We use the standard CIFAR-10 and MNIST train/test splits, but with the attacked variants of the data for training and testing our attribution classifiers. We do not include an ‘unknown’ class in these experiments, but note that such a class would be beneficial in future experiments to account for new models, hyperparameters, norms, or even attacks that are unseen or unknown.

| Attack   | Models | Hyperparameters | Norm |
|----------|--------|-----------------|------|
| FGSM     | AlexNet| Epsilon: 1.0, 2.0, 5.0 | $L_2$ |
|          | VGG16  | Epsilon: 0.03, 0.1, 0.2 | $L_\infty$ |
|          | ResNet50 |                  |      |
| DeepFool | AlexNet| Overshoot: 0.01, 0.1, 1.0 | $L_2$ |
|          | VGG16  | Overshoot: 0.01, 0.1, 1.0 | $L_\infty$ |
|          | ResNet50 |                |      |
| C&W      | AlexNet| LR: 0.1, 0.2, 0.5 | $L_2$ |
|          | VGG16  | Conf.: 0.01, 0.1, 1.0 |      |
|          | ResNet50 |                |      |

Table 1: An overview of the adversarial attack algorithms, the models used to create each attack, and the hyperparameters the algorithms were optimized with. Through combinations of ‘Attack’, ‘Model’, ‘Hyperparameters’, and ‘Norm’ we create a diverse set of adversarial datasets to use throughout our experiments, i.e. FGSM $L_2$ Epsilon 1.0 Model: ResNet50 is a single adversarial dataset. Total datasets include: FGSM $L_2$: 9 datasets, FGSM $L_\infty$: 9 datasets, DeepFool $L_2$: 9 datasets, DeepFool $L_\infty$: 9 datasets, C&W $L_2$: 27 datasets.

Results

The results of our experimentation are organized by the three initial questions we sought to answer. All of our results are displayed as attribution accuracy: the fraction of attacked images that were correctly attributed by our classifier. In all experiments, each attacked dataset is the same size, making it easy to compare accuracy to random performance (random = $\frac{1}{n \cdot \text{datasets}}$). We consider attribution successful if our classifier performs better than random by a statistically significant margin. Bold values of the overall attribution accuracy indicate successful attribution within this framework. Where results are broken down to per-class accuracy, accuracy is intentionally not bold for readability of the table. Our experimental results show attribution using the full adversarial dataset however, we note that experimentation through constraining the number of adversarial examples we train on could give further insight into attribution as it approximates a real-world scenario.

Attack Algorithm Attribution

The first question we sought to answer through these experiments was whether or not there was some underlying perturbation signal that could be distinguished from one attack algorithm to another. We display results for all three attack algorithms. Table 2 and Table 3 display the results of three-class attack algorithm attribution for CIFAR-10 and MNIST on a per model basis. We consider DeepFool and FGSM with different norms ($L_2$ and $L_\infty$) separately. We expand the $L_2$ case to a nine-class problem that considers attack algorithm and model attribution simultaneously. Figure 4 and Figure 5 are confusion matrices for CIFAR-10 and MNIST respectively.

As we can see for both the CIFAR-10 and MNIST datasets, attack algorithms are able to be distinguished with high confidence on the test set. For example, as we examine the per-class accuracy for each attack algorithm (right three columns of Tables 2 and 3), we can see that for almost all classes, we achieve an accuracy higher than random chance.

Model Attribution

The second question we sought to answer through this framework was whether or not a particular open-source architecture leaves behind a characteristic signal in the perturbed adversarial data. We examined model attribution on a per-attack basis in Table 4. We note that each attack algorithm could distinguish the particular model that was used to create that variation of the adversarial dataset. Figure 4 and Figure 5 display the result of performing attack algorithm and model attribution simultaneously. These results support our hypothesis that attribution, specifically for distinguishing models, is possible. Additionally, by combining attack and model attribution in the framework, we can distinguish both the attack algorithm and the model simultaneously, which may aid in characterizing certain adversaries that repeatedly use particular attacks in such a way.

Hyperparameter Attribution

Our final question we sought to answer through this framework is individual attack algorithm hyperparameter attribution. Each class of attacks has a set of individual hyperparameters that are used to create the attack and are described in Table 1. Attack algorithms are evaluated individually due to the fact that different attack algorithms do not share hyperparameters. An example experimentation for hyperparameter attribution is as follows: using the DeepFool $L_2$ attack created with an AlexNet CNN and the hyperparameters from Table 1, hyperparameter attribution aims to distinguish Overshoot values 0.01, 0.1, and 1.0. As shown in Table 5, our attribution classifier fails to be able to find an underlying signal that is attributable to the DeepFool $L_2$ attack for each model. This indicates that our framework begins to break down for attacks such as these. Similarly, in Table 6 we see that our framework breaks down for the FGSM $L_\infty$ attack algorithm for each model on this task. Due to this particular type of attribution failing in some cases while succeeding in others, especially on separate datasets, this type of attribution may not be a reliable distinguishing factor in a real-world scenario. However, more experimentation would need

\footnote{Note that results displayed only cover one set of hyperparameters outlined in Table 1}
### CIFAR-10 Adversarial Attack Algorithm Attribution

| Attack Algorithms | Model       | Attribution Accuracy | Per-Class Accuracy |
|-------------------|-------------|----------------------|--------------------|
| C&W $L_2$ vs DeepFool $L_2$ vs FGSM $L_2$ | AlexNet | 0.70 | 0.62 | 0.48 | 0.97 |
|                  | VGG16     | 0.70 | 0.30 | 0.83 | 0.97 |
|                  | ResNet50  | 0.78 | 0.57 | 0.78 | 0.99 |
| C&W $L_2$ vs DeepFool $L_\infty$ vs FGSM $L_\infty$ | AlexNet | 0.58 | 0.48 | 0.38 | 0.87 |
|                  | VGG16     | 0.50 | 0.60 | 0.10 | 0.79 |
|                  | ResNet50  | 0.56 | 0.16 | 0.75 | 0.77 |

Table 2: Reporting attribution accuracy for cross attack algorithms as per class accuracy per architecture (model) on CIFAR-10. The hyperparameters chosen for each attack maximize adversarial accuracy and minimize perceptibility and are described in Table 1. This table presents the overall accuracy of the attack algorithm attribution under ‘Attribution Accuracy’ followed by the breakdown of per class accuracy.

### MNIST Adversarial Attack Algorithm Attribution

| Attack Algorithms | Model       | Attribution Accuracy | Per-Class Accuracy |
|-------------------|-------------|----------------------|--------------------|
| C&W $L_2$ vs DeepFool $L_2$ vs FGSM $L_2$ | AlexNet | 0.66 | 0.93 | 0.61 | 0.44 |
|                  | VGG16     | 0.78 | 0.91 | 0.80 | 0.63 |
|                  | ResNet50  | 0.73 | 0.99 | 0.65 | 0.56 |
| C&W $L_2$ vs DeepFool $L_\infty$ vs FGSM $L_\infty$ | AlexNet | 0.99 | 0.99 | 0.99 | 0.99 |
|                  | VGG16     | 1.00 | 1.00 | 1.00 | 1.00 |
|                  | ResNet50  | 0.99 | 0.99 | 0.99 | 0.99 |

Table 3: Reporting attribution accuracy for cross attack algorithms as per class accuracy per architecture (model) on MNIST. The hyperparameters chosen for each attack maximize adversarial accuracy and minimize perceptibility and are described in Table 1. This table presents the overall accuracy of the attack algorithm attribution under ‘Attribution Accuracy’ followed by the breakdown of per class accuracy.

### Adversarial Model Attribution: AlexNet vs VGG16 vs ResNet50

| Attack Algorithm | CIFAR-10 Accuracy | MNIST Accuracy |
|------------------|-------------------|---------------|
| C&W $L_2$        | 0.50              | 0.99          |
| DeepFool $L_2$   | 0.60              | 0.84          |
| DeepFool $L_\infty$ | 0.60          | 1.00          |
| FGSM $L_2$       | 0.70              | 0.87          |
| FGSM $L_\infty$  | 0.83              | 0.99          |

Table 4: Reporting best results for model attribution, distinguishing an AlexNet CNN from a VGG16 and ResNet50 architecture, where each attack algorithm hyperparameters are selected by smallest (most imperceptible) perturbation that maximizes adversarial accuracy. Hyperparameters and norm choices are described for each experiment in Table 1. It should be noted that as a secondary experiment to verify that our attribution classifier was or was not distinguishing only the ‘magnitude’ of an adversarial example’s perturbation, we also conducted an experiment to determine the significance of magnitude of adversarial noise as it pertains to our attribution classifier. Due to the DeepFool and C&W attacks being optimized, no two examples within each attack dataset have the same magnitude of perturbation, or have the same amount of “noise” per example. To account for magnitude differences and to ensure that our network is not learning the difference between those magnitudes rather than some underlying signal as we’ve predicted, we separate or ‘bin’ the datasets into specific ranges using the absolute difference of original to perturbed image. These ranges allowed us to study attribution on the same scale. However, due to class imbalances when separating the adversarial data in this way, conclusions could not be accurately drawn as to whether it had meaningful results. A further study of attack algorithm optimization norm and this “binning” process could give insights into the magnitude of the perturbation as it pertains to the underlying signal and what our attribution classifier is actually distinguishing.

We also include an additional experiment and visualization shown in Figure 6 to expand our hyperparameter attribution to attack algorithm attribution and hyperparameter attribution simultaneously on the AlexNet model. As we can see from the t-SNE plot, we can clearly distinguish the sub-classes of the attack algorithms C&W $L_2$ and FGSM $L_2$, represented by the blue and purple colors, respectively, but fail to make clear distinctions between the sub-classes of the DeepFool $L_2$ algorithm represented as orange, which are overlapped and cannot be separated by the attribution classifier. This corresponds to Table 5 for the AlexNet model where the DeepFool $L_2$ attack algorithm does not perform to be done to evaluate whether combinations of attack algorithm or attack model with attack hyperparameters could provide a valuable form of attribution when presented to a system.

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Figure 4: An expansion of the three-class Attack Algorithm Attribution to the nine-class Attack Algorithm (and Model) Attribution on CIFAR-10. For readability, values below 10% are not shown, so rows may not sum to 1.

Figure 5: An expansion of the three-class Attack Algorithm Attribution to the nine-class Attack Algorithm (and Model) Attribution on MNIST. For readability, values below 10% are not shown, so rows may not sum to 1.

### CIFAR-10 Adversarial Hyperparameter Attribution

| Attack    | AlexNet | VGG16 | ResNet50 |
|-----------|---------|-------|----------|
| C&W $L_2$ | 0.66    | 0.68  | 0.50     |
| DeepFool $L_2$ | 0.32  | 0.33  | 0.33     |
| DeepFool $L_\infty$ | 0.28  | 0.34  | 0.36     |
| FGSM $L_2$ | 0.53    | 0.48  | 0.52     |
| FGSM $L_\infty$ | 0.70  | 0.67  | 0.70     |

Table 5: Adversarial attack hyperparameter attribution on CIFAR-10.

### MNIST Adversarial Hyperparameter Attribution

| Attack    | AlexNet | VGG16 | ResNet50 |
|-----------|---------|-------|----------|
| C&W $L_2$ | 0.46    | 0.57  | 0.49     |
| DeepFool $L_2$ | 0.49  | 0.49  | 0.49     |
| DeepFool $L_\infty$ | 1.00  | 0.94  | 0.91     |
| FGSM $L_2$ | 0.77    | 0.42  | 0.88     |
| FGSM $L_\infty$ | 0.32  | 0.32  | 0.32     |

Table 6: Adversarial attack hyperparameter Attribution on MNIST.

better than random chance on the hyperparameter attribution experiment. However, we are still able to distinguish the particular attack algorithm as shown in Figure 6.

**Discussion of Results**

Our results from both the CIFAR-10 and MNIST datasets show that attribution, based upon our three main questions, is in fact possible through a very basic experimental setup. To highlight a few experiments of this work that indicate promising areas of attribution for real-world uses, we first examine the attack algorithm attribution and model attribution. Both of these tasks were not only robust in attributing attacks to their respective algorithm, but they were also robust to distinguishing underlying signals within their own attack algorithm. This indicates that with or without the pres-
in identifying bad actors that introduce attacks in such a way.

However, it is important to note that model attribution may not be the most optimal choice of attribution factor for real-world use-cases. This is due to number of factors including adversaries ensembling models to train adversarial data, in which case our framework would most likely break down due to underlying signals from multiple models being present within a single adversarial example. Additionally, model attribution may be impossible if the adversary gains access to our own attribution model and is able to train adversarial examples that could thwart our framework for attributing it. Such scenarios would render this type of attribution as significantly less robust as other types like attack algorithm attribution or a combination of attack algorithm and attack hyperparameters, however a further study would need to be made to understand this more and how useful model attribution is as its own distinguishing factor.

Our framework does however begin to break down when attempting to attribute the individual hyperparameters to an attack algorithm for both the CIFAR-10 and MNIST datasets. This may be due to the fact that the individual algorithms are not very sensitive to the range of hyperparameter values used and the resultant attacks are highly similar. In the case of FGSM $L_{\infty}$, it is simply the magnitude of the perturbation that is being varied and the attribution classifier is unable to distinguish between these datasets. Additionally there is a clear performance difference between the CIFAR-10 and MNIST results and future work is planned to investigate this discrepancy.

Though our experimentation only allows for known classes to be attributed, we note that further research into unknown classes, or unseen attacks, is necessary to realize this work in a real-world setting. It is intractable to assume a system has been trained on an example of every possible adversarial input into a system, however, for the purpose of our experiments, not having an unknown class allowed us to answer the more basic question of whether or not an underlying signal in the adversarial perturbation is present and can be used to distinguish it from other examples.

 existed of additional attacks inputted into a system, we can identify an algorithm or even a particular model architecture that an adversary may have used and modified for their own needs. We also show that the combination of attack algorithm and model presented to our framework can also be recovered simultaneously with high fidelity, which could aid

**Conclusion**

In this work, we have attempted to answer the question of whether we can discover the attribution of an adversarial attack. We have shown through extensive experimentation that there are underlying signals in the attack algorithm, the model, and the hyperparameters used to optimize attacks that a classifier can recover. We believe this opens a new area of adversarial machine learning of interest to many communities. Not only could this provide a means to defending networks against adversarial attacks, but it could mean providing the ability to uncover the actors and/or tool-chains behind real-world attacks.

We note that inputs into a system are rarely as large and diverse as an entire adversarial dataset. Therefore, to further constrain our problem to the most realistic experimentation possible, we want to investigate iteratively lowering the sample size of the training set throughout the attribution experimentation. This will help us to understand whether at-

**Table 7:** Attribution and per-class accuracy for attack algorithms with different $L_p$ norm constraints on CIFAR-10.

| Attack  | Model  | Accuracy | $L_{\infty}$ | $L_2$ |
|---------|--------|----------|--------------|-------|
| DeepFool | AlexNet | 0.60     | 0.60         | 0.60  |
|         | VGG16  | 0.60     | 0.60         | 0.60  |
|         | ResNet50 | 0.60     | 0.60         | 0.60  |
| FGSM    | AlexNet | 0.85     | 1.00         | 0.90  |
|         | VGG16  | 0.90     | 1.00         | 0.80  |
|         | ResNet50 | 0.70     | 1.00         | 0.40  |

**Table 8:** Attribution and per-class accuracy for attack algorithms with different $L_p$ norm constraints on MNIST.

| Attack  | Model  | Accuracy | $L_{\infty}$ | $L_2$ |
|---------|--------|----------|--------------|-------|
| DeepFool | AlexNet | 0.99     | 0.99         | 0.99  |
|         | VGG16  | 0.99     | 0.99         | 0.99  |
|         | ResNet50 | 0.99     | 0.99         | 0.99  |
| FGSM    | AlexNet | 1.00     | 1.00         | 1.00  |
|         | VGG16  | 1.00     | 1.00         | 1.00  |
|         | ResNet50 | 0.99     | 0.99         | 0.99  |
tribution is still possible in a real-world setting where the adversary may only attack a system with a single input.

Additionally, to further expand our experimentation, we also plan to utilize additional open-source frameworks for generating adversarial data, such as Cleverhans and FoolBox (Rauber, Brendel, and Bethge 2017). These frameworks and others provide open-source code for generating and fine-tuning adversarial attack methods and we anticipate the possibility of attribution being used to distinguish methods that are produced by these frameworks. We also plan to introduce different types of attacks, such as target object detection models, in addition to classification models, to determine if various types of adversarial attacks can be attributed within this framework.

References

Akhtar, N.; and Mian, A. 2018. Threat of adversarial attacks on deep learning in computer vision: A survey. *IEEE Access* 6: 14410–14430.

Carlini, N.; and Wagner, D. 2017. Towards evaluating the robustness of neural networks. In *2017 IEEE Symposium on Security and Privacy*, 39–57. IEEE.

Chakraborty, A.; Alam, M.; Dey, V.; Chattopadhyay, A.; and Mukhopadhyay, D. 2018. Adversarial attacks and defences: A survey. *arXiv preprint arXiv:1810.00069* .

DARPA. 2020 (accessed August 22, 2020). *Reverse Engineering of Deceptions (RED).* [https://beta.sam.gov/opp/108cad02B824285afScal17481f4/view](https://beta.sam.gov/opp/108cad02B824285afScal17481f4/view)

Edwards, B.; Furnas, A.; Forrest, S.; and Axelrod, R. 2017. Strategic aspects of cyberattack, attribution, and blame. *Proceedings of the National Academy of Sciences* 114(11): 2825–2830.

Goodfellow, I. J.; Shlens, J.; and Szegedy, C. 2014. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572* .

Grosse, K.; Manoharan, P.; Papernot, N.; Backes, M.; and McDaniel, P. 2017. On the (Statistical) Detection of Adversarial Examples. *ArXiv abs/1702.06280* .

Guitton, C.; and Korzak, E. 2013. The sophistication criterion for attribution: Identifying the perpetrators of cyber-attacks. *The RUSI Journal* 158(4): 62–68.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 770–778.

Krizhevsky, A.; Hinton, G.; et al. 2009. Learning multiple layers of features from tiny images. *Department of Computer Science, University of Toronto* .

Krizhevsky, A.; Sutskever, I.; and Hinton, G. E. 2012. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, 1097–1105.

LeCun, Y.; Cortes, C.; and Burges, C. 2010. MNIST handwritten digit database. *ATT Labs [Online]. Available: http://yann.lecun.com/exdb/mnist* 2.

Li, J. B.; Qu, S.; Li, X.; Szurley, J.; Kolter, J. Z.; and Metze, F. 2019. Adversarial Music: Real World Audio Adversary Against Wake-word Processing Systems. In *Conference on Neural Information Processing Systems*.

MITRE; Microsoft; et al. 2020. Adversarial ML Threat Matrix URL [https://github.com/mitre/advmthreatmatrix](https://github.com/mitre/advmthreatmatrix) Moosavi-Dezfooli, S.-M.; Fawzi, A.; and Frossard, P. 2016. Deepfool: a simple and accurate method to fool deep neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2574–2582.

Office of the Director of National Intelligence. 2018. A Guide to Cyber Attribution URL [https://www.dni.gov/files/CTIC/documents/ODNLA_Guide_to_Cyber_Attribution.pdf](https://www.dni.gov/files/CTIC/documents/ODNLA_Guide_to_Cyber_Attribution.pdf)

Pang, T.; Du, C.; Dong, Y.; and Zhu, J. 2018. Towards Robust Detection of Adversarial Examples. In *Thirty-second Conference on Neural Information Processing Systems*.

Papernot, N.; Faghri, F.; Carlini, N.; Goodfellow, I.; Feinman, R.; Kurakin, A.; Xie, C.; Sharma, Y.; Brown, T.; Roy, A.; et al. 2016a. Technical report on the cleverhans v2.1.0 adversarial examples library. *arXiv preprint arXiv:1610.00768* .

Papernot, N.; and McDaniel, P. 2017. Extending defensive distillation. *arXiv preprint arXiv:1705.05264* .

Papernot, N.; McDaniel, P.; Wu, X.; Jha, S.; and Swami, A. 2016b. Distillation as a defense to adversarial perturbations against deep neural networks. In *2016 IEEE Symposium on Security and Privacy (SP)*, 582–597. IEEE.

Pitropakis, N.; Panaousis, E.; Giannakoulas, A.; Kalpakis, G.; Rodrigue, R. D.; and Sarigiannidis, P. 2018. An enhanced cyber attack attribution framework. In *International Conference on Trust and Privacy in Digital Business*, 213–228. Springer.

Qiang, L.; Zeming, Y.; Baoxu, L.; Zhengwei, J.; and Jian, Y. 2016. Framework of cyber attack attribution based on threat intelligence. In *Interoperability, Safety and Security in IoT*, 92–103. Springer.

Rauber, J.; Brendel, W.; and Bethge, M. 2017. Foolbox: A python toolbox to benchmark the robustness of machine learning models. *arXiv preprint arXiv:1707.04131* .

Rid, T.; and Buchanan, B. 2015. Attributing cyber attacks. *Journal of Strategic Studies* 38(1-2): 4–37.

Roth, M. 2020a. Council Decision (CFSP) 2020/1537 of 22 October 2020 amending Decision (CFSP) 2019/797 concerning restrictive measures against cyber-attacks threatening the Union or its Member States. *OJ L 351I URL [http://data.europa.eu/eli/reg/impl/2020/1125](http://data.europa.eu/eli/reg/impl/2020/1125)*.

Roth, M. 2020b. Council Implementing Regulation (EU) 2020/1125 of 30 July 2020 implementing Regulation (EU) 2019/797 concerning restrictive measures against cyber-attacks threatening the Union or its Member States. *OJ L 246 URL [http://data.europa.eu/eli/reg/impl/2020/1125](http://data.europa.eu/eli/reg/impl/2020/1125)*.

Simonyan, K.; and Zisserman, A. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* .

Szegedy, C.; Zaremba, W.; Sutskever, I.; Bruna, J.; Erhan, D.; Goodfellow, I.; and Fergus, R. 2013. Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199* .

Tencent Keen Security Lab. 2019. Experimental Security Research of Tesla Autopilot URL [https://keenlab.tencent.com/en/whitepapers/Experimental_Security_Research_of_Tesla_Autopilot.pdf](https://keenlab.tencent.com/en/whitepapers/Experimental_Security_Research_of_Tesla_Autopilot.pdf). Tramèr, F.; Kurakin, A.; Papernot, N.; Goodfellow, I.; Boneh, D.; and McDaniel, P. 2017. Ensemble adversarial training: Attacks and defenses. *arXiv preprint arXiv:1705.07204* .

Weilin Xu, David Evans, Y. Q. 2018. Feature Squeezing: Detecting Adversarial Examples in Deep Neural Networks. In *Network and Distributed System Security Symposium*.
Wheeler, D. A.; and Larsen, G. N. 2003. Techniques for cyber attack attribution. Technical report, Institute for Defense Analyses, Alexandria, VA.

Yang, P.; Chen, J.; Hsieh, C.-J.; Wang, J.-L.; and Jordan, M. 2020. ML-LOO: Detecting Adversarial Examples with Feature Attribution. Proceedings of the AAAI Conference on Artificial Intelligence 34(04): 6639–6647. doi:10.1609/aaai.v34i04.6140. URL https://ojs.aaai.org/index.php/AAAI/article/view/6140

Yu, N.; Davis, L. S.; and Fritz, M. 2019. Attributing fake images to gans: Learning and analyzing gan fingerprints. In Proceedings of the IEEE International Conference on Computer Vision, 7556–7566.