MUTEN: Boosting Gradient-Based Adversarial Attacks via Mutant-Based Ensembles

Yuejun Guo, Qiang Hu, Maxime Cordy, Michail Papadakis, Yves Le Traon

1 Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg

Abstract

Deep Neural Networks (DNNs) are vulnerable to adversarial examples, which causes serious threats to security-critical applications. This motivated much research on providing mechanisms to make models more robust against adversarial attacks. Unfortunately, most of these defenses, such as gradient masking, are easily overcome through different attack means. In this paper, we propose MUTEN, a low-cost method to improve the success rate of well-known attacks against gradient-masking models. Our idea is to apply the attacks on an ensemble model which is built by mutating the original model elements after training. As we found out that mutant diversity is a key factor in improving success rate, we design a greedy algorithm for generating diverse mutants efficiently. Experimental results on MNIST, SVHN, and CIFAR10 show that MUTEN can increase the success rate of four attacks by up to 0.45.

1 Introduction

Deep neural networks (DNNs) have achieved impressive success in a wide range of artificial intelligence tasks, such as image classification [Rawat and Wang, 2017] and speech recognition [Zhang et al., 2018]. However, most DNNs suffer from being fooled by adversarial examples, which can result in serious security issues [Finlayson et al., 2019; Eykholt et al., 2018]. Such an adversarial example is typically crafted by adding a subtle (elusive) perturbation to a benign input in a way that misleads a DNN model. The adversarial examples are useful not only to reveal security threats in DNNs, but also to improve their robustness, e.g., through adversarial training [Madry et al., 2018].

Many adversarial attacks have been investigated. In general, there are two types of methods depending on what model information is available. Black-box attacks have no knowledge of the model, while the white-box attacks have access to model information such as its architecture, gradient, and weights. Most adversarial attacks are gradient-based, in the sense that they utilize the gradient of the loss function with the hope to compute the perturbation direction that will maximize the likelihood of misclassification.

The adversarial phenomena, together with the increasing use of machine learning models in real-world applications, have motivated much research on effective ways to generate adversarial examples and defend against them (making the models robust to adversarial attacks). Gradient masking [Papernot et al., 2017] is one such protection means which is commonly used by researchers. It refers to the phenomenon where the gradient cannot be used to optimize the DNN loss function and produce a corresponding perturbation. Gradient masking can result from intentional actions (defenses relying on gradient obfuscation) or natural properties of deep models (where successive computations or specific components cause gradient vanishing); see Figure 1(a) for an illustration.

Perhaps paradoxically, despite its popularity the use of gradient masking as a defense mechanism has been fiercely dismissed [Athalye et al., 2018a; Uesato et al., 2018]. The main reason is that the security it offers is superficial and gives a "false sense of security". For instance, Athalye et al. [Athalye et al., 2018a] show that although gradient masking successfully defends against common gradient-based attacks (e.g., PGD [Madry et al., 2018] and C&W [Carlini and Wagner, 2017]), it is easily overcome through alternative means (e.g., approximated derivatives, Expectation Over Transformation [Athalye et al., 2018b] and reparameterization).

In this paper, we further reduce the trust that one can have in this defense mechanism and show that common attacks can easily overcome gradient masking. We propose MUTEN, a fast and effective way to attack models with masked gradients. Unlike previous work circumventing gradient masking [Athalye et al., 2018a; Uesato et al., 2018], MUTEN does not rely on new attack means and can be applied jointly with any existing algorithms (we consider, more specifically, FGSM [Goodfellow et al., 2015], BIM [Kurakin et al., 2017], PGD [Madry et al., 2018] and C&W [Carlini and Wagner, 2017]). Thereby, our work strengthens the claims that the robustness promised by gradient masking is a mere illusion.

The effectiveness of our approach leans on Liu et al.’s work [Liu et al., 2017], where they show that adversarial examples crafted from an ensemble of surrogate models transfer relatively well to the original model. Unlike their method, though, MUTEN avoids the prohibitive cost of training mul-
2 Background

2.1 Gradient-Based Attacks

FGSM  Goodfellow et al. [Goodfellow et al., 2015] proposed one of the simplest methods, fast gradient sign method (FGSM), to generate adversarial examples. Let $x$ and $x'$ be

$$x' = x + \epsilon \cdot \text{sign}(\nabla_x J(x, y))$$

where $\epsilon$ controls the perturbation size. $\text{sign}(\cdot)$ is the sign function. The sign of a real number is -1 for a negative value, 1 for a positive value, and 0 for value 0. $\nabla_x J(x, y)$ computes the gradient of the training loss $J$ given $x$ and its true class $y$.

BIM  Based on FGSM, Kurakin et al. [Kurakin et al., 2017] proposed an iterative version, basic iterative method (BIM, also called i-FGSM), which applies FGSM multiple times with a small step size to craft $x'$:

$$x_{n+1}' = \text{Clip}_{x,\epsilon}(x_n' + \alpha \cdot \text{sign}(\nabla_x J(x_n', y)))$$

where $x_0' = x$ and $\text{Clip}_{x,\epsilon}$ is a clip function applied after each iteration to ensure that the result is still in $\epsilon$-neighbourhood of $x$. $n$ is the iteration index and $\alpha$ is the step size.

PGD  Madry et al. [Madry et al., 2018] proposed the projected gradient descent (PGD) to improve BIM. The difference is that BIM starts from the original point, while PGD randomly chooses the starting point within a $\epsilon$ norm ball.

C&W  The C&W attack, proposed by Carlini and Wagner [Carlini and Wagner, 2017], is known as one of the strongest attacks to DNNs. Instead of using the training loss, C&W uses a designed loss function $f$ to craft the adversarial example $x'$ which minimizes $D(x, x') + c \cdot f(x')$ where $D$ is a distance metric and $c$ is a constant that controls the distance and the confidence of $x'$.

2.2 Mutation of Deep Learning Models

Post-training mutation of DNNs has been applied mainly for quality assurance purposes. Due to the unique characters of DNN models, various mutation operators have been proposed at source level (modifying the training data or the training program) or at model level [Ma et al., 2018].

In this paper, we apply model-level mutations, where a mutant is created directly by changing the neurons, weights or, layers slightly without training. In general, modifying the layers requires specific architectures of the DNN models and degrades the performance (accuracy) significantly, and is less applicable. Both the weight- and neuron-level operators work efficiently to generate mutants and are more widely used.

Recent studies have shown the utility of mutation in different tasks. Ma et al. [Ma et al., 2018] propose to mutate test data class by class to figure out the weakness in test data, which is helpful to check to bias in data. Hu et al. [Hu et al., 2019] points out that by a defined killing score metric, the mutants can be used to validate how robust a DNN model is against an input data or its segment. In [Wang et al., 2019], Wang et al. assume that the adversarial examples are near the decision boundary, thus, the data that change the labels by different mutants are considered as adversarial.

3 Approach

We aim to improve the success rate of gradient-based adversarial attacks applied to gradient-masking models. The main idea of MUTEN is to produce a collection of diverse mutant models to build an ensemble, and attack the ensemble instead of the single original model.
3.1 Diverse Mutant Generation

To build an ensemble without extra training, we employ the model-level mutation. Since previous research has shown that mutating layers always degrade the performance (test accuracy) significantly [Ma et al., 2018], we consider 5 operators working only at the weight- and neuron-level. Gaussian fuzzing (GF) operator adds noise to the selected weights following the Gaussian distribution. The weight shuffling (WS) rearranges the selected weights. The neuron effect blocking (NEB) resets the connection weight of a selected neuron to the next layer to zero. The neuron activation inverse (NAI) operator inverts the activation status of a neuron. The neuron switch (NS) exchanges two neurons within the same layer. The mutation ratio controls how much percentage of weights or neurons are selected for mutation in each layer. As applying more mutations has a higher likelihood to decrease model performance, we randomly set it between 1% and 4% following the previous findings of Ma et al. [Ma et al., 2018].

To measure mutant diversity, we use the centered kernel alignment (CKA) [Kornblith et al., 2019] metric and the PageRank algorithm [Moler, 2011]. More precisely, CKA measures the similarity between DNN representations. Given the input data \( X \), let \( H_1 \) and \( H_2 \) be two feature matrices of \( X \) by two models, respectively. \( H_1 \) and \( H_2 \) are considered as the DNN representations. The similarity between \( H_1 \) and \( H_2 \) is defined by

\[
CKA(K, L) = \frac{HSIC(K, L)}{\sqrt{HSIC(K, K)HSIC(L, L)}} \tag{1}
\]

where \( K \) and \( L \) are the kernel matrices by passing \( H_1 \) and \( H_2 \) through kernels. HSIC is the Hilbert-Schmidt independence criterion. Like [Chen et al., 2020], we use the output of the last hidden layer in a DNN as the feature.

The PageRank algorithm aims at measuring the importance/rank of website pages where a page linked to by many pages has a high rank. Inspired by this, taking a mutant as a website page and the similarity as the linking weight, we assume that the mutant with a low rank is diverse within the mutant set and is dissimilar with the others.

Algorithm 1 shows our overall generation method. To increase the diversity of generated mutants, we use 20 pairs of mutation operators and ratios. Given a model \( M \) and a required number of mutants \( n \), the mutant set \( \text{set} \) and a similarity matrix \( D \) are initialized to be empty, and a counting index \( count \) is used to control the termination of the algorithm (Line 1). In each iteration, a pair of mutation operator and ratio is randomly selected from all the candidates (Line 3) to generate a mutant (Line 4). After the first iteration, the mutant set \( Mu \) is updated with a mutant (Lines 5-6). When another new mutant is generated, first, we compute the linear CKA similarity between this mutant and the ones in \( Mu \) to update the similarity matrix \( D \) (Lines 7-9). If the size of mutation set, \( |Mu| \), is smaller than \( n \), the procedure continues, otherwise, \( D \) is fed into the \text{pageRank} function to compute the diversity and update the mutant set (Lines 11-13). The maximum size of \( Mu \) is \( n \). The iteration terminates until it reaches a preset number of iterations. Figure 2 shows the linear CKA similarity of 10 mutants in types of diverse, random, and similar, respectively. Diverse mutants are more dissimilar from each other.

\[
\text{Algorithm 1 Greedy mutant generation algorithm}
\]

**Input:** \( M \): DNN model
- \( O = \{GF, WS, NEB, NAI, NS\} \): mutation operators
- \( R = \{0.01, 0.02, 0.03, 0.04\} \): mutation ratios
- \( n \): required number of mutants
- \( \text{ite} \): number of iterations

**Output:** \( Mu \): a set of mutants

1: Initialize \( Mu, D, count = 0 \)
2: while \( count < \text{ite} \) do
3: \( (o, r) = \text{randomSelect}(O, R) \)
4: \( m = \text{mutantGenerator}(M, o, r) \)
5: if \( |Mu| == 0 \) then
6: \( Mu = \{m\} \)
7: else
8: \( D = \text{computeCka}(m, Mu) \)
9: if \( |Mu| < n \) then
10: \( Mu = Mu \cup \{m\} \)
11: else
12: \( Mu = \text{pageRank}(D, Mu, m) \)
13: end if
14: end if
15: \( count = count + + \)
16: end while
17: return \( Mu \)

3.2 Ensemble Model Construction

Figure 3 illustrates how we construct an ensemble. Given the training data, a model is trained with a specific architecture and parameters. By the greedy algorithm mentioned in Section 3.1, multiple diverse mutants are obtained. In the example, we show the effect of the mutation operators GF, NEB, and NS, and the modified weights and neurons are highlighted in blue. At last, an ensemble model is built by gathering all the original model and its mutants. When performing an adversarial attack, we use the simple average strategy [Demir, 2016]. That is, the attack accesses each base model to obtain the gradient given an input data, then the perturbation is calculated based on the average of all the gradients.

4 Experiments

To evaluate the effectiveness of our approach in increasing adversarial attack success rate, we conducted experiments using TensorFlow 2.3.0 and Keras 2.4.3. We implemented MUTEN by extending the DeepMutation++ tool [Hu et al., 2019] and apply the library of CKA² and fast-pagerank³ to compute the rank of diversity. To allow for reproducibility, our full implementation and evaluation subjects are available on GitHub.³

³https://github.com/google-research/google-research/tree/master/representation_similarity
³https://github.com/asajadi/fast-pagerank
³Link anonymized for double-blind review.
Figure 2: CKA similarity of 10 mutants (diverse, random and similar). Darker color indicates a higher similarity between models. Dataset: MNIST; Model: Lenet-5.

(a) Diverse
(b) Random
(c) Similar

Figure 3: Example of building an ensemble model.

4.1 Experimental Setup

**DNN models and datasets** We conduct the experiments on 3 widely used datasets, MNIST [Lecun et al., 1998], SVHN [Netzer et al., 2011], and CIFAR10 [Krizhevsky, 2009]. MNIST is a 10-class grayscale handwritten digit dataset. SVHN is a real-world image dataset including 10 classes of street view house numbers. CIFAR10 is a 10-class dataset with color images. For MNIST and SVHN, we employ the Lenet-5 model as [Athalye et al., 2018a]. For CIFAR10, we use VGG16 and ResNet20V1 because, as deep models, they are subject to natural gradient vanishing phenomena. Table 1 summarizes the detailed information of the datasets and models. As we generate weight- and neuron-level mutants, the number of weights and neurons are also given in the third and fourth columns, respectively.

**Attacks and parameter setting** We evaluate MUTEN with four state-of-the-art gradient-based attacks (see Section 2), *i.e.*, FGSM, BIM, PGD ($l_{\infty}$-norm), C&W ($l_{2}$-norm). The attacks are implemented based on the IBM ART framework.

4.2 Results

We conducted three series of experiments to evaluate MUTEN from different perspectives. Since it is meaningless to attack misclassified data as being considered as “adversarial” for the model, each attack crafts one example based on each benign data. Each experiment was repeated five times to reduce the influence of randomness in both the creation of mutants and the application of the attacks. Reported results are the average of those five runs.

**Effectiveness** Firstly, we evaluate the effectiveness of MUTEN measured as the success rate of the applied attacks. The success rate of the four attacks applied to the original model is taken as the baseline. Figure 4 shows the success rate of MUTEN with different attack configurations. As the success rate converges mostly when the ensemble includes 5 mutants (see next section), we only present the result with this number. Overall, compared with the four baselines, MUTEN achieves a higher success rate, especially as the maximum perturbation size increases. For example, in the case of PGD with VGG16, the success rate by MUTEN reaches 0.97, while the baseline increases it by 0.62 with the maximum perturbation size. When the threshold is very small (for instance, $\epsilon < 0.2$ for MNIST and $\epsilon < 255$ for ResNet20V1 by FGSM), the success rate achieved by our approach is lower than or keeps similar to the baseline. The reason is that the ensemble is an average over multiple models and so as the gradient, given a very small perturbation, the attack requires more iterations to converge, which is demonstrated by FGSM and BIM (which is an iterative version of FGSM).

**Impact of the number of mutants** Secondly, we investigate how the number of mutants in the ensemble model impacts the effectiveness of MUTEN. We use the commonly used configurations ($\epsilon = \frac{8}{255}$, $c = 0.3$) for the attacks and

| Dataset   | Model    | #Weights | #Neurons | #Tests | Accuracy(%) |
|-----------|----------|----------|----------|--------|-------------|
| MNIST     | Lenet-5  | 107550   | 236      | 10000  | 98.89       |
| SVHN      | Lenet-5  | 136650   | 236      | 26032  | 88.93       |
| CIFAR10   | ResNet20V1 | 270896   | 794      | 10000  | 90.71       |
|           | VGG16    | 2851008  | 1674     | 10000  | 91.17       |

Table 1: DNN models and datasets

| Dataset | FGSM | BIM | PGD | C&W(e) |
|---------|------|-----|-----|--------|
| MNIST   | 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4 | 7.8, 9, 10, 11, 12, 13 |
| SVHN    | 2.75, 4.5, 6.25, 8, 10, 15, 20 | 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4 |
| CIFAR10 | 2.75, 4.5, 6.25, 8, 10, 15, 20 | 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4 |

Table 2: Attack configurations. “e” and $c$ stand for the maximum perturbation and initial constant, respectively.

[Netzer et al., 2011]. 2011, and CIFAR10 [Krizhevsky, 2009].

[perturbation and initial constant, respectively.

https://github.com/Trusted-AI/adversarial-robustness-toolbox
consider a number of mutants ranging from 1 to 10. Figure 5 shows the results for CIFAR10 with VGG16. In general, the effectiveness of MUTEN increases as more mutant is integrated but tends to saturate quickly in the cases of FGSM, BIM and PGD. Concerning the improvement of success rate, it increases from 0.20 to 0.33 in FGSM, 0.34 to 0.47 in BIM, 0.32 to 0.43 in PGD, and -0.09 to 0.21 in C&W. In the case of FGSM, IFGSM, and PGD, a very high improvement of 0.32 to 0.43 in PGD, and -0.09 to 0.21 in C&W. In the case of the strongest attack, C&W, the success rate is lower than the baseline when the ensemble includes 1 mutant, which also happens to the other models. The reason is that for C&W, when the parameter $c$ is very small, the gradient loss has a small contribution to the loss function used by the attack algorithm (see Section 2.1). By contrast, letting the gradient loss be more important by increasing $c$, the success rate boosts quickly. Thus, in this case, to increase the success rate of C&W, one can either adjust $c$ to be greater or include more mutants. Note that, attacking an ensemble requires multiple times due to that the attack computes the average gradient over each base model. As a result, the time cost is linearly related to the number of models in the ensemble. Figure 7 shows the ratio of time cost of attacking an ensemble to a single model. Therefore, in practical applications, one has to consider the trade-off between a high success rate and a small number of mutants.

**Diversity of mutants** Thirdly, we investigate if the diversity contributes to MUTEN. We produce three types of mutants, diverse, random, and similar. The random mutants are generated by random selection, and similar mutants are created by limiting the test accuracy to be at least 95% reserved for the original model. Figure 6 shows the result of CIFAR10 with model VGG16. In general, the diverse ensemble per-

![Graphs showing success rate versus attack configuration](image-url)
Figure 5: Success rate VS. number of mutants. The shade area indicates where MUTEN outperforms the baseline. Dataset: CIFAR10; Model: VGG16.

forms the best, and the random ensemble works better than the similar one. In the case of FGSM, BIM, and PGD, when the perturbation is small (for instance, smaller than \frac{1}{255}), the difference of using three types of mutants is not big. By increasing the number of iterations of the greedy algorithm, the mutants can be more diverse, and the difference between random and diverse ensembles will be greater.

Figure 6: Success rate VS. type of mutants. Each ensemble model includes 5 mutants. The shade area indicates where MUTEN outperforms the baseline. Dataset: CIFAR10; Model: VGG16.

Figure 7: Ratio of time cost VS. number of mutants. Dataset: CIFAR10; Model: VGG16.

4.3 Discussion

Extensions of MUTEN Overall, using the diverse mutant-based ensemble is helpful to improve the effectiveness of craft adversarial examples. As it is easy and simple to generate a large number of mutants, MUTEN can be taken as a plug-in module in white-box attacks. Besides, since the number of mutants linearly relates to the efficiency, the number can be adjusted to balance between the time cost and the desired number of adversarial examples.

Threats to validity The internal threat comes from our implementation. To counter this, we use some popular libraries as mentioned in the section of experiments, and carefully check the code. The external threat is the selected DNN models and datasets. We choose popular datasets with well-known models, and the model ranges from simple to complex. The construct threat is mainly about the method. As the diversity of mutants is important to obtain a good result, the metric to measure the similarity between mutants and the method to rank the diversity of mutants, and the ensemble strategy [Demir, 2016] could be changed to improve the performance.

5 Conclusion
We proposed MUTEN to effectively improve the gradient-based adversarial attacks. The main idea is to build an ensemble by diverse mutants to modify the gradient for the attacks to easier figure out the perturbation direction. Besides, since no extra training is required to produce a large number of mutants, MUTEN can be regarded as a simple plug-in module in white-box attacks. The experiments on different datasets and models have demonstrated that MUTEN performs promisingly to increase the success rate of four state-of-the-art gradient-based adversarial attacks with only a few mutants. Additionally, the diversity of mutants have been verified to be necessary to achieve effectiveness.
References

[Athalye et al., 2018a] Anish Athalye, Nicholas Carlini, and David Wagner. Obfuscated gradients give a false sense of security: circumventing defenses to adversarial examples. In ICML, volume 80, pages 274–283, Stockholmsmässan, Stockholm Sweden, July 2018. PMLR.

[Athalye et al., 2018b] Anish Athalye, Logan Engstrom, Andrew Ilyas, and Kevin Kwok. Synthesizing robust adversarial examples. In ICML, volume 80, pages 284–293, Stockholmsmässan, Stockholm, Sweden, July 2018. PMLR.

[Carlini and Wagner, 2017] Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In IEE Symposium on Security and Privacy (SP), pages 39–57, San Jose, CA, USA, May 2017.

[Chen et al., 2020] Junjie Chen, Zhuo Wu, Zan Wang, Hanno You, Lingming Zhang, and Ming Yan. Practical accuracy estimation for efficient deep neural network testing. ACM Trans. Softw. Eng. Methodol., 29(4), October 2020.

[Demir, 2016] Necati Demir. Ensemble methods: elegant techniques to produce improved machine learning results, 2016.

[Eykholt et al., 2018] Kevin Eykholt, Ivan Evtimov, Earlene Fernandes, Bo Li, Amir Rahmati, Chaowei Xiao, Atul Prakash, Tadayoshi Kohno, and Dawn Song. Robust physical-world attacks on deep learning models. In CVPR, pages 1625–1634, June 2018.

[Finlayson et al., 2019] Samuel G. Finlayson, John D. Bowers, Joichi Ito, Jonathan L. Zittrain, Andrew L. Beam, and Isaac S. Kohane. Adversarial attacks on medical machine learning. Science, 363(6433):1287–1289, 2019.

[Goodfellow et al., 2015] Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples, 2015.

[Hu et al., 2019] Qiang Hu, Lei Ma, Xiaofei Xie, Bing Yu, Yang Liu, and Jianjun Zhao. Deepmutation++: a mutation testing framework for deep learning systems. In IEEE/ACM International Conference on Automated Software Engineering, pages 1158–1161, San Diego, CA, USA, December 2019.

[Kornblith et al., 2019] Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton. Similarity of neural network representations revisited. In ICML, Long Beach, California, 2019.

[Krizhevsky, 2009] Alex Krizhevsky. Learning multiple layers of features from tiny images. Technical report, University of Toronto, Toronto, 2009.

[Kurakin et al., 2017] Alexey Kurakin, Ian J. Goodfellow, and Samy Bengio. Adversarial examples in the physical world. ICLR Workshop, 2017.

[Lecun et al., 1998] Yann Lecun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278 – 2324, November 1998.

[Liu et al., 2017] Yanpei Liu, Xinyun Chen, Chang Liu, and Dawn Song. Delving into transferable adversarial examples and black-box attacks. In ICLR, November 2017.

[Ma et al., 2018] Lei Ma, Fuyuan Zhang, Jiyuan Sun, Minhui Xue, Bo Li, Felix Juefei-Xu, Chao Xie, Li Li, Yang Liu, Jianjun Zhao, and Yadong Wang. Deepmutation: mutation testing of deep learning systems. In International Symposium on Software Reliability Engineering, pages 100–111, Memphis, TN, USA, October 2018.

[Madry et al., 2018] Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. In ICLR, Vancouver, BC, Canada, April 2018.

[Moler, 2011] Cleve B Moler. Experiments with MATLAB, Society for Industrial and Applied Mathematics, 2011.

[Netzer et al., 2011] Yuval Netzer, Tao Wang, Adam Coates, Alessandro Bissacco, Bo Wu, and Andrew Ng. Reading digits in natural images with unsupervised feature learning. NIPS, January 2011.

[Nicolae et al., 2018] Maria-Irina Nicolae, Mathieu Sinn, Minh Ngoc Tran, Beat Buesser, Ambriish Rawat, Martin Wistuba, Valentina Zantedeschi, Nathalie Baracaldo, Bryant Chen, Heiko Ludwig, Ian Molloy, and Ben Edwards. Adversarial robustness toolbox v1.2.0. CoRR, 1807.01069, 2018.

[Papernot et al., 2017] Nicolas Papernot, Patrick McDaniel, Ian Goodfellow, Somesh Jha, Z. Berkay Celik, and Ananthram Swami. Practical black-box attacks against machine learning. In Proceedings of the 2017 ACM on Asia Conference on Computer and Communications Security, pages 506–519, April 2017.

[Rawat and Wang, 2017] Waseem Rawat and Zenghui Wang. Deep convolutional neural networks for image classification: a comprehensive review. Neural Computation, 29(9):2352–2449, 2017.

[Uesato et al., 2018] Jonathan Uesato, Brendan O’Donoghue, Pushmeet Kohli, and Aäron van den Oord. Adversarial risk and the dangers of evaluating against weak attacks. In ICML, volume 80, pages 5032–5041, Stockholmsmässan, Stockholm, Sweden, July 2018. PMLR.

[Wang et al., 2019] Jingyi Wang, Guoliang Dong, Jun Sun, Xinyu Wang, and Peixin Zhang. Deep adversarial sample detection for deep neural network through model mutation testing. In IEEE/ACM 41st International Conference on Software Engineering, pages 1245–1256, Montreal, QC, Canada, May 2019.

[Zhang et al., 2018] Zixing Zhang, Jürgen Geiger, Jouni Pohjainen, Amir El-Desoky Moussa, Wenyu Jin, and Björn Schuler. Deep learning for environmentally robust speech recognition: an overview of recent developments. ACM Transactions on Intelligent Systems and Technology, 9(5), April 2018.