Abstract—Production machine learning systems are consistently under attack by adversarial actors. Various deep learning models must be capable of accurately detecting fake or adversarial input while maintaining speed. In this work, we propose one piece of the production protection system: detecting an incoming adversarial attack and its characteristics. Detecting types of adversarial attacks has two primary effects: the underlying model can be trained in a structured manner to be robust from those attacks and the attacks can be potentially filtered out in real time before causing any downstream damage. The adversarial image classification space is explored for models commonly used in transfer learning.

Index Terms—Machine Learning, Adversarial Attacks, White Box Attacks, Image Classification

I. INTRODUCTION

In our previous work [1] we attempted to find machine learning model characteristics through probing black box models. In that work, our goal was to classify the classifiers used. We looked at three stages of strategic discovery: probe, collect, and detect. On the image side, we would probe by sending in a picture, collect the model output (1000d vector for ImageNet), and using that output and the model name, trained a new classifier. We could now tell if a model output came from ResNet50, DenseNet121, etc. at 0.99 average precision (AP).

We took this one step forward and fine-tuned MobileNetV2 on different 50-class datasets. We then ran inference from those fine-tuned models on a mix of super resolution datasets and collected the model output alongside the fine-tuned model’s name. We trained a classifier and we were able to predict which dataset MobileNetV2 was trained on based on a single model output at 0.97 AP.

We were successfully able to classify both which model the prediction came from alongside the dataset that the model was fine-tuned on. Extending this work, we now introduce the adversarial version in this paper. We attempt to detect if a model was attacked and the attacker’s characteristics. This defensive step completes the analysis of the vulnerable surface of a machine learning model. We can detect which dataset was used to train a model, which model was used, if an attack occurred, and finally which attack was used, all from a single model output.

A. Background

The adversarial attack surface [2] [3] [4] [5] represents all of the ways an attacker can manipulate or avoid detection from machine learning systems. As machine learning models are incorporated to more production systems, developers need to find ways to harden and strengthen those systems from adversarial actors. Adversarial attacks will exploit different qualities about a machine learning system - typically, focusing on vulnerabilities discovered from either the dataset or the model architecture.

Wang, et. al [6] outlines seven different adversarial attack concepts encountered during the machine learning training process. In our paper, we focus on Learning Algorithm (attacked by) Gradient Descent Attack (among other). Wang, et. al asserts, “it is observed that ML methods are highly vulnerable to adversarial attacks during both the training and prediction phases [and] DNNs [deep neural networks] are vulnerable to subtle input perturbations that result in substantial changes in outputs.”

A novel approach to detect adversarial attack comes from using Trapdoors in a feature embedding of convolutional networks as discussed by Shan et. al [7]. Instead inspecting the output of a model, they attempt to discover an adversarial attack during inference. They use the optimization of adversarial algorithms against the attacker by placing trapdoors that attempt to shortcut the attack from one class to another ($y_i$ to $y_x$). This leads the attacker to a false local minimum while reducing the effect on performance on the rest of the network.

Another approach which couples a model to the original network is proposed by Metzen et. al [8]. Metzen grabs feature embeddings at various depths in the network and uses a subnet to classify if the model is being attacked. He suggests that this could be used as a mitigating factor during inference to block adversarial actors.

B. Contributions

While the above methods couple to a single machine learning model, our novel approach attempts to create a universal detector for adversarial attacks and their characteristics. In our previous work, we demonstrated the ability of an attacker to detect the underlying dataset and model architecture from strategic probing of the machine learning system. This work
demonstrably shows the defense against adversarial attacks on image classification models: We show (i) the effectiveness of common white box adversarial attacks, (ii) that we can detect whether a model output is the results of an adversarial attack (i.e. the perturbation of the attack is too strong), (iii) that we can detect from a model’s output, which model the adversarial method attacked, and (iv) from a model’s output, the attack method used.

C. Reproducability

To validate the experiment we share a Reproducible Google Collaboratory [9] which can run a subset of the dataset used.

II. EXPERIMENT

We apply six (6) different adversarial attacks to five (5) different pre-trained models. We use the ImageNetV2 [10] test dataset and attempt to answer four (4) questions using sklearn’s [11] standard Random Forest Algorithm. The experimental diagram is proposed in [Figure 1]:

A. Adversarial Attacks

We begin by describing the six different white box attacks from the adversarial attack package, Foolbox [12]. In this experiment: FGM, FGSM, PGD, LinfPGD, L2PGD, L2DeepFool

Gradient Sign Attack (FGSM)
Computes the gradient $g(x_0) = \nabla_x L(x_0, \ell_0)$ once and then seeks the minimum step size $\varepsilon$ such that $x_0 + \varepsilon sign(g(x_0))$ is adversarial. (Goodfellow et al., 2014). (Rauber et al. 2018 [13])

Gradient Sign Attack (FGM)
Extends the FGSM to other norms [from infinity norm] and is therefore called the Fast Gradient Method. (adversarial-robustness-toolbox [14])

DeepFool L2 Attack
In each iteration DeepFool (Moosavi-Dezfooli et al., 2015) computes for each class $\ell \neq \ell_0$ the minimum distance $d(\ell, \ell_0)$ that it takes to reach the class boundary by approximating the model classifier with a linear classifier. It then makes a corresponding step in the direction of the class with the smallest distance. (Rauber et al. 2018 [13])

Projected Gradient Descent (PGD)
Projected Gradient Descent (PGD) [15] is also an iterative extension of FGSM and very similar to Basic Iterative Method [16] (BIM). The main difference with BIM resides in the fact that PGD projects the attack result back on the $\varepsilon$-norm ball around the original input at each iteration of the attack. (adversarial-robustness-toolbox [14])

Linf Projected Gradient Descent (LinfPGD)
Linf Projected Gradient Descent is a PGD attack with order = Linf. (Foolbox [12])

L2 Projected Gradient Descent (L2PGD)
L2 Projected Gradient Descent is a PGD attack with order = L2. (Foolbox [12])

The adversarial attacks listed above have the following hyper parameters: FGM (Epsilon:5), FGSM (Epsilon:.03), PGD (Epsilon:.03, Steps:10), LinfPGD (Epsilon:.1, Steps:10), L2PGD (Epsilon:.05, Steps:10), L2DeepFool (Epsilon:5, Steps:10).

B. Pre-trained Models

The pre-trained models used are from keras.applications and vary in input, performance, and model size. The list [Table I] contains: MobileNetV2, NASNetMobile, DenseNet121, ResNet50, ResNet50V2

C. Metrics

To analyze if we can detect a model is being attacked, at a universal level, we look at just the prediction itself.

1) How well does the adversarial attack perform on this model and dataset?
2) Once a prediction is made, can we tell if it is the result of an adversarial input or not?
3) Once a prediction is made, can we tell what model the prediction came from after an adversarial attack?
4) Once a prediction is made, which attack method was used?
Fig. 2. Original model accuracy and adversarial input accuracy for the six attacks on the five models.

TABLE II
ADVERSARIAL ATTACK ACCURACY

| Model          | Clean Ave | Adv. Ave | Clean Std | Adv. Std |
|---------------|-----------|----------|-----------|----------|
| MobileNetV2   | 70.07     | 4.63     | 2.69      | 3.36     |
| NASNetMobile  | 72.80     | 12.40    | 3.99      | 6.96     |
| DenseNet121   | 73.47     | 2.53     | 4.17      | 2.33     |
| ResNet50      | 0.33      | 0.27     | 0.35      | 0.22     |
| ResNet50V2    | 69.93     | 6.87     | 3.23      | 3.18     |

Fig. 3. Binary classification of fake or clean input images. Vertical dashed red line is random guessing.

TABLE III
ATTACK MADE BASED ON MODEL PREDICTION

| Image Type | mAP  | Average Recall | Average F1 |
|------------|------|----------------|------------|
| Clean      | 0.693| 0.627          | 0.660      |
| Adversarial| 0.627| 0.690          | 0.655      |

On average the models performed at above 70% accuracy on the sample ImageNetV2 images [Figure 2, Table II]. For the adversarial attacks the accuracy was on average below 10%. None of the proposed attacks had any affected on the Residual Network (ResNet50) while having an effect on the ResNet50V2 network. Discussion of this anomaly is present in the discussion session [III-E]. ResNet50 is excluded from the next parts of the experiment. Most of the white box attacks on the five models have little variance besides for NASNetMobile. Overall, the attacks were successful and will lead to a good downstream performance in this experiment.

B. Adversarial Input

We investigate if we can find out if an attack occurred after we predicted the input [Figure 3, Table III]. We take the class predictions from each of the models and attempt to use a random forest algorithm to predict if it came from an adversarial input or a clean input. This investigation will
Fig. 4. Model Attacked based on Model Prediction. Vertical dashed red line is random guessing.

| Model                 | mAP   | Avg. Recall | Avg. F1 |
|-----------------------|-------|-------------|---------|
| MobileNetV2           | 0.542 | 0.702       | 0.600   |
| NASNetMobile          | 0.830 | 0.802       | 0.813   |
| DenseNet121           | 0.618 | 0.723       | 0.660   |
| ResNet50V2            | 0.793 | 0.603       | 0.672   |

*Figure 4 Statistics*

TABLE IV

MODEL ATTACKED FROM CLASSE PREDICTION

After running each attack on each model, we attempt to decipher which attack was made by looking at a model output [Figure 5, Table V]. We expected that since each attack optimizes a different variable, that we could recover that bias at a high rate. However, we find that we can predict which attack type at 37% AP (random guessing 20%).

E. ResNet50 Immunity

The resnet50 model was resilient to all the white-box attacks from the foolbox package. This is a package error which involves how foolbox handles preprocessing images to send to models via the foolbox TensorFlowModel class.

IV. DISCUSSION

Adversarial Training focuses on using adversarial examples during the training step of model building. By detecting the incoming attacks, model builders can focus on tailoring their models to the most frequent attacks that are coming to their systems. Adversarial Training has gained increased popularity with new techniques reducing the amount of computational power necessary to make models more robust [16]. A recent paper, Using Single-Step Adversarial Training to Defend Iterative Adversarial Examples, proposed an iterative approach to introducing adversarial examples in increasing robustness of an underlying model [17]. Using the detection methods proposed in this paper and an adversarial training pipeline, it is possible to protect a production system from the most frequent attacks.

Table V

ATTACK TYPE FROM MODEL PREDICTION

| Attack              | Precision | Recall | F1  |
|---------------------|-----------|--------|-----|
| L2DeepFool          | 0.50      | 0.38   | 0.43|
| FGM                 | 0.18      | 0.27   | 0.21|
| L2PGD               | 0.21      | 0.26   | 0.23|
| FGSM                | 0.21      | 0.35   | 0.26|
| LinfPGD             | 0.77      | 0.57   | 0.66|

*Figure 5 Statistics*
V. Future Work

Detecting the incoming attacks threat vector allows a targeted system to protect and respond to these attacks. This paper introduces the attack detection method and a future work will focus on using these predictions in an attack early warning system. Each predicted attack will flow to a decision system that directs the inference engine to deflect, protect, or avoid the incoming request. Once an attacker is identified, we can revoke privileges or black list those attack venues.

VI. Conclusion

We were successfully able to detect if a model was attack by varied adversarial attacks using only the model output. Not only were we able to detect if a model was attacked at 66% AP, but also which model was attack at 70% AP. Less impressive is classifying which attack type was used at 37% AP. In an adversarial defense system, we envision the routing of inference through an adversarial detection system to help avoid negative downstream consequences. In addition, we show a detection model could be trained with only a handful of adversarial examples and can run in less than a millisecond (0.12ms).

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