Abstract

This paper considers the problem of helping humans exercise scalable oversight over deep neural networks (DNNs). Adversarial examples can be useful by helping to reveal weaknesses in DNNs, but they can be difficult to interpret or draw actionable conclusions from. Some previous works have proposed using human-interpretable adversarial attacks including copy/paste attacks in which one natural image pasted into another causes an unexpected misclassification. We build on these with two contributions. First, we introduce Search for Natural Adversarial Features Using Embeddings (SNAFUE) which offers a fully automated method for finding copy/paste attacks. Second, we use SNAFUE to red team an ImageNet classifier. We reproduce copy/paste attacks from previous works and find hundreds of other easily-describable vulnerabilities, all without a human in the loop.

1 Introduction

It is important to have scalable methods that allow humans to exercise effective oversight over deep neural networks. Adversarial examples are one type of tool which can be used to study weaknesses in DNNs \cite{szegedy2013intriguing,goodfellow2014explaining,carlini2017towards}. Typically, adversarial examples are generated by optimizing perturbations to the input of a network. And some previous works offer examples of adversaries being used to develop generalizable interpretations of DNNs \cite{szegedy2013intriguing,goodfellow2014explaining,carlini2017towards,dreamer}. However, there are limitations to what one can learn about flaws in DNNs from synthesized features \cite{porikli2019interpreting}. First, synthetic adversarial perturbations are often difficult to describe and thus offer limited help with human-centered approaches to interpretability. Second, even when synthetic adversarial features are interpretable, it is unclear without additional testing whether they fool a DNN due to their interpretable features or due to hidden motifs \cite{dong2018boosting,carlini2017towards}. This makes developing a generalizable understanding from them difficult. Third, there is a gap between research and practice in adversarial robustness \cite{carlini2017towards}. Real-world failures of DNNs are often due to atypical natural features or combinations thereof \cite{papernot2016limitations}, but synthesized features are off this distribution.

Here, we work to diagnose weaknesses in DNNs using natural, interpretable features. We introduce using a Search for Natural Adversarial Features Using Embeddings (SNAFUE) to find novel adversarial combinations of natural features. We apply SNAFUE to find copy/paste attacks for an image classifier in which one natural image is inserted as a patch into another to induce a targeted misclassification. Figure 1 outlines this approach. First, we use a generator to synthesize robust feature-level adversarial patches \cite{dreamer} which are designed to make any image from a particular source class misclassified as a target. Second, we use the target model’s latent activations to create embeddings of both these synthetic patches and a dataset of natural patches. Finally we select the natural patches that embed most similarly to the synthetic ones.

https://github.com/thestephencasper/snafe
Figure 1: SNAFUE, our automated method for finding targeted copy/paste attacks. This example illustrates an experiment which found that cats can make photocopiers misclassified as printers. (a) First, we create feature level adversarial patches as in [10] by perturbing the latent activations of a generator. (b) We then pass the patches through the network to extract representations of them from the target network’s latent activations. Finally, we select the natural patches whose latents are the most similar to the adversarial ones.

We apply SNAFUE at the ImageNet scale. First, we use SNAFUE to replicate all successful known examples of copy/paste attacks from previous works with no human involvement. Second, we demonstrate its scalability by identifying hundreds of vulnerabilities. Figure 2 and Figure 9 show examples which illustrate easily-describable misassociations between features and classes in the network. Overall, this work makes two contributions.

1. **Algorithmic**: We introduce Search for Natural Adversarial Features Using Embeddings (SNAFUE) as a tool for scalable human oversight.

2. **Diagnostic**: We apply SNAFUE by red-teaming an image classifier. We demonstrate that it automatically identifies weaknesses due to natural features that are uniquely human-interpretable.

Meanwhile, in concurrent work [9], we compare SNAFUE to other interpretability tools by using them to help humans rediscover trojans in a network. We find that SNAFUE offers an effective and unique tool for helping humans interpret and debug DNNs. Code is available at https://github.com/thestephencasper/snafue.

2 Related Work

**Describable Synthetic Adversarial Attacks**: Conventional adversarial attacks are effective but difficult for a human to interpret. They tend to be imperceptible and, when exaggerated, typically appear as random or mildly-textured noise [52][19]. Thus, from a human-interpretability perspective, they demonstrate little aside from how the network can be vulnerable to this specific class of perturbations. Some works have used perturbations inside the latents of image generators to synthesize more describable synthetic attacks [37][47][50][39][49][24][55]. These works however, have not
focused on interpretability and only studied small networks trained on simple datasets (MNIST [34], Fashion MNIST [57], SVHN [42], CelebA [38], BDD [58], INRIA [12], and MPII [1]). In the trojan detection literature, some methods have aimed to reconstruct trojan features using regularization and transformations. Thus far, however, they have been limited to recovering small, few-pixel triggers while failing to reconstruct triggers that take the form of larger objects [54, 20].

Natural Adversarial Features: Several approaches have been used for discovering natural adversarial features. One is to analyze examples in a test set that a DNN mishandles [22, 15, 28], but this limits the search for weaknesses to a fixed dataset and cannot be used for discovering adversarial combinations of features. Another approach is to search for failures over an easily-describable set of perturbations [17, 33, 51], but this requires performing a zero-order search over a fixed set of changes.

Copy Paste Attacks: Copy/paste attacks have been a growing topic of interest and offer another method for studying natural adversarial features. Some interpretability tools have been used to design copy/paste adversarial examples including feature-visualization [8] and methods based on network dissection [3, 41, 23]. Our approach is related to that of [10] who introduce robust feature level adversarial patches and use them for interpreting DNNs and designing copy-paste attacks. However, copy/paste attacks from [8, 41, 23, 10] have been limited to simple proofs of concept with manually-designed copy/paste attacks. They also required a human process of interpretation, trial, and error in the loop. We build off of these with SNAFUE which is the first method that identify adversarial combinations of natural features for vision models in a way that is (1) not restricted to a fixed set of transformations or a limited set of source and target classes and (2) efficiently automatable.

3 Methods

Figure 1 outlines our approach for finding copy/paste adversaries for image classification. For all experiments, we report the success rate defined as the proportion of the time that a patched image was classified as the target class minus the proportion of the time the unpatched natural image was. Additional details are in Appendix A.1.

Synthetic adversarial patches: First, we create synthetic robust feature level adversarial patches as in [10] by perturbing the latent activations of a BigGAN [6] generator. The synthetic adversarial
Figure 3: Our automated replications of all 9 prior examples of ImageNet copy/paste attacks of which we are aware from [8, 23] and [10]. Each set of images is labeled source class → target class. Each row of 10 patches is labeled with their mean success rate.

Candidate patches: Patches for SNAFUE can come from any source and do not need labels. Features do not necessarily have to be natural and could, for example, be procedurally generated. Here, we used a total of \( N = 265,457 \) natural images from five sources: the ImageNet validation set [46] (50,000) TinyImageNet [32] (100,000), OpenSurfaces [4] (57,500), the non OpenSurfaces images from Broden [3] (37,953), plus four trojan triggers (4) (see Section 4).

Embeddings: We used the \( N = 265,457 \) natural patches along with \( M = 10 \) adversarial patches, and passed them through the target network to get an \( L \)-dimensional embedding of each using the post-ReLU latents from the penultimate (avgpooling) layer of the target network. The result was a
nonnegative $N \times L$ matrix $U$ of natural patch embeddings and a $M \times L$ matrix $V$ of adversarial patch embeddings. A different $V$ must be computed for each attack, but $U$ only needs to be computed once. This plus the fact that embedding the natural patches does not require insertion into a set of source images makes SNAFUE much more efficient than a brute-force search. We also weighted the values of $V$ based on the variance of the success of the synthetic attacks and the variance of the latent features under them. Details are in Appendix A.1.

Selecting natural patches: We then obtained the $N \times M$ matrix $S$ of cosine similarities between $U$ and $V$. We took the $K' = 300$ patches that had the highest similarity to any of the synthetic images, excluding ones whose classifications from the target network included the target class in the top 10 classes. Finally, we evaluated all $K'$ natural patches under random insertion locations over all 50 source images from the validation set and subsampled the $K = 10$ natural patches that increased the target network’s post-softmax confidence in the target class the most. Screening the $K'$ natural patches for the best 10 caused only a marginal increase in computational overhead. The method was mainly bottlenecked by the cost of training the synthetic adversarial patches (for 64 batches of 32 insertions each).

Automation of interpretations: Unlike previous proofs of concept, SNAFUE does not rely on a human in the loop. However, we still rely on a human after the loop for analyzing the final results.
and making a final interpretation by default. To test how easily this may be automatable, we test a method for turning many images into a single caption in Appendix A.3.

4 Experiments

Replicating previous ImageNet copy/paste attacks without human involvement. First, we set out to replicate all known successful ImageNet copy/paste attacks from previous works without any human involvement. To our knowledge, there are 9 such attacks, 3 each from [8, 23, 10].

We used SNAFUE to find 10 natural patches for all 9 attacks. Figure 3 shows the results. In all cases, we are able to find successful natural adversarial patches. We also find in most cases that we find similar adversarial features to the ones identified in the prior works. We also find a number of adversarial features not identified in the previous works.

SNAFUE is scalable and effective between similar classes. There are many natural visual features that image classifiers may encounter and many more possible combinations thereof, so it is important that tools for interpretability and diagnostics with natural features are scalable. Here, we test the scalability and effectiveness of SNAFUE with a broad search for vulnerabilities. Based on prior proofs of concept [8, 41, 23, 10] copy/paste attacks tend to be much easier to create when the source and target class are related (see Figure 3). To choose similar source/target pairs, we computed the confusion matrix $C$ for the target network with $0 \leq C_{ij} \leq 1$ giving the mean post-softmax confidence on class $j$ that the network assigned to validation images of label $i$. Then for each of the 1,000 ImageNet classes, we conducted 5 attacks using that class as the source and each of its most confused 5 classes as targets. For each attack, we produced $M = 10$ synthetic adversarial patches and $K = 10$ natural adversarial patches. Figure 2 and Figure 4 show examples from these attacks with many additional examples in Appendix Figure 9. Patches often share common features and immediately

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2 The attacks presented in [23] were not universal within a source class and were only developed for a single source image each. When replicating their results, we use the same single sources. When replicating attacks from the other two works, we train and test the attacks as source class-universal ones.

3 [10] test a fourth attack involving patches making traffic lights appear as flies, the examples they identified were not successful at causing targeted misclassification.

4 [41] also test copy paste attacks, but not on ImageNet networks.
lend themselves to descriptions from a human. In Appendix A.3, we find that these patches also often lend themselves to common descriptions from neural captioning models.

At the bottom of Figure 4, are histograms for the mean attack success rate for all patches and for the best patches (out of 10) for each attack. The synthetic feature-level adversaries were generally highly successful, and the the natural patches were also successful a significant proportion of the time. In this experiment, 3,451 (6.9%) out of the 50,000 total natural images from all attacks were at least 50% successful at being targeted adversarial patches under random insertion locations into random image of the source class. This compares to a 10.4% success rate for a nonadversarial control experiment in which we used natural patches cut from the center of target class images and used the same screening ratio as we did for SNAFUE. Meanwhile, 963 (19.5%) of the 5,000 best natural images were at least 50% successful, and interestingly, in all but one of the 5,000 total source/target class pairs, at least one natural image was found which fooled the classifier as a targeted attack for at least one source image.

Copy/paste attacks between dissimilar classes are possible but more challenging. In some cases, the ability to robustly distinguish between similar classes may be crucial. For example, it is important for autonomous vehicles to effectively tell red and yellow traffic lights apart. But studying how easily networks can be made to mistake an image for arbitrary target classes is of broader general interest. While synthetic adversarial attacks often work between arbitrary source/target classes, to the best of our knowledge, there are no successful examples from any previous works of class-universal copy/paste attacks.

We chose to examine the practical problem of understanding how vision systems in vehicles may fail to detect pedestrians because it provides an example where failures due to novel combinations of natural features could realistically pose safety hazards. To test attacks between dissimilar classes, we chose 10 ImageNet classes of clothing items (which frequently co-occur with humans) and 10 of traffic-related objects. We conducted 100 total attacks with SNAFUE using each clothing source and traffic target. Figure 5 shows these results. Outcomes were mixed.

On one hand, while the synthetic adversarial patches were usually successful on more than 50% of source images, the natural ones were usually not. Only one out of the 1,000 total natural patches (the leftmost natural patch in Figure 5) succeeded for at least 50% of source class images. This suggests a limitation of either SNAFUE or of copy/paste attacks in general for targeted attacks between unrelated source and target classes. On the other hand, 54% of the natural adversarial patches were successful for at least one source image, and such a natural patch was identified for 87 of all 100 source/target class pairs.

SNAFUE is unique and relatively effective compared to other interpretability/diagnostic tools. Finally, we test how SNAFUE compares to related tools meant to help humans better understand and diagnose bugs in models. In concurrent work, we evaluate interpretability tools for DNNs based on how effective they are at helping humans identify trojans that have been implanted into DNNs. We test SNAFUE against 8 other interpretability tools for DNNs based on feature synthesis/search. We find that SNAFUE and robust feature level adversaries are the most successful overall and that combinations of methods are more helpful than individual ones.

5 Discussion and Broader Impact

Implications for scalable human oversight. Having effective diagnostic tools to identify problems with models is important for trustworthy AI. The most common way to evaluate a model is with a test set. But good testing performance does not imply that a system will generalize safely in deployment. Test sets do not typically reveal failures such as spurious features, out of distribution inputs, and adversarial vulnerabilities. Thus, it is important to have scalable tools that allow humans to exercise effective oversight over deep neural networks.

Interpretability tools are useful for building more trustworthy AI because of the role they can play in helping humans exercise oversight. But many techniques from the literature suffer from limitations including a lack of scalability and usefulness for identifying novel flaws. This has led to criticism, with

[^5]: \{academic gown, apron, bikini, cardigan, jean, jersey, maillot, suit, sweatshirt, trenchcoat\} × \{fire engine, garbage truck, racer, sports car, streetcar, tow truck, trailer truck, trolleybus, street sign, traffic light\}
a number of works noting that few interpretability tools are used by practitioners in real applications \cite{4,36,40,31,45}. Toward practical methods to find weaknesses in DNNs, we introduce SNAFUE as an automated method for finding natural adversarial features.

**SNAFUE identifies distinct types of problems.** In some cases, networks may learn flawed solutions because they are given the wrong learning objective while in other cases, they may fail to converge to a desirable solution even with the correct objective \cite{26}. SNAFUE can discover both types of issues. In some cases, it discovers failures that result from dataset biases. Examples include when it identifies that cats make envelopes misclassified as cartons or that young children make bicycles-built-for-two misclassified as tricycles (Figure 2 rows 1-2). In other cases, SNAFUE identifies failures that result from the particular representations a model learns, presumably due to equivalence classes in the DNN's representations. Examples include equating black and white birds with killer whales, parallel lines with spatulas, and red/orange cars with fiddler crabs (Figure 2 rows 3-5).

**Limitations.** We find that it scales well and can easily identify hundreds of sets of copy/paste vulnerabilities that are very easy for a human to interpret and describe. However, we also find limitations including how SNAFUE is less effective for dissimilar source and target classes. In Appendix A.4, we categorize and discuss different types of failures with SNAFUE.

**Three directions for future work.**

1. **Diagnostics in the wild:** Vision datasets are full of biases, including harmful ones involving human demographic groups \cite{16}. A compelling use of SNAFUE and similar techniques could be for discovering these in deployed systems. This could be valuable for exploring the practical relevance of diagnostic tools.

2. **Debugging:** In addition to its use for interpretability, SNAFUE also produces adversarial data which can be used for adversarial training or probing the network to guide targeted procedural edits. Correcting vulnerabilities to copy/paste attacks could be useful applications or tests for model editing tools (e.g. \cite{13,11,56,39}). In the real world, vision systems often fail due to distractor features, atypical contexts, and occlusion \cite{22}. Debugging with copy/paste attacks may be well-equipped to address these failures.

3. **NLP:** Using a version of SNAFUE in natural language processing could be helpful for identifying natural phrases that could cause language models to fail. This could be valuable for language models because the discrete nature of their inputs makes it difficult to use gradient-based methods to construct adversarial perturbations in input space. However, SNAFUE could be used to produce interpretable adversaries from synthetic adversarial insertions to the latents. Other recent works have aimed to generate adversarial triggers for language models that appear as natural language phrases. However, these often depend on either using reinforcement learning to train language generators which can be unstable and computationally expensive \cite{44} or on using humans in the loop \cite{59}. Because SNAFUE is automated and can work flexibly with any dataset of candidate features, it may offer a competitive alternative to existing tools.

All of the proposals for building safe AI outlined in \cite{25} explicitly call for adversarial robustness and/or oversight via interpretability tools. Finding and fixing bugs in advanced AI systems will hinge on interpretability, adversaries, and adversarial training. Consequently, continued work toward scalable techniques for interpretability and diagnostics will be important for safer AI.

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Appendix

A.1 Additional Methodological Details

Network and data: We attack a ResNet18 \cite{21} trained on ImageNet \cite{46}.

Details on synthetic patches: As in \cite{10}, we optimized these patches under transformation using an auxiliary classifier to regularize them to not appear like the target class. Unlike \cite{10}, we do not use a GAN discriminator for regularization or use an auxiliary classifier to regularize for realistic-looking patches. Also in contrast with \cite{10}, we perturbed the inputs to the generator in addition to its internal activations in a certain layer because we found that it produced improved adversarial patches.

Image and patch scaling: All synthetic patches were parameterized as $64 \times 64$ images. Each was trained under transformations including random resizing. Similarly, all natural patches were a uniform resolution of $64 \times 64$ pixels. All adversarial patches were tested by resizing them to $100 \times 100$ and inserting them into $256 \times 256$ source images at random locations.

Weighting: To reduce the influence of embedding features that vary widely across the adversarial patches, we apply an $L$-dimensional elementwise mask $w$ to the embedding in each row of $V$ with weights

$$w_j = \begin{cases} 0 & \text{if } cv_i(V_{ij}) > 1 \\ 1 - cv_i(V_{ij}) & \text{else} \end{cases}$$

where $cv_i(V_{ij})$ is the coefficient of variation over the $j$'th column of $V$, with $\mu_j = \frac{1}{M} \sum_i V_{ij} \geq 0$ and $cv_i(V_{ij}) = \sqrt{\frac{\sum_i (V_{ij} - \mu_j)^2}{\mu_j + \epsilon}}$ for some small positive $\epsilon$.

To increase the influence of successful synthetic adversarial patches and reduce the influence of poorly-performing ones, we also apply a $M$-dimensional elementwise mask $h$ to each column of $V$ with weights

$$h_i = \frac{\delta_i - \delta_{\min}}{\delta_{\max} - \delta_{\min}}$$

where $\delta_i$ is the mean fooling confidence increase of the post-softmax value of the target output neuron under the patch insertions for the $i$'th synthetic adversary. If any $\delta$ is negative, we replace it with zero, and if the denominator is zero, we set $h_i$ to zero.

Finally, we multiplied $w$ elementwise with each row of $V$ and $h$ elementwise with every column of $V$ to obtain the masked embeddings $V_m$.

A.2 Screening

By default, for all experiments in this paper, we train 30 synthetic adversarial patches, select the most adversarial 10, then screen over 300 natural patches, and select the most adversarial 10. These numbers were arbitrary, and because it is fully-automated, SNAFUE allows for flexibility in how many synthetic adversaries to create and how many natural adversaries to screen. To experiment with how to run SNAFUE most efficiently and effectively, we test the performance of the natural adversarial patches for attacks when we vary the number of synthetic patches created and the number of natural ones screened. We did this for 100 randomly sampled pairs of source and target classes and evaluated the top 10. Figure\cite{6} shows the results.

As expected, when the number of natural patches that are screened increases, the performance of the selected ones increases. However, we find that creating more synthetic patches does not strongly influence the performance of the final natural ones. All of our choices of numbers of synthetic patches from 4 to 64 performed comparably well, likely due to redundancy. One positive implication of this is that SNAFUE can be done efficiently with few synthetic adversaries. These were the main bottleneck in our runtime, so this has useful implications for speeding up runtimes. However, a negative implication of this is that redundant synthetic adversaries may fail to identify all possible
weaknesses between a source and target class. Future work experimenting with the synthesis of diverse adversarial patches will likely be valuable.

A.3 Are humans needed at all?

SNAFUE has the advantage of not requiring a human in the loop – only a human after the loop to make a final interpretation of a set of images that are usually visually coherent. But can this step be automated too? To test this, we provide a proof of concept in which we use BLIP \[35\] and ChatGPT \[48\] to caption the sets of images from the attacks in Figure 2.

First, we caption a set of 10 natural patches with BLIP \[35\], and second, we give them to ChatGPT (v3.5) following the prompt “The following is a set of captions for images. Please read these captions and provide a simple "summary" caption which describes what thing that all (or most) of the images have in common.”

Results are shown with the images in Figure 7. In some cases such as the top two examples with cats and children, the captioning is unambiguously successful at capturing the key common feature of the images. In other cases such as with the black and white objects or the red cars, the captioning is mostly unsuccessful, identifying the objects but not the all of the key qualities about them. Notably, in the case of the images with stripe/bar features, ChatGPT honestly reports that it finds no common theme. Future work on improved methods that produce a single caption summarizing the common feature in many images may be highly valuable for further scaling interpretability work. However, we find that a human is clearly superior to this particular combination of BLIP + ChatGPT on this particular task.

A.4 Failure Modes for SNAFUE

Here we discuss various non-mutually exclusive ways in which SNAFUE can fail to find informative, interpretable attacks.

1. **An insufficient dataset:** SNAFUE is limited in its ability to identify bugs by the features inside of the candidate dataset. If the dataset does not have a feature, SNAFUE simply cannot find it.

2. **Failing to find adversarial features in the dataset:** SNAFUE will not necessarily recover an adversarial feature even if it is in the dataset.

3. **Target class features:** Instead of finding novel fooling features, SNAFUE sometimes identifies features that simply resemble the target class yet evade filtering. Figure 8 (top) gives an example of this in which hippopotamuses are made to look like Indian elephants via the insertion of patches that evade filtering because they depict African elephants.
4. **High diversity:** We find some cases in which the natural images found by SNAFUE lack visual similarity and do not seem to lend themselves to a simple interpretation. One example of this is the set of images for damselfly to dragonfly attacks in Figure 8 (middle).

5. **Ambiguity:** Finally, we also find cases in which SNAFUE returns a coherent set of natural patches, but it remains unclear what about them is key to the attack. Figure 8 (bottom) shows images for a redbone to vizsla attack, and it seems unclear from inspection alone the role that brown animals, eyes, noses, blue backgrounds, and green grass have in the attack because multiple images share each of these qualities in common.

### A.5 Examples of Natural Adversarial Patches

See Figure 9.
Figure 9: Examples of natural adversarial patches for several targeted attacks. Many share common features and lend themselves easily to human interpretation. Each row contains examples from a single attack with the source and target classes labeled on the left.