LaVAN: Localized and Visible Adversarial Noise

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Abstract

Most works on adversarial examples for deep-learning based image classifiers use noise that, while small, covers the entire image. We explore the case where the noise is allowed to be visible but confined to a small, localized patch of the image, without covering any of the main object(s) in the image. We show that it is possible to generate localized adversarial noises that cover only 2\% of the pixels in the image, none of them over the main object, and that are transferable across images and locations, and successfully fool a state-of-the-art Inception v3 model with very high success rates.

Padlock (92.7\%)  Tiger Cat (94.4\%)  Car Mirror (94.5\%)  Stingray (90.5\%)

1 Adversarial Noise

Deep neural-network architectures achieve remarkable results on image classification tasks. However, they are also susceptible to being fooled by adversarial examples: input instances which were modified in a particular way, and as a result, are misclassified by the network. Of course, for the adversarial example to be interesting, the change should be such that it does not confuse a human looking at the picture. Beyond the clear security implications, adversarial examples are also interesting as they may provide insights into the strengths, weaknesses, and blind-spots of these ubiquitous state-of-the-art classification models.

Most work on generating adversarial examples (we provide a more detailed review in section 5) focus either on noise which—while being imperceptible to humans—covers the entire image \cite{1, 2}, or on visible noise that covers prominent features of the main object in the image in a “natural” way (i.e., glasses with a specific pattern around a person’s eyes in a face identification task \cite{3}). In contrast, we look at visible noise that is localized to a small area of the image (a bounded box with up to 2\% of the pixels), and which does not cover the main object in the image. Figure 1 shows examples of such noised images that are misclassified by a state-of-the-art Inception V3 network with very high confidence.

A recent work by Brown et al \cite{4} introduces a visible noise similar to ours. The works are complementary to a large extent. Their work focuses on the security implications and attempts to generate universal noise “patches” that can be physically printed and put on any image, in either a black-box (when the attacked network is unknown) or white-box (when the attacked network is known) setup. As a consequence, the resulting adversarial patches in \cite{4} are relatively large (in a white-box setup,
the generated noise has to cover about 10% of the image to be effective in about 90% of the tested conditions, and a disguised patch has to cover about 35% of the image for a similar result) and also visually resemble the target class to some extent. We do not attempt to produce a physical attack and are more interested in investigating the blind-spots of state-of-the-art image classifiers, and the kinds of noise that can cause them to misclassify.

We show that in a white-box setting, we can generate localized visible noise that can be transferred to almost arbitrary images, covers only up to 2% of the image, looks like static noise to a person (i.e., does not resemble the target class in any meaningful way), does not cover any part of the main object in the image, and yet manages to make the network misclassify with very high confidence. Moreover, by inspecting the gradients of the network over noised images, we show that the network does not identify the noised patch as the main cause of misclassification, and in some cases hardly assigns it any blame at all. This is in contrast to the hypothesis posed in [4], in which the noise is said to be “much more salient” to the neural network than real-world objects.

The localized noises we generate are universal in the sense that they can be applied to many different images and locations. However, they are specific to a model they were trained on (i.e., equivalent to the white-box setups in [4]).

We believe these results highlight an interesting blind-spot in current state-of-the-art network architectures.

2 Localized noise for a single image and location

In the first setup, we explore generating a visible but localized adversarial noise that is specific to a single image and location.

2.1 Setting and Method

Our method mostly follows that standard adversarial noise generation setup: we assume access to a trained model $M$ that assigns membership probabilities $p_M(y|x)$ to input images $x \in \mathbb{R}^{n \times w \times h \times c}$. We denote by $\hat{y} = p_M(x)$ the vector of all class probabilities, and by $y = \arg\max_{y'} p_M(y =
We depart from this standard methodology by:

1. We want the noise $\delta$ to be confined to a small area over the image $x$, and to replace this area rather than be added to it. This is achieved by setting a mask $m \in \{0, 1\}^n$, and taking the noised image to be $(1 - m) \odot x - m \odot \delta$, where $\odot$ is element-wise multiplication.

2. Instead of training the noise to either minimize the probability of the target class or to minimize the probability of any other class (including the source class), we use a loss that does both things—it attempts to move the prediction towards the target class and away from the highest scored class. We use the network activations prior to the final softmax layer, denoted as $M(x)$, $M(y = y'|x)$. This decouples the outputs for the different classes, and speeds up convergence.

$$\arg \max_{\delta} [M(y = y'|x)(1 - m) \odot x + m \odot \delta) - M(y = y_{source})(1 - m) \odot x + m \odot \delta)]$$

The process is detailed in algorithm 1.

**Algorithm 1** Localized Noising Process

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**Input:** image $x$, model $p_M$, target class $y_{target}$, target probability $s$, mask $m$.  

$y_{source} = \arg \max_y p_M(y|x)$

noise = $\vec{0}$

$x' = (1 - m) \odot x + m \odot \text{noise}$

repeat

$\vec{y} = p_M(x')$

$L_{\text{target}} = \ell(\vec{y}, y_{target}) = M(y = y_{target}|x')$

$L_{\text{argmax}} = \ell(\vec{y}, y_{argmax}) = M(y = y_{argmax}|x')$

$\nabla_{\text{target}} = \frac{\partial L_{\text{target}}}{\partial x}$

$\nabla_{\text{argmax}} = \frac{\partial L_{\text{argmax}}}{\partial x}$

noise = noise $- \epsilon \cdot (\nabla_{\text{target}} - \nabla_{\text{argmax}})$

$x' = (1 - m) \odot x + m \odot \text{noise}$

until $p_M(y = y_{target}|x') \geq s$

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2.2 Experiments and Results

We use the PyTorch-provided pre-trained Inception V3 network [5] trained on ImageNet. We use images of size 299x299 and noise a square patch of size 42x42, roughly 2% of the image. We generate noise this way for 100 random (image,target-class,location) triplets. The location is chosen around the corners (we focus on the corners as they have the most chance of not covering the main object of the image). We consider the noising process successful if the network classifies the noised image to the desired target class with a confidence of at least 90%. For each image, we train the noise until we reach the desired confidence, or up to 10,000 epochs.

We managed to successfully generate localized noise this way to 79% of the 110 configurations we tried. When relaxing the requirement such that the network chooses the target class as the argmax (but perhaps with less than 90% probability), we manage to noise 91% of the configurations. By further relaxing the criteria to classify to any class other than the source one, noising success reaches 98%. Figure 1 shows examples of such noised images.

2.3 Shortcomings

While we managed to produce a high confidence, targeted localized noise to 75 out of 100 (image,target-class,location) triplets we tried, the resulting noise is highly dependent on the exact
image and location: attempts to move the noise even a pixel to each direction results in the network classifying to the original class with high confidence. Similarly, attempts to move the noise to a different image fail, unless we transfer, together with the noise, also a border of about 25% pixels to each side of the source image. In the next section, we generate noise that can be moved across images and locations.

3 Transferable localized noise

We now explore transferable (“universal”) localized noises: a noise patch which can be applied across different images and image positions.

3.1 Method

We extend the localized noising process in Algorithm 1 by choosing, at each iteration, a random image \(x\) from a “training set” of 100 images, and a random location. We adjust the noise vector and the mask so that they correspond to the target location, apply the noise to the image, and take a gradient step over the noise away from the source class of \(x\) and towards the shared target class \(y_{\text{target}}\). Thus, at each iteration the same noise is applied on a random image and location, both sampled separately from uniform distributions of the possible images and locations respectively. This is very similar to the algorithm presented in [4], with a somewhat different loss function, as described above. We stopped the noise generation process after the prediction model misclassifies with the desired confidence (i.e. Target class probability \(\geq 0.9\)) for 30 consecutive iterations. Overall we generated transferable noise patches for 20 different targets. The generated noises are presented in Figure 3.

3.2 Experiments and Results

We first provide anecdotal results of applying a trained noise to unseen images: Figure 2 shows some examples of images with transferable noises. To evaluate the noise in a more rigorous way, we used a separate test set, consisting of 100 images from the ImageNet data set, that did not participate in the noise generation process. We placed each transferable noise patch on each image on the bottom right corner. Though only 43% of our attempts made the model predict the target class with confidence \(\geq 0.9\), in 89% of the cases it predicted the desired target as the most likely one, and in 100% of the cases, the transferable noise patches prevented the model from predicting the original source class.

We further evaluate the strength and impact of the transferable noises. This time, we applied a noise patch to every second pixel in an image, and evaluate the model’s prediction using the following metrics: (1) probability of predicting the source class; (2) probability of predicting the target class; (3) argmax indication (i.e. whether the class received the highest probability among other class) for the target class, source class, or neither classes. Table 4 shows the result of this process for the (image: Gondola, target: Volcano) pair.
Figure 3: Transferable noises for different target classes
As can be seen, the noise is very robust, reducing the source class probability to near 0 across the image, and similarly increasing the target class probability.

We repeated this process for each of the 20 targets and each of the 100 images in our test set. In average, applying the transferable noise to $82\%$ of the possible locations caused the target class to receive a score $\geq 0.9$, and in $98\%$ of the locations on average, it caused the model to not predict the original-source class.

4 Noise perceived by the network

We managed to generate small transferable, localized noise that fools a state-of-the-art network into misclassifying an example.

In [4], the authors suggest that the localized noise works because it is much more salient than natural looking objects in the scene, capturing all of the network’s attention. To try and examine this claim, we take some noised images and attempt to “fix” them.

Figure 5: Gradient updates required to fix the Baseball (86%) misclassification. Noised area is well represented in the gradients.
First, we attempt to fix a noised image by feeding it into the network and taking gradient steps over the image towards the original source class\footnote{This is similar to the salience map computation in \cite{6}, but we accumulate the absolute values of several gradient steps, until reaching the desired outcome.}. For example, we take a noised image of a Killer Whale classified as a Baseball, and take gradient steps over the entire image until it is classified as a Killer Whale. Figure 5(center) shows the absolute values of the cumulative updates that were needed to overcome the noise and re-classify as a Whale. Notice that while a lot of the gradient efforts are within the noise patch, there is also a lot of activity outside of the patch, accenting features of the Whale’s body.

What if instead of attempting to optimize towards the source class, we optimize the noised image away from the target class? I.e., rather than pushing the noised image to “be a whale again”, we push it to “stop being a baseball”? The resulting cumulative gradients are displayed in Figure 5(right). We see less gradient activity overall, and, somewhat surprisingly, there again seems to be at least as much activity outside the noise patch as it is within it. This gradient behavior persists on different image/noise cases, with a combination of gradient within the noise box and outside of it.

Some noise cases are more intriguing. For example, Figure 6 shows the case of a Sports Car being noised to a iPod at 98%. When driving the image towards Sports Car (Figure 6 center), the gradient seem to accent the car’s front and its surrounding, while almost completely ignoring the noised patch. In order to restore the original class, the network’s gradients work to enhance features of the original class rather than diminishing the intruding noise. This pattern persists when optimizing the noised image away from iPod (Figure 6 right): there are hardly any updates within the noised area.

Figure 6: Gradient updates required to fix the iPod (98%) misclassification. Noised area is mostly ignored in the gradients.

This suggests that, at least in some image/noise combinations, the localized visible noise is not only very effective at misleading the classifier and triggering the target class, it is also quite stealthy—at least according to the target gradients wrt to the image, the classifier attributes the target to various elements in the image, but not to the noisy patch itself.

5 Related Work

Most works focus on adding a small amount of noise, imperceptible to the human eye, but covering the entire image. It was shown that it is possible to construct such noises to thwart multiclass image classifiers \cite{1,2,7}, and, more recently, also structured classifiers in tasks such as image segmentation and pose estimation \cite{8}. In all these cases the noise covers the entire image, including the salient objects within it. We focus on cases where the noise may be larger, but only affect a small part of the image.

Several works explore setups that do not noise the entire image. Sharif et al \cite{3} causes a face recognition system to identify an incorrect face by adding glasses with a specially constructed frame texture, and Evtimov et al \cite{9} causes misclassification of traffic signs by adding a specific pattern of rectangular, solid-colored patches on top of a traffic sign. These are very impressive works in which the attack transfers to images taken in the real world. However, from the noise locality perspective, in both these cases, the noise patches attack very prominent characteristics of the objects to
be classified. The glasses hide areas around the eyes, which are very indicative for face recognition. Similarly, many traffic signs can be abstracted as a specific arrangement of solid-colored rectangles on a solid-colored background, so it is not too surprising that messing with the rectangles formation can fool a traffic-sign classifier. Su et al. [10] demonstrate that, in about 70% of 32x32 images from CIFAR-10, it is possible to find a single pixel whose change in value can cause a misclassification (the number drops to between 20% and 30% for a targeted attack towards a specific target class). However, this requires a very small image size, and the offending pixel usually at the center of the classified image. Papernot et al [11] show that, when considering black-and-white digits classification, changing a small percentage of pixels from black to white can cause misclassification. The pixels are spread out across the entire image and look as harming noise to a human observer. In contrast to all these works, in our case, the pixels are localized to a specific region of the image and do not cover the source-class object at all. Finally, the recent adversarial patch work by Brown et al [4] is very similar to our setting, and was discussed throughout this report. They focus on printable patches that are immune to scaling or ration, and that can be used for physical attacks. As a consequence, their patches are required to be very large, covering upward from 10% of the image in order to be effective. We demonstrate that, when relaxing these requirements, networks can be fooled also by much smaller patches of visible noise, that cover a substantially smaller area of the image. Moreover, we show that—at least according to its gradients—the network does not recognize the attacking patches as the source of the misclassification.

6 Conclusions

We show that it is easy to construct visible but localized adversarial noise patches that cover only 2% of the pixels in the image, none of them on the main salient object, and that cause a state-of-the-art image classifier to misclassify to arbitrary labels. Such noise patches are not imaged specific, and the same patch can be applied to arbitrary images and locations, causing a misclassification to the desired target class with very high success rates. Interestingly, in many cases, the noise is not identified in the network’s saliency map over the gradients.

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