Standard detectors aren't (currently) fooled by physical adversarial stop signs

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Abstract

An adversarial example *is an example that has been adjusted to produce the wrong label when presented to a system at test time. If adversarial examples existed that could fool a detector, they could be used to (for example) wreak havoc on roads populated with smart vehicles. Recently, we described our difficulties creating physical adversarial stop signs that fool a detector. More recently, Evtimov* et al. *produced a physical adversarial stop sign that fools a proxy model of a detector. In this paper, we show that these physical adversarial stop signs do not fool two standard detectors (YOLO and Faster RCNN) in standard configuration. Evtimov* et al.*'s construction relies on a crop of the image to the stop sign; this crop is then resized and presented to a classifier. We argue that the cropping and resizing procedure largely eliminates the effects of rescaling and of view angle. Whether an adversarial attack is robust under rescaling and change of view direction remains moot. We argue that attacking a classifier is very different from attacking a detector, and that the structure of detectors – which must search for their own bounding box, and which cannot estimate that box very accurately – makes it quite likely that adversarial patterns are strongly disrupted. Finally, an adversarial pattern on a physical object that could fool a detector would have to be adversarial in the face of a wide family of parametric distortions (scale; view angle; box shift inside the detector; illumination; and so on). Such a pattern would be of great theoretical and practical interest. There is currently no evidence that such patterns exist.*

1. Introduction

An *adversarial example* is an example that has been adjusted to produce the wrong label when presented to a system at test time. Adversarial examples are of interest only because the adjustments required seem to be very small and are easy to obtain [23, 7, 5]. Numerous search procedures generate adversarial examples [14, 16, 15]. There is fair evidence that it is hard to tell whether an example is adversarial (and so (a) evidence of an attack and (b) likely to be misclassified) or not [20, 8, 21, 12, 2, 4]. Current procedures to build adversarial examples for deep networks appear to subvert the feature construction implemented by the network to produce odd patterns of activation in late stage RELU's; this can be exploited to build one form of defence [10]. There is some evidence that other feature constructions admit adversarial attacks, too [12]. The success of these attacks can be seen as a warning not to use very highly non-linear feature constructions without having strong mathematical constraints on what these constructions can do; but taking that position means one cannot use methods that are largely accurate and effective.

Printing adversarial images then photographing them can retain their adversarial property [9, 1], which suggests adversarial examples might exist in the physical world. Adversarial examples in the physical world could cause a great deal of mischief. For example, imagine possessing a template that, with a can of spray paint, could turn a stop sign into a yield sign (or worse!). As a result, it is important to know whether (a) such examples could exist and (b) how robust their adversarial property is in practice.

In earlier work, we showed that it was difficult to build physical examples that fooled a stop-sign detector [11]. In particular, if one actually takes video of adversarial stop-signs out of doors, the adversarial pattern does not appear to affect the performance of the detector by much. We speculated that this might be because adversarial patterns were disrupted by being viewed at different scales, rotations, and orientations. This generated some discussion. OpenAI demonstrated a search procedure that could produce an image of a cat that was misclassified when viewed at multiple scales [1]. There is some blurring of the fur texture on the cat, but this would likely be imperceptible to most observers. OpenAI also demonstrated a search procedure that could produce an image of a cat that was misclassified when viewed at multiple scales *and* orientations [1]. However, there are significant visible artifacts on that image; few would feel that it had not obviously been tampered with.

Recently, Evtimov *et al.* have demonstrated several physical stop-signs that are misclassified. However, their

work attacks a *classifier*, not a *detector*. In this paper, we show that standard off-the-shelf detectors that have not seen adversarial examples in training detect their stop signs rather well, under a variety of conditions. We explain (a) why their result is puzzling; (b) why their result may have to do with specific details of their classifier construction and (b) why the distinction between a classifier and a detector means their work has not put the core issue – can one build physical adversarial stop-signs? – to rest.

2. Experimental Results

Evtimov *et. al* have demonstrated a construction of physical adversarial stop signs [3]. They demonstrate poster attacks (the stop sign is covered with a poster that looks like a faded stop sign) and sticker attacks (the attacker makes stickers placed on particular locations on a stop sign), and conclude that one can make physical adversarial stop signs. There are two types of tests: stationary tests, where the sign is imaged from a variety of orientations and directions; and drive-by tests, where the sign is viewed from a camera based on a car.

We applied the MS-COCO pretrained standard YOLO and Faster RCNN detectors on the images and videos from their paper. First, we applied both detectors on the images shown in the paper (reproduced as Figure 1 for reference). All adversarial stop-signs are detected by both detectors (Figure 2 and Figure 3).

We downloaded videos provided by the authors at https://iotsecurity.eecs.umich.edu/#roadsigns, and applied the detectors to those videos. We find:

- YOLO detects the adversarial stop signs produced by poster attacks about as well as the true stop signs (figure 4, and the videos we provide at https://www.youtube.com/watch?v=EfbonX1lE5s);
- YOLO detects the adversarial stop signs produced by sticker attacks about as well as the true stop signs (figure 5, and the videos we provide at https://www.youtube.com/watch?v=GOjNKQtFs64);
- Faster RCNN detects the adversarial stop signs produced by poster attacks about as well as the true stop signs (figure 6, and the videos we provide at https://www.youtube.com/watch?v=x53ZUROX1q4);
- Faster RCNN detects the adversarial stop signs produced by sticker attacks about as well as the true stop signs (figure 7, and the videos we provide at https://www.youtube.com/watch?v=p7wwvWdn2pA);
- Faster RCNN detects stop signs rather more accurately than YOLO;
- both YOLO and Faster RCNN detect small stop signs less accurately; as the sign shrinks in the image, YOLO fails significantly earlier than Faster RCNN.

These effects are so strong that there is no point in significance testing, etc.

At our request, the authors kindly provided full resolution versions of the videos at https://iotsecurity.eecs.umich.edu/#roadsigns. We applied YOLO and Faster RCNN detectors to those videos. We find:

- YOLO detects the adversarial stop signs produced by poster attacks well (figure 8, and the videos we provide at https://www.youtube.com/watch?v=afIr6_cvoqY and https://www.youtube.com/watch?v=rqLhTZZ0U2w);
- YOLO detects the adversarial stop signs produced by sticker attacks (figure 9, and the videos we provide at https://www.youtube.com/watch?v=Ep-aE8T3Igs and https://www.youtube.com/watch?v=nCcoJBQ8C3c);
- Faster RCNN detects the adversarial stop signs produced by poster attacks very well (figure 10, and the videos we provide at https://www.youtube.com/watch?v=10DDFs73_6M and https://www.youtube.com/watch?v=KQyzQtuyZxc);
- Faster RCNN detects the adversarial stop signs produced by sticker attacks very well (figure 11, and the videos we provide at https://www.youtube.com/watch?v=FRDyz7tDVdM and https://www.youtube.com/watch?v=F-iefz8jGQg);
- Faster RCNN detects stop signs rather more accurately than YOLO;
- YOLO works better on higher resolution video;
- Faster RCNN detect even far and small stop signs accurately.

These effects are so strong that there is no point in significance testing, etc.

3. Classifiers and Detectors are Very Different Systems

The details of the system attacked are important in assessing these claims. The attack is on a classifier, rather than on a detector. There are two classifiers, distinguished by architecture and training details. LISA-CNN consists of three convolutional layers followed by a fully connected

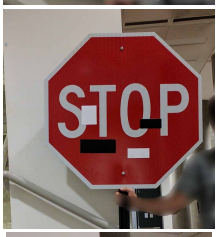
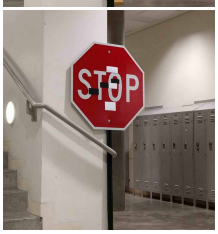
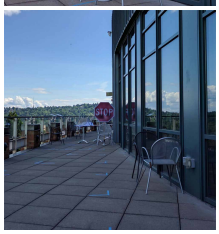
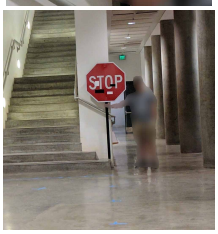
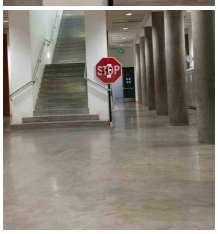
Distance/Angle	Subtle Poster	Camoutflage Graffiti	Camoutflage Art (LISA-CNN)	Camoutflage Art (GTSRB*-CNN)
5' 0°				
5' 15°				
10' 0°				
10' 30°				
40' 0°				
Targeted-Attack Success	100%	66.67%	100%	80%

Figure 1: Table IV of [3], reproduced for the readers' convenience. This table shows figures of different adversarial constructions, from different distances and viewed at different angles.

layer ([3], p5, c1), trained to classify signs into 17 classes ([3], p4, c2), using the LISA dataset of US road signs [13]. The other is a publicly available implementation (from [24]) of a classifier demonstrated to work well at road signs (in [19]); this is trained on the German Traffic Sign Recognition Benchmark ([22]), with US stop signs added. Both classifiers are accurate ([3], p5, c1). Each classifier is applied to 32×32 images ([3], p4, c2). However, in both stationary and drive by tests, the image is cropped and resized ([3], p8, c2) by unspecified means to yield the classifier input.

An image classification system is presented with an image, and produces a class label. A detection system, in contrast, must determine interesting spatial domains in the image (usually bounding boxes), and classify each of these, Figure 12. How this occurs depends somewhat on the architecture. Faster RCNN predicts interesting boxes, then classifies them [18]. YOLO uses a grid of cells, where each cell uses features computed from much of the image to predict boxes and labels near that cell, with confidence infor-

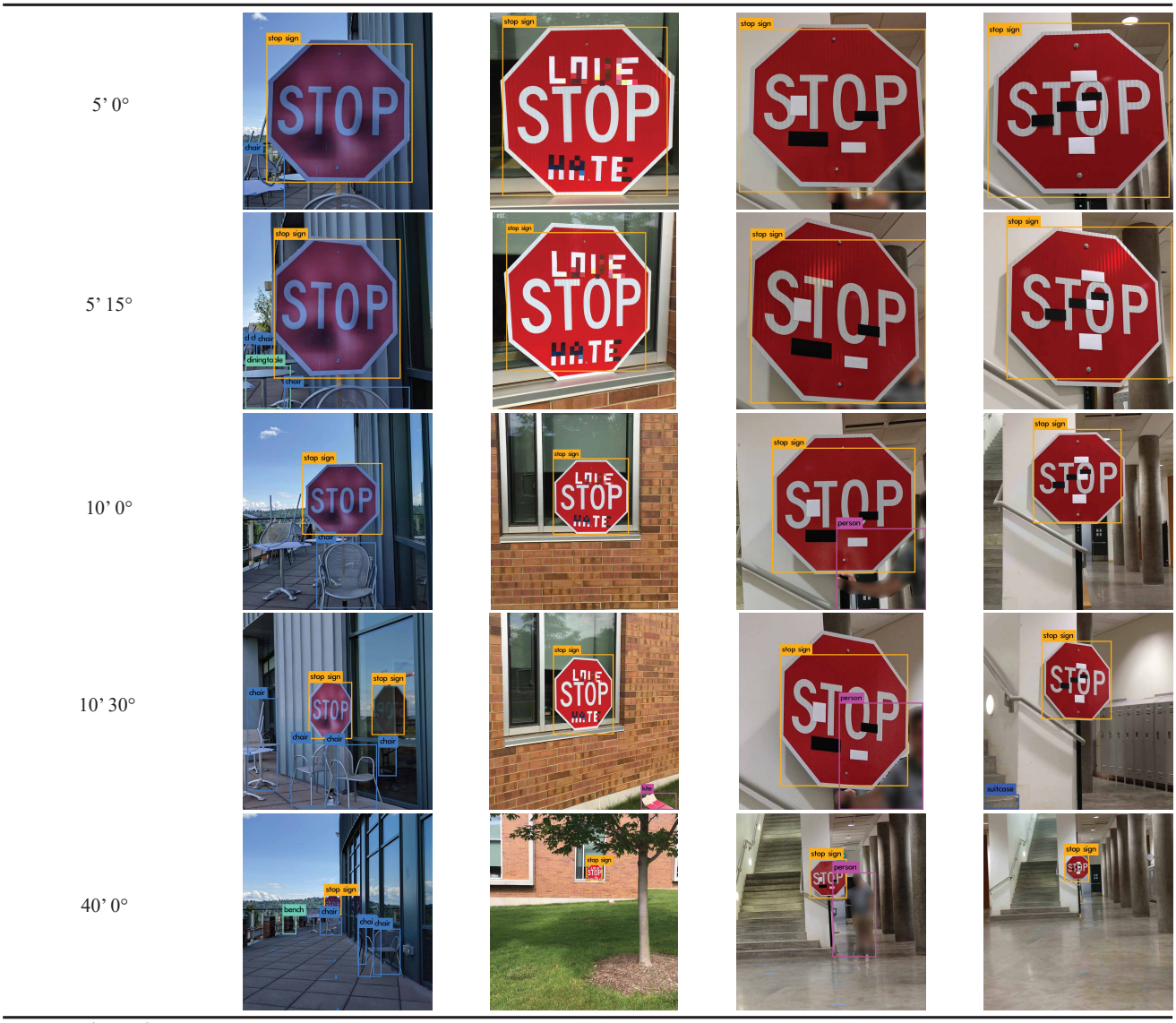


Figure 2: YOLO detection results on the stop signs of figure 1.

mation [17]. One should think of this architecture as an efficient way of predicting interesting boxes, then classifying them.

The process of Evtimov *et al.* – acquire image; crop to sign; classify that box – can be seen as a proxy detection system, where the cropping procedure spoofs the process in a detector that produces bounding boxes. We speculate that several features of this proxy detection system (from now on, proxy model) make it a relatively poor model of a modern detection system. These features also make it relatively vulnerable to adversarial constructions.

Close cropping can remove scale and translation effects: The details of the crop and resize procedure are not revealed in [3]. However, these details matter. We believe their results are most easily explained by assuming the sign was cropped reasonably accurately to its bounding box, then resized. If the sign is cropped reasonably accurately to its bounding box, then resized, many of the visual effects of slant and resizing are removed. This means the claim that the adversarial construction is invariant to slant and resizing is moot. Close cropping is not a feature of modern detection systems, and would make the proxy model poor.

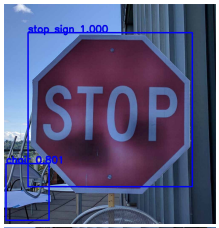
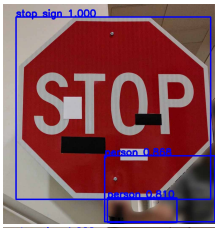
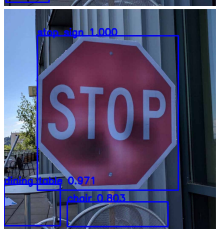
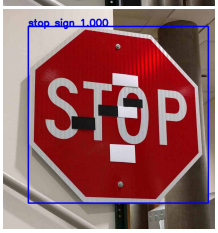
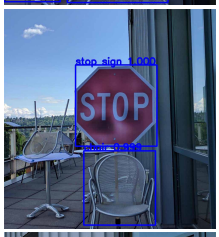
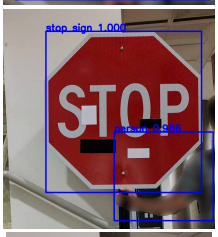
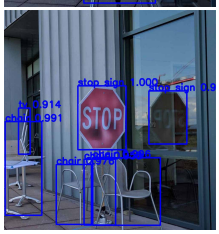
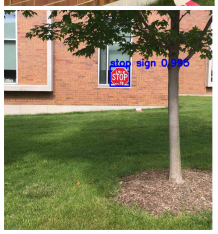
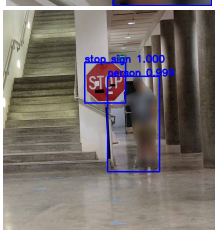
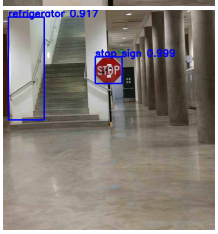
Distance/Angle	Subtle Poster	Camoutflage Graffiti	Camoutflage Art (LISA-CNN)	Camoutflage Art (GTSRB*-CNN)
5' 0°				
5' 15°				
10' 0°				
10' 30°				
40' 0°				
Targeted-Attack Success	0%	0%	0%	0%

Figure 3: Faster RCNN detection results on the stop signs of figure 1.

Low resolution boxes: Almost every pixel in an accurately cropped box will testify to the presence of a stop sign. Thus, very low resolution boxes may mean that fewer pixels need to be modified to confuse the underlying classifier. In contrast to the 32x32 boxes of [3], YOLO uses a 7x7 grid on a 448x448 dimension image; each grid cell predicts predict bounding box extents and labels. This means that each prediction in YOLO observes at least 64x64 pixels. The relatively low resolution of the classifier used makes the proxy model poor.

Cropping and variance: Detection systems like YOLO or Faster RCNN cannot currently produce accurate bounding boxes. Producing very accurate boxes requires searching a larger space of boxes, and so creates problems with false positives. While there are post-processing methods to improve boxes [6], this tension is fundamental (for example, see figure 2 and 3). In turn, this means that the classification procedure within the detector must cope with a range of shifts between box and object. We speculate that, in a detection system, this could serve to disrupt adversarial patterns, because the pattern might be presented to the classification process inside the detector in a variety of lo-

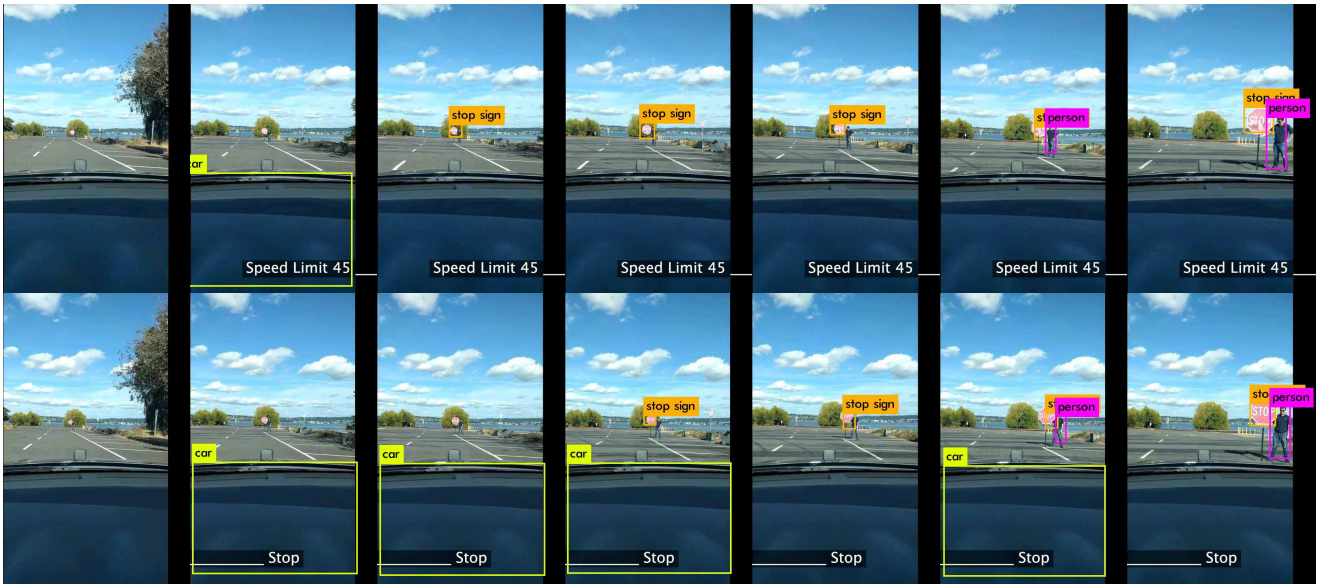


Figure 4: In relatively low resolution, YOLO detects printed poster physical adversarial stop sign and real stop sign similarly.

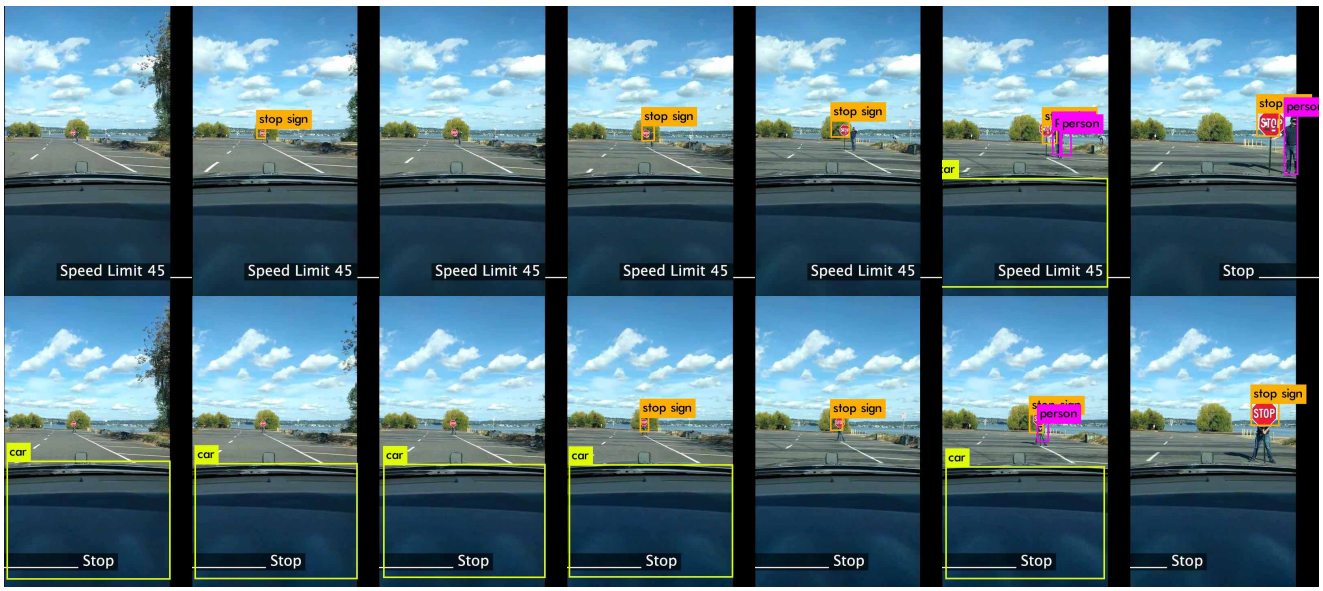


Figure 5: In relatively low resolution, YOLO detects sticker physical adversarial stop sign and real stop sign similarly.

cations relative to the bounding box. In other words, the adversarial property of the pattern would need to be robust to shifts and rescales within the box. At the very least, this effect means that one cannot draw conclusions from the experiments of [3].

Cropping and context: The relatively high variance of bounding boxes around objects in detector systems has another effect. The detector system sees object context information that may have been hidden in the proxy model. For example, cells in YOLO do not distinguish between pixels covered by a box and others when deciding (a) where the box is and (b) what is in it. While the value of this information remains moot, its absence means the proxy model is a poor model.

4. Discussion

We do not claim that detectors are necessarily immune to physical adversarial examples. Instead, we claim that there is no evidence as of writing that a physical adversarial example can be constructed that fools a detector. In earlier

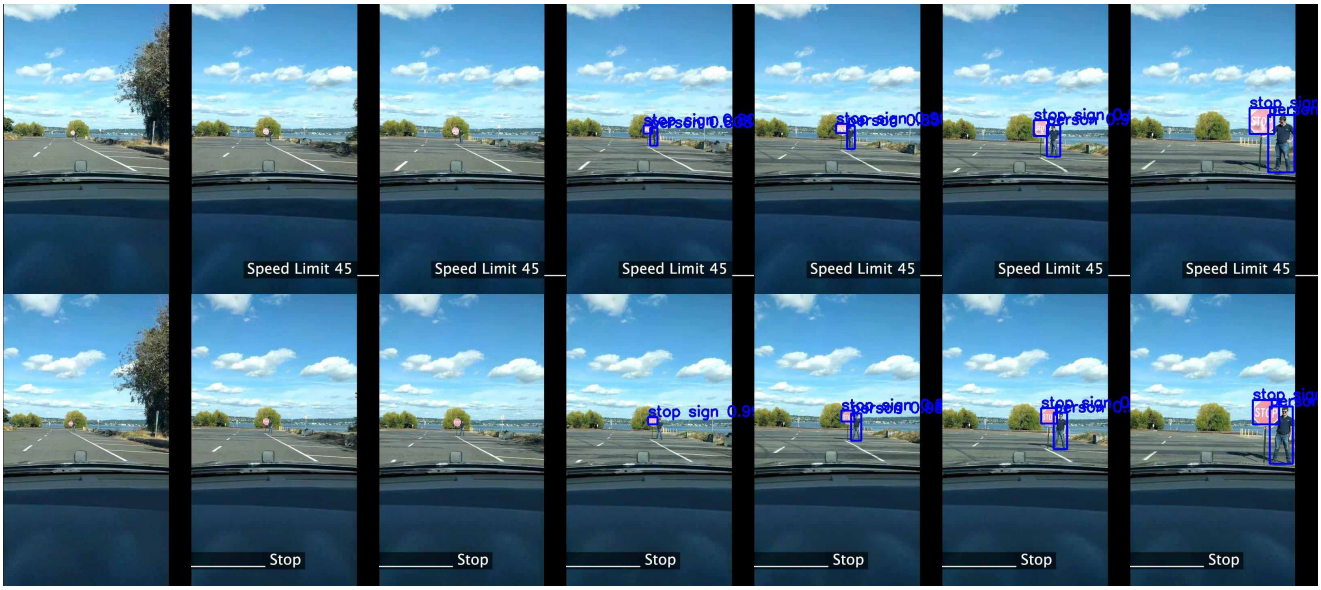


Figure 6: In relatively low resolution, Faster RCNN detects printed poster physical adversarial stop sign and real stop sign similarly.

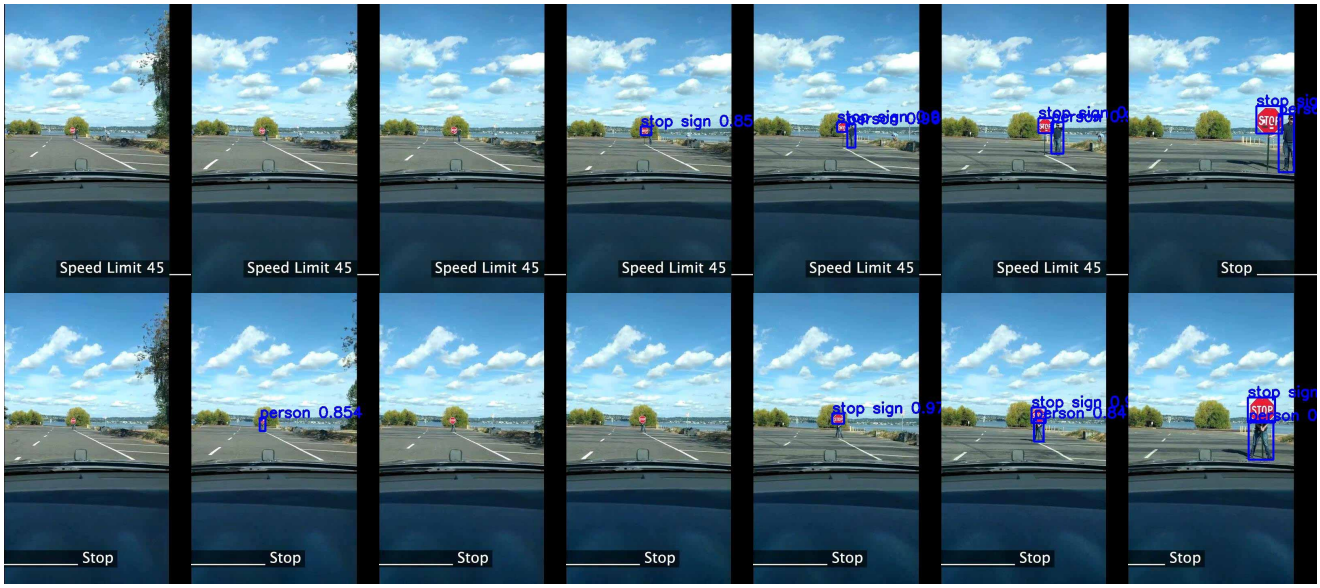


Figure 7: In relatively low resolution, Faster RCNN detects sticker physical adversarial stop sign and real stop sign similarly.

work, we said we had not produced such examples. The main point of this paper is to point out that others have not, too; and that fooling a detector is a very different business from fooling a classifier.

There is a tension between the test-time accuracy of a classifier, and the ability to construct adversarial examples that are "like" and "close to" real images but are misclassified. In particular, if there are lots of such things, why is the classifier accurate on test? How does the test procedure "know" not to produce adversarial examples? The usual, and natural, explanation is that the measure of the space of adversarial examples $\mathcal{A}$ under the distribution of images $P(I)$ is "small". Notice that $\mathcal{A}$ is interesting only if $P(\mathcal{A})$ is small *and* for most $u \in \mathcal{A}$, $P(u)$ is "big" (i.e. there is not much point in an adversarial example that doesn't look like an image) *and* there there is at least some of $\mathcal{A}$ "far" from true classifier boundaries (i.e. there is not much point in replacing a stop sign with a yield sign, then complaining it is

Figure 8: In higher resolution video, YOLO detects printed poster physical adversarial stop sign well. YOLO works better on higher resolution than lower resolution video.

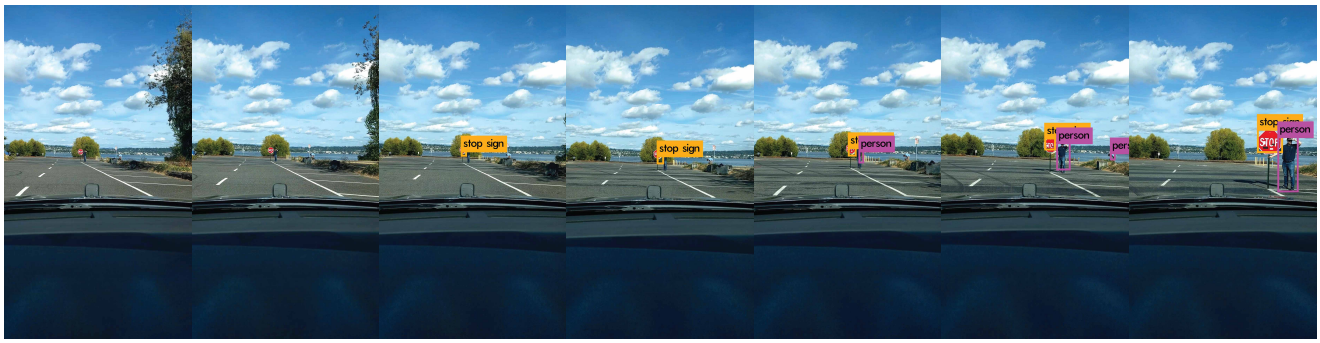


Figure 9: In higher resolution video, YOLO detects sticker physical adversarial stop sign well. YOLO works better on higher resolution than lower resolution video.

mislabelled). This means that $\mathcal{A}$ must have small volume, too. If $\mathcal{A}$ has small volume, but it is easy for an optimization process to find an adversarial example close to any particular example, then there must also be a piece of $\mathcal{A}$ quite close to most examples (one can think of "bubbles" or "tubes" of bad labels threading through the space of images). In this view, Evtimov *et al.*'s paper presents an important puzzle. If one can construct an adversarial pattern that remains adversarial for a three dimensional range of views (two angles and a scale), this implies that close to any particular pattern there is a three parameter "sheet" inside $\mathcal{A}$ – but how does the network know to organize its errors into a form that is consistent with nuisance viewing parameters?

One answer is that it is trained to do so because it is trained on different views of objects, meaning that $\mathcal{A}$ has internal structure learned from training examples. While this can't be disproved, it certainly hasn't been proved. This answer would imply that, in some way, the architecture of the network can generalize across viewing parameters better than it generalizes across labels (after all, the existence of an adversarial example is a failure to generalize labels correctly). Believing this requires fairly compelling evidence. Ockham's razor suggests another answer: Evtimov *et al.*, by cropping closely to the stop sign, removed most of the effect of slant and scale, and so the issue does not arise.

Whether physical adversarial examples exist that fool a detector is a question of the first importance. Here are quite good reasons they might not. An adversarial pattern on a physical object that could fool a detector would have to be adversarial in the face of a wide family of parametric distortions (scale; view angle; box shift inside the detector; illumination; and so on). There is no evidence that such patterns exist. More likely to exist, but significantly less of a nuisance, is a pattern that, viewed under the right circumstances (and so just occasionally) would fool a detector.

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Figure 10: In higher resolution video, Faster RCNN detects printed poster physical adversarial stop sign very well.

Figure 11: In higher resolution video, Faster RCNN detects sticker physical adversarial stop sign very well.

Figure 12: Detectors must take a whole frame, and determine what box of pixels to classify. The process of finding the box in modern detectors has quite distinctive properties, discussed in the text, that make cropping images to object bounding boxes a poor proxy model.

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