Fooling neural networks

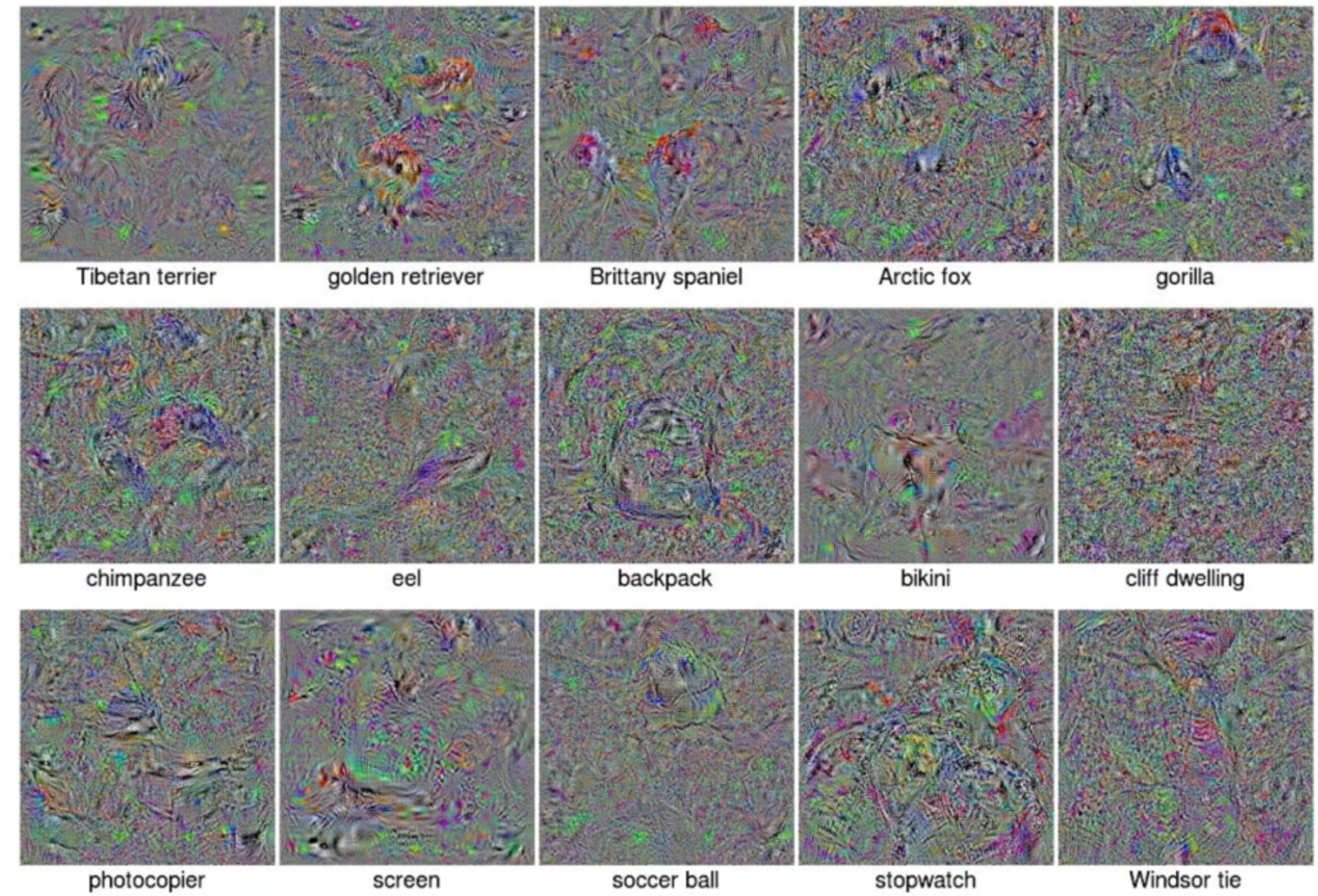
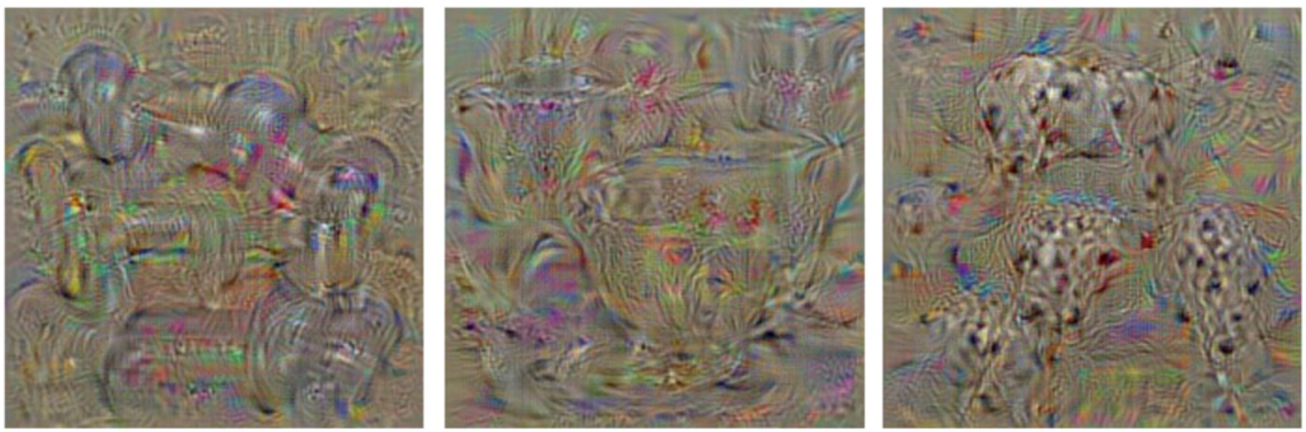


Image source

Last time: Generation of preferred inputs

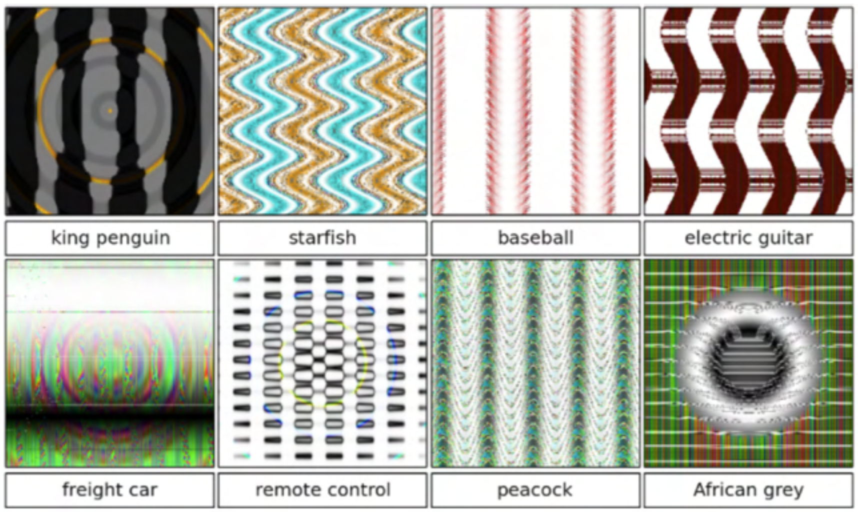


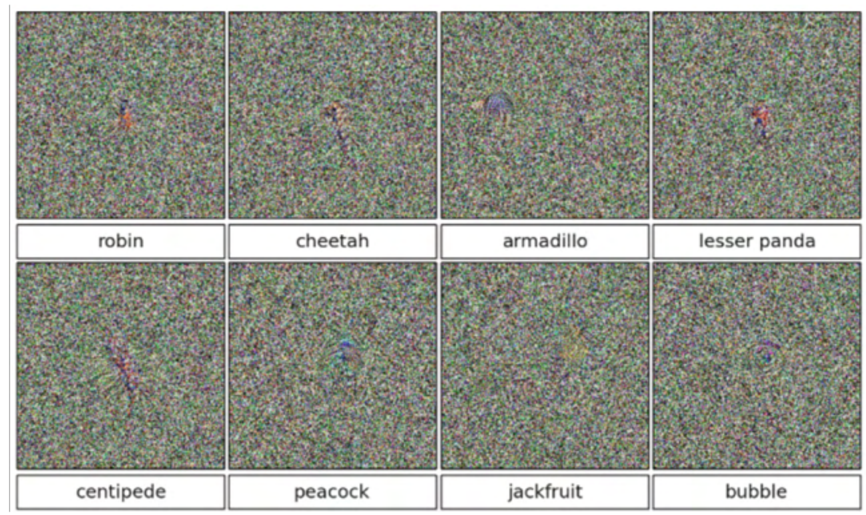
dumbbell cup dalmatian

K. Simonyan, A. Vedaldi, and A. Zisserman, [Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps](), ICLR 2014

Last time: Generation of preferred inputs

- Actually, it is easy to generate perceptually incoherent or totally meaningless images that will be classified as any given class with high confidence

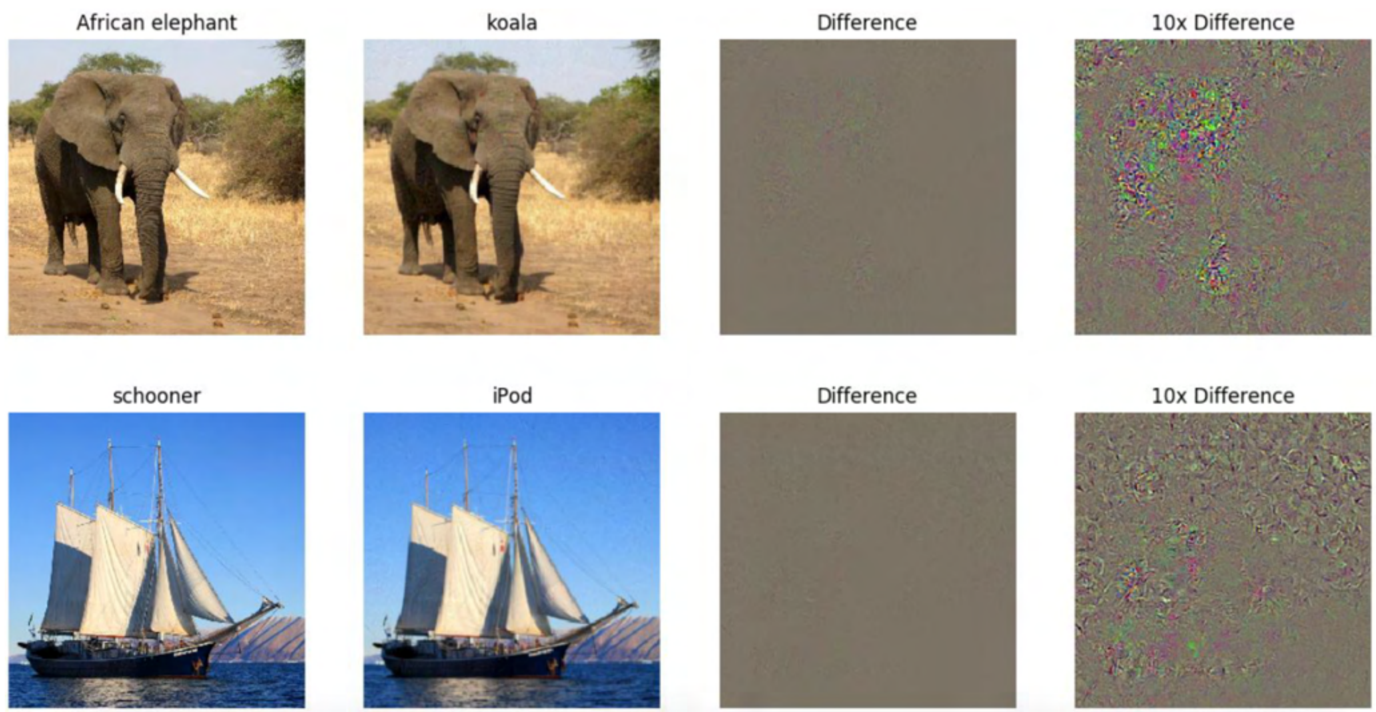




A. Nguyen, J. Yosinski, J. Clune, Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images, CVPR 2015

Adversarial examples

- We can “fool” a neural network by imperceptibly perturbing an input image so it is misclassified



Source: Stanford CS231n

Adversarial examples: Outline

- Basic definition, analysis of fooling linear classifiers
- Generating adversarial examples
  - Fast gradient sign, iterative variants
  - Universal adversarial perturbations
- Why are neural networks easy to fool?
- Defending against adversarial examples
  - Adversarial training
  - Learning to reject adversarial examples
  - Robust architectures
  - Image pre-processing
- Trends and open questions
  - Broadening the scope of adversarial examples
  - Adversarial examples and human perception

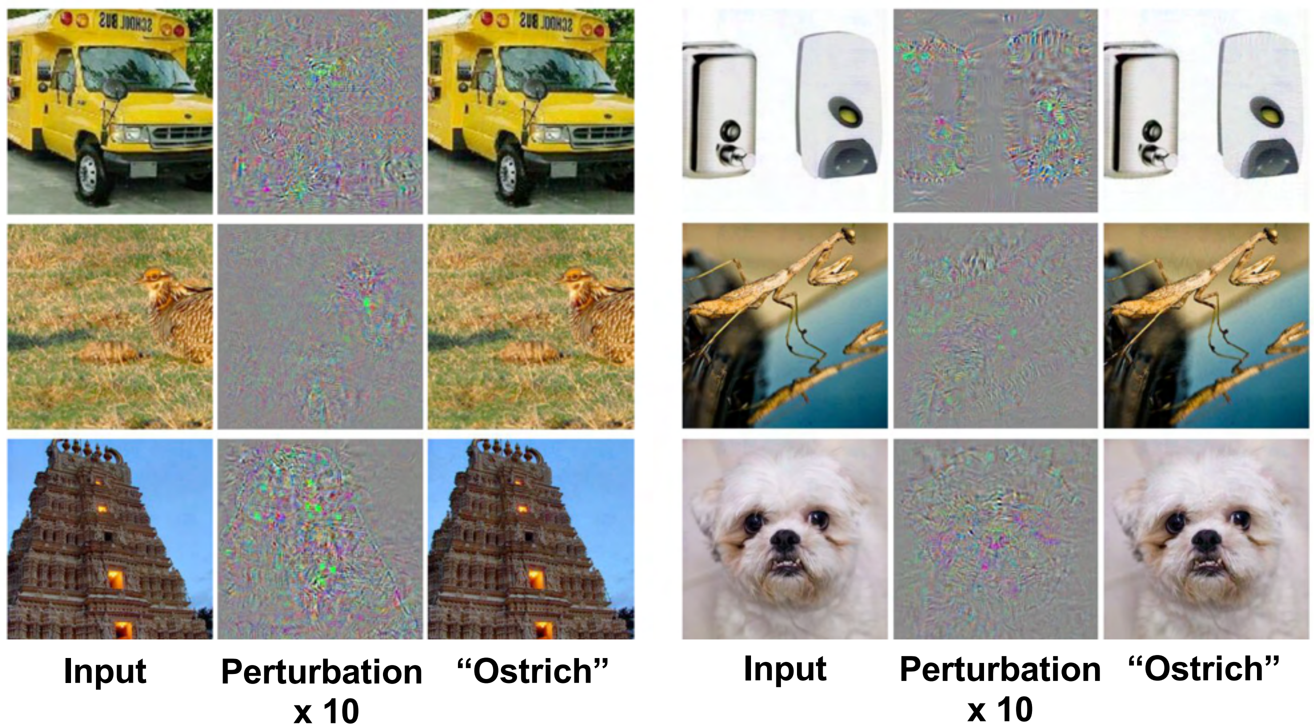
Finding the smallest adversarial perturbation

- Start with correctly classified image x
- Find perturbation r minimizing $\|r\|_2$ such that
  - $x + r$ is misclassified (or classified as specific target class)
  - All values of $x + r$ are in the valid range
- This is constrained non-convex optimization, which the authors solve with L-BFGS

C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, R. Fergus, Intriguing properties of neural networks, ICLR 2014

Finding the smallest adversarial perturbation

- Sample results:



C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, R. Fergus, [Intriguing properties of neural networks](), ICLR 2014

Gradient ascent

- Rather than searching for the smallest possible perturbation, it is easier to take small gradient steps in desired direction
- Decrease score (increase loss) of *correct* class y^*:

$$x \leftarrow x - \eta \frac{\partial f(x, y^*)}{\partial x} \quad \text{or} \quad x \leftarrow x + \eta \frac{\partial L(x, y^*)}{\partial x}$$

- Increase score (decrease loss) of *incorrect* target class $\hat{y}$:

$$x \leftarrow x + \eta \frac{\partial f(x, \hat{y})}{\partial x} \quad \text{or} \quad x \leftarrow x - \eta \frac{\partial L(x, \hat{y})}{\partial x}$$

Fooling a linear classifier

- Increase score of target class $\hat{y}$:

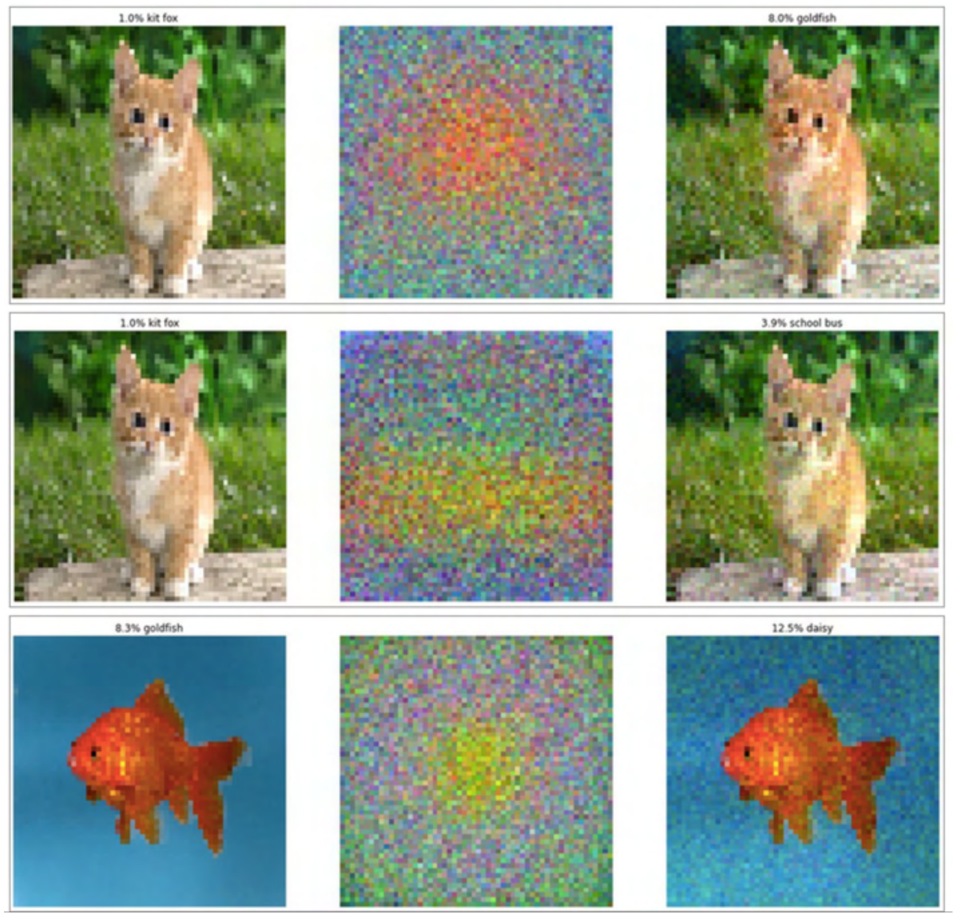
$$x \leftarrow x + \eta \frac{\partial f(x, \hat{y})}{\partial x}$$

- For a linear classifier with $f(x, \hat{y}) = \hat{w}^T x$:

$$x \leftarrow x + \eta\, \hat{w}$$

- To fool a linear classifier, add a small multiple of the target class weights to the test example

Fooling a linear classifier



http://karpathy.github.io/2015/03/30/breaking-convnets/

Analysis of the linear case

- Response of classifier with weights w to adversarial example $x + r$:

$$w^T(x + r) = w^T x + w^T r$$

- Suppose the pixel values have precision ϵ, i.e., the classifier is normally expected to predict the same class for x and $x + r$ as long as $\|r\|_\infty \le \epsilon$
- How to choose r to maximize the increase in activation $w^T r$ subject to $\|r\|_\infty \le \epsilon$?

$$r \;= \epsilon \operatorname{sgn}(w)$$

I. Goodfellow, J. Schlens, C. Szegedy, Explaining and harnessing adversarial examples, ICLR 2015

Analysis of the linear case

- Response of classifier with weights w to adversarial example $x + r$, $r = \epsilon \, \mathrm{sgn}(w)$:

$$w^T(x + r) = w^T x + \epsilon \, w^T \mathrm{sgn}(w)$$

- If w has dimensionality d and average element magnitude m, how much will the activation increase?
  - By $\epsilon d m$, i.e., linearly as a function of d
- The higher the dimensionality, the easier it is to make many small changes to the input that cause a large change in the output

I. Goodfellow, J. Schlens, C. Szegedy, [Explaining and harnessing adversarial examples](), ICLR 2015

Toy example

x	2	-1	3	-2	2	2	1	-4	5	1
w	-1	-1	1	-1	1	-1	1	1	-1	1

$$w^T x = -2 + 1 + 3 + 2 + 2 - 2 + 1 - 4 - 5 + 1 = -3$$

$$\sigma(w^T x) = \frac{1}{1 + e^{-(-3)}} = 0.047$$

http://karpathy.github.io/2015/03/30/breaking-convnets/

Toy example

x	2	-1	3	-2	2	2	1	-4	5	1
w	-1	-1	1	-1	1	-1	1	1	-1	1
$x + r$	1.5	-1.5	3.5	-2.5	2.5	1.5	1.5	-3.5	4.5	1.5

$$w^T x = -2 + 1 + 3 + 2 + 2 - 2 + 1 - 4 - 5 + 1 = -3$$

$$\sigma(w^T x) = \frac{1}{1 + e^{-(-3)}} = 0.047$$

$$w^T(x + r) = -3 + 10 * 0.5 = 2$$

$$\sigma(w^T(x + r)) = \frac{1}{1 + e^{-2}} = 0.88$$

http://karpathy.github.io/2015/03/30/breaking-convnets/

Adversarial examples: Outline

- Basic definition, analysis of fooling linear classifiers
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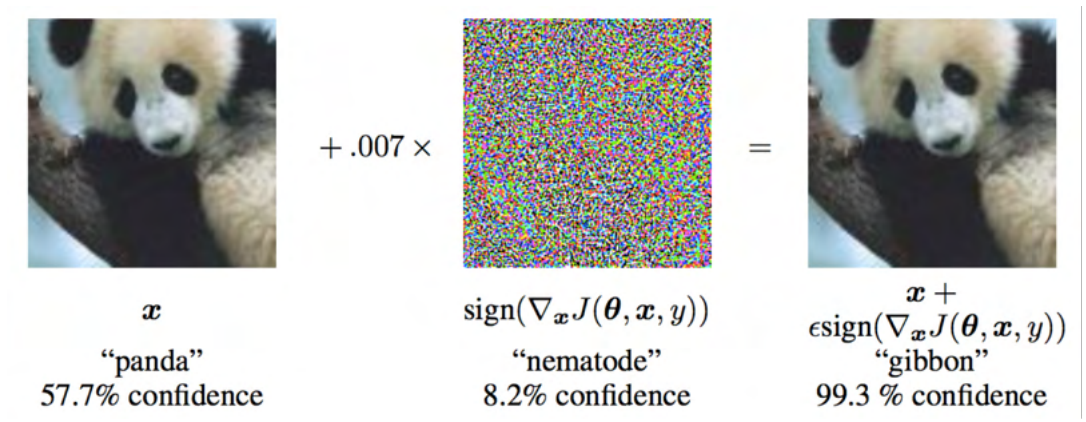
Generating adversarial examples

- **Fast gradient sign method:** Find the gradient of the loss w.r.t. correct class y^*, take element-wise sign, update in resulting direction:

$$x \leftarrow x + \epsilon \,\mathrm{sgn}\left(\frac{\partial L(x, y^*)}{\partial x}\right)$$



I. Goodfellow, J. Schlens, C. Szegedy, Explaining and harnessing adversarial examples, ICLR 2015

Generating adversarial examples

- **Fast gradient sign method:**

$$x \leftarrow x + \epsilon \operatorname{sgn}\left(\frac{\partial L(x, y^*)}{\partial x}\right)$$

- **Iterative gradient sign method:** take multiple smaller steps until misclassified, each time clip result to be within ϵ-neighborhood of original image
- ***Least likely class* method:** try to misclassify image as class $\hat{y}$ with *smallest* initial score:

$$x \leftarrow x - \epsilon \operatorname{sgn}\left(\frac{\partial L(x, \hat{y})}{\partial x}\right)$$

A. Kurakin, I. Goodfellow, S. Bengio, [Adversarial examples in the real world](), ICLR 2017 workshop

Generating adversarial examples

Comparison of methods for $\epsilon = 32$

A. Kurakin, I. Goodfellow, S. Bengio, [Adversarial examples in the real world](), ICLR 2017 workshop

Generating adversarial examples

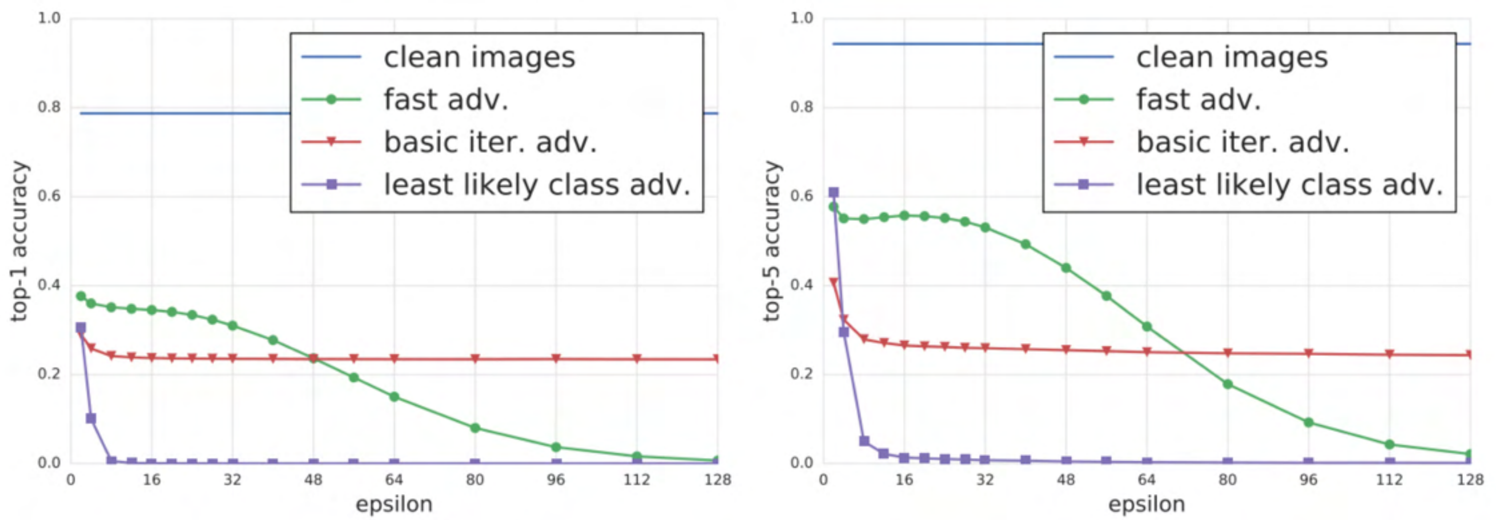
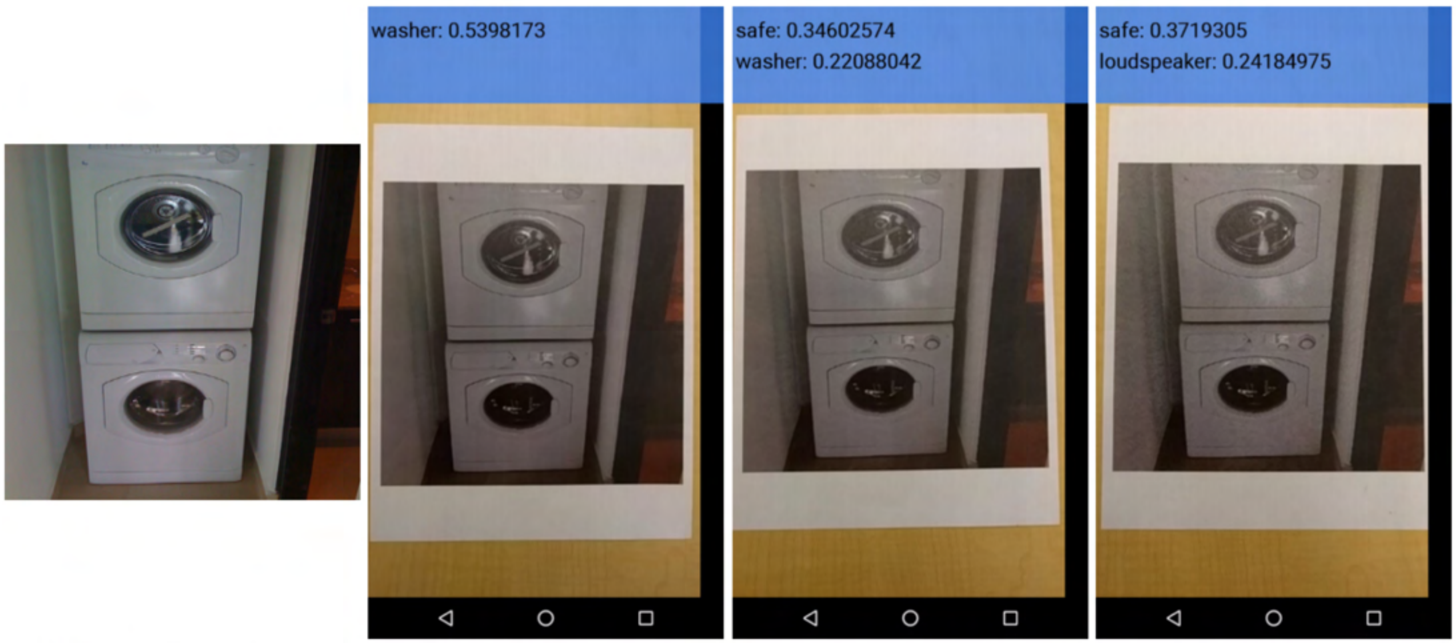


Figure 2: Top-1 and top-5 accuracy of Inception v3 under attack by different adversarial methods and different ϵ compared to "clean images" — unmodified images from the dataset. The accuracy was computed on all $50,000$ validation images from the ImageNet dataset. In these experiments ϵ varies from 2 to 128.

A. Kurakin, I. Goodfellow, S. Bengio, [Adversarial examples in the real world](), ICLR 2017 workshop

Printed adversarial examples

- “Black box” attack on a cell phone app: take a clean image, add perturbation, print out, classify with TensorFlow Camera Demo app



(a) Image from dataset (b) Clean image (c) Adv. image, $\epsilon = 4$ (d) Adv. image, $\epsilon = 8$

A. Kurakin, I. Goodfellow, S. Bengio, [Adversarial examples in the real world](), ICLR 2017 workshop

Printed adversarial examples

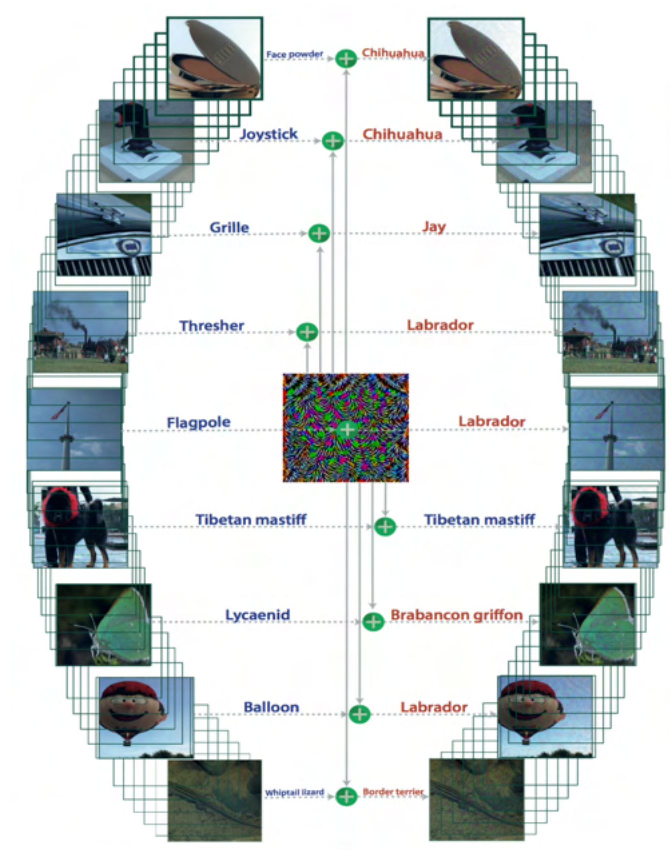
- Accuracies for printed vs. digital images:

Adversarial method	Photos				Source images			
	Clean images		Adv. images		Clean images		Adv. images	
	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5
fast $\epsilon = 16$	81.8%	97.0%	5.1%	39.4%	100.0%	100.0%	0.0%	0.0%
fast $\epsilon = 8$	77.1%	95.8%	14.6%	70.8%	100.0%	100.0%	0.0%	0.0%
fast $\epsilon = 4$	81.4%	100.0%	32.4%	91.2%	100.0%	100.0%	0.0%	0.0%
fast $\epsilon = 2$	88.9%	99.0%	49.5%	91.9%	100.0%	100.0%	0.0%	0.0%
iter. basic $\epsilon = 16$	93.3%	97.8%	60.0%	87.8%	100.0%	100.0%	0.0%	0.0%
iter. basic $\epsilon = 8$	89.2%	98.0%	64.7%	91.2%	100.0%	100.0%	0.0%	0.0%
iter. basic $\epsilon = 4$	92.2%	97.1%	77.5%	94.1%	100.0%	100.0%	0.0%	0.0%
iter. basic $\epsilon = 2$	93.9%	97.0%	80.8%	97.0%	100.0%	100.0%	0.0%	1.0%
l.l. class $\epsilon = 16$	95.8%	100.0%	87.5%	97.9%	100.0%	100.0%	0.0%	0.0%
l.l. class $\epsilon = 8$	96.0%	100.0%	88.9%	97.0%	100.0%	100.0%	0.0%	0.0%
l.l. class $\epsilon = 4$	93.9%	100.0%	91.9%	98.0%	100.0%	100.0%	0.0%	0.0%
l.l. class $\epsilon = 2$	92.2%	99.0%	93.1%	98.0%	100.0%	100.0%	0.0%	0.0%

A. Kurakin, I. Goodfellow, S. Bengio, Adversarial examples in the real world, ICLR 2017 workshop

Universal adversarial perturbations

- Goal: for a given network, find an *image-independent* perturbation vector that causes *all images* to be misclassified with high probability



S.-M. Moosavi-Dezfooli, A. Fawzi, O. Fawzi, P. Frossard, [Universal adversarial perturbations](), CVPR 2017

Universal adversarial perturbations

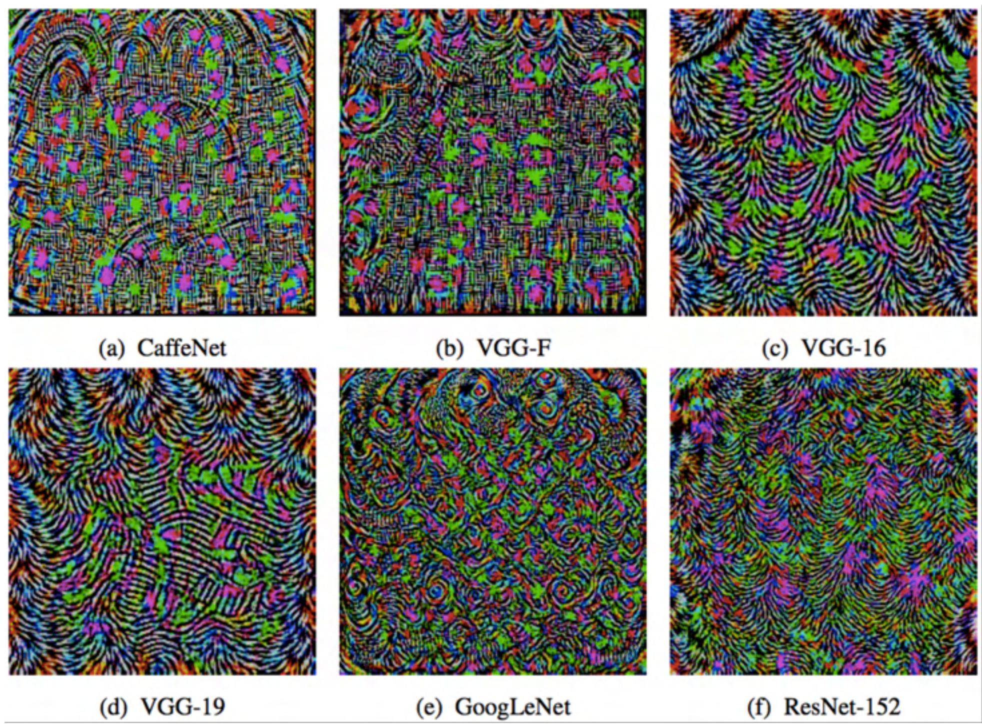
Approach:

- Start with $r = 0$
- Cycle through training examples x_i (in multiple passes)
  - If $x_i + r$ is misclassified, skip to x_{i+1}
  - Find minimum perturbation Δr that takes $x_i + r + \Delta r$ to another class
  - Update $r \leftarrow r + \Delta r$, enforce $\|r\| \leq \epsilon$
- Terminate when fooling rate on training examples reaches target value

S.-M. Moosavi-Dezfooli, A. Fawzi, O. Fawzi, P. Frossard, Universal adversarial perturbations, CVPR 2017

Universal adversarial perturbations

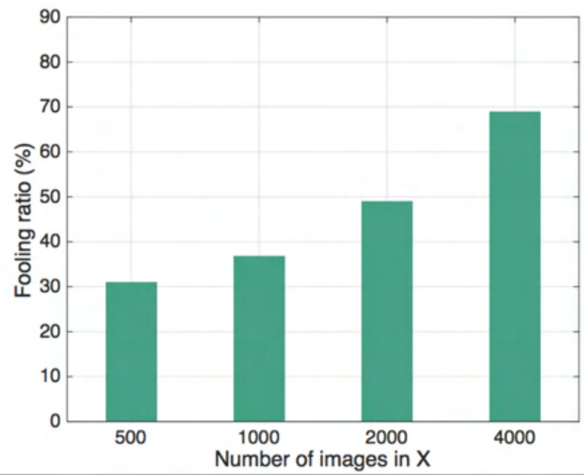
- Perturbation vectors computed from different architectures:



(a) CaffeNet (b) VGG-F (c) VGG-16 (d) VGG-19 (e) GoogLeNet (f) ResNet-152

S.-M. Moosavi-Dezfooli, A. Fawzi, O. Fawzi, P. Frossard, [Universal adversarial perturbations](), CVPR 2017

Universal adversarial perturbations



Fooling ratio on validation set vs. training set (X) size for GoogLeNet

Fooling rates on different models after training on 10,000 images

		CaffeNet [8]	VGG-F [2]	VGG-16 [17]	VGG-19 [17]	GoogLeNet [18]	ResNet-152 [6]
ℓ_2	X	85.4%	85.9%	90.7%	86.9%	82.9%	89.7%
	Val.	85.6	87.0%	90.3%	84.5%	82.0%	88.5%
ℓ_∞	X	93.1%	93.8%	78.5%	77.8%	80.8%	85.4%
	Val.	93.3%	93.7%	78.3%	77.8%	78.9%	84.0%

S.-M. Moosavi-Dezfooli, A. Fawzi, O. Fawzi, P. Frossard, Universal adversarial perturbations, CVPR 2017

Universal adversarial perturbations

- Universal perturbations turn out to generalize well across models!

Fooling rate when computing a perturbation for one model (rows) and testing it on others (columns)

	VGG-F	CaffeNet	GoogLeNet	VGG-16	VGG-19	ResNet-152
VGG-F	**93.7%**	71.8%	48.4%	42.1%	42.1%	47.4 %
CaffeNet	74.0%	**93.3%**	47.7%	39.9%	39.9%	48.0%
GoogLeNet	46.2%	43.8%	**78.9%**	39.2%	39.8%	45.5%
VGG-16	63.4%	55.8%	56.5%	**78.3%**	73.1%	63.4%
VGG-19	64.0%	57.2%	53.6%	73.5%	**77.8%**	58.0%
ResNet-152	46.3%	46.3%	50.5%	47.0%	45.5%	**84.0%**

S.-M. Moosavi-Dezfooli, A. Fawzi, O. Fawzi, P. Frossard, Universal adversarial perturbations, CVPR 2017

Adversarial examples: Outline

- Basic definition, analysis of fooling linear classifiers
- Generating adversarial examples
  - Fast gradient sign, iterative variants
  - Universal adversarial perturbations
- Why are neural networks easy to fool?

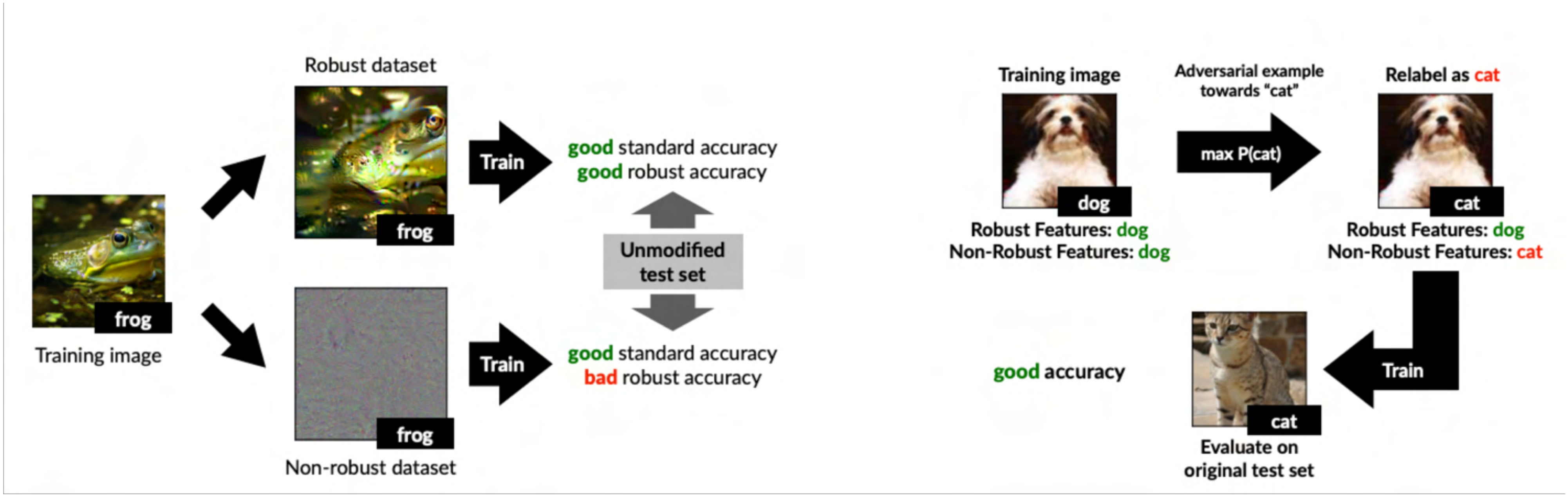
Properties of adversarial examples: Summary

- For any input image, it is usually easy to generate a very similar image that gets misclassified by the same network
- To obtain an adversarial example, one does not need to do precise gradient ascent
- Adversarial images can (somewhat) survive transformations like being printed and photographed
- It is possible to attack many images with the same perturbation
- Adversarial examples that can fool one network have a high chance of fooling a network with different parameters and even architecture

Why are deep networks easy to fool?

- Networks are “too linear”: it is easy to manipulate output in a predictable way given the input
- The input dimensionality is high, so one can get a large change in the output by changing individual inputs by small amounts
- Neural networks can fit anything, but nothing prevents them from behaving erratically between training samples
  - Counter-intuitively, a network can both generalize well on natural images and be susceptible to adversarial examples
- Adversarial examples generalize well because different models learn similar functions when trained to perform the same task (or because adversarial examples are a function of the data rather than of the network)?

Adversarial examples are not bugs, but features?



Disentangle features into robust and non-robust

Construct a dataset which appears mislabeled to humans (via adversarial examples) but results in good accuracy on the original test set

A. Ilyas et al. [Adversarial Examples are not Bugs, they are Features](). NeurIPS 2019

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Defending against adversarial examples

- Adversarial training: networks can be made somewhat resistant by augmenting or regularizing training with adversarial examples (Goodfellow et al. 2015, Tramer et al. 2018)

Defending against adversarial examples

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- Adversarial objectives can also be formulated (Madry et al., 2018)

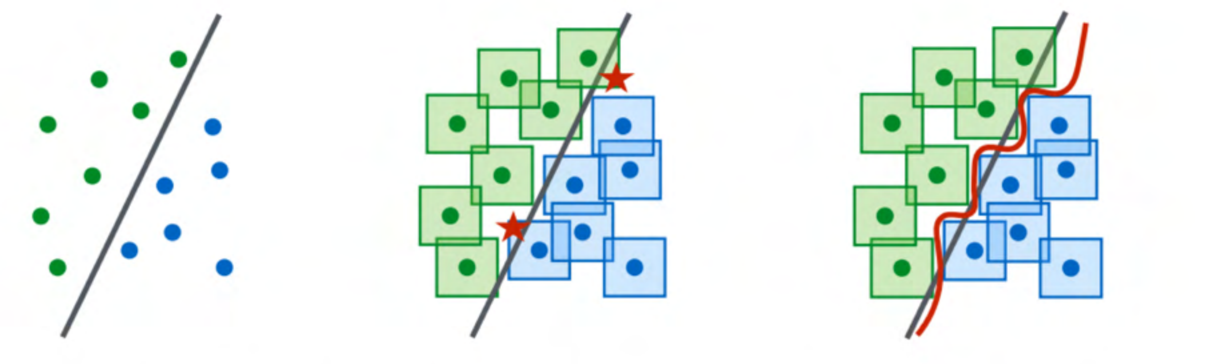


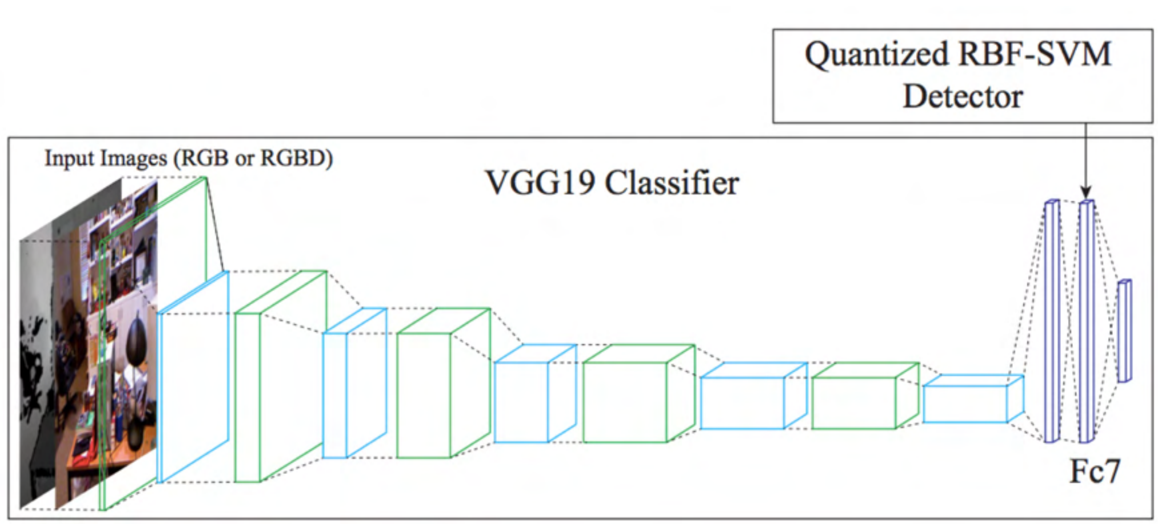
Figure 3: A conceptual illustration of standard vs. adversarial decision boundaries. Left: A set of points that can be easily separated with a simple (in this case, linear) decision boundary. Middle: The simple decision boundary does not separate the ℓ_∞-balls (here, squares) around the data points. Hence there are adversarial examples (the red stars) that will be misclassified. Right: Separating the ℓ_∞-balls requires a significantly more complicated decision boundary. The resulting classifier is robust to adversarial examples with bounded ℓ_∞-norm perturbations.

Defending against adversarial examples

- Adversarial training: networks can be made somewhat resistant by augmenting or regularizing training with adversarial examples (Goodfellow et al. 2015, Tramer et al. 2018)
- Adversarial objectives can also be formulated (Madry et al., 2018)
  - There is even evidence that such models may give better performance when transferred to different tasks (Salman et al., 2020)

Defending against adversarial examples

- Train a separate model to reject adversarial examples: SafetyNet



J. Lu, T. Issaranon, D. Forsyth, [SafetyNet: Detecting and Rejecting Adversarial Examples Robustly](), CVPR 2017

Defending against adversarial examples

- Robust architectures

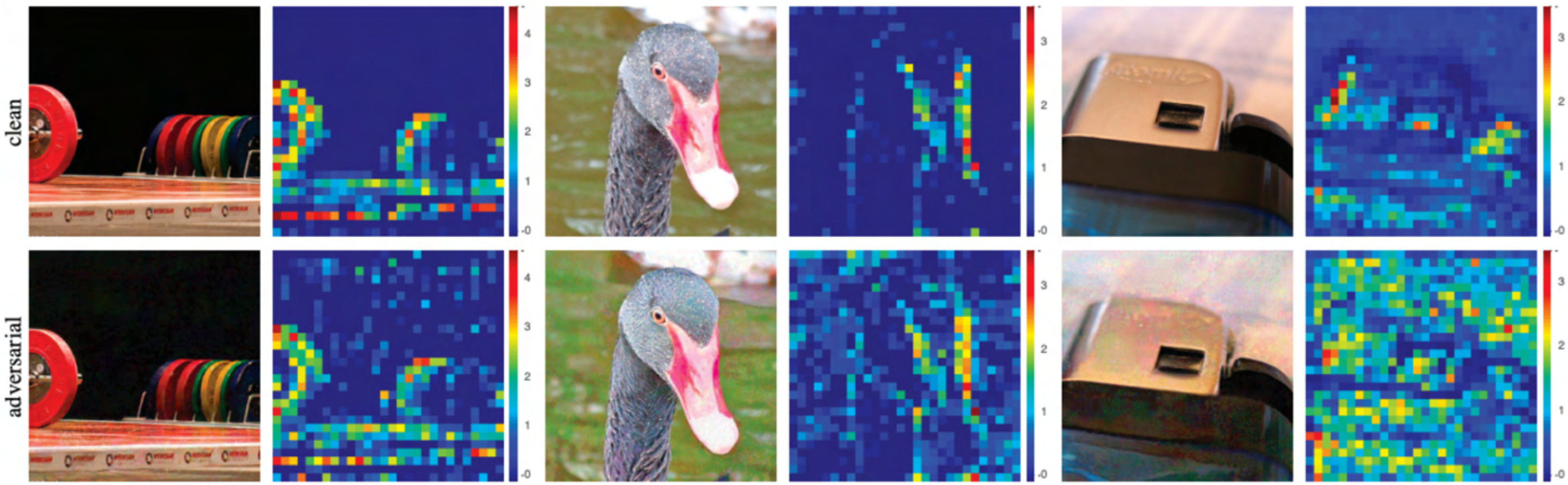
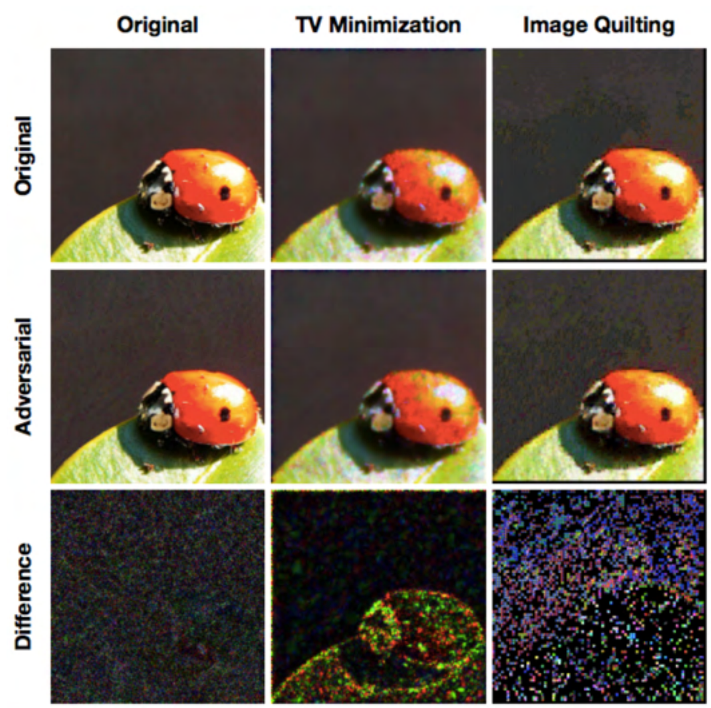


Figure 2. More examples similar to Figure 1. We show feature maps corresponding to clean images (top) and to their adversarial perturbed versions (bottom). The feature maps for each pair of examples are from the same channel of a res_3 block in the same ResNet-50 trained on clean images. The attacker has a maximum perturbation $\epsilon = 16$ in the pixel domain.

C. Xie et al., [Feature Denoising for Improving Adversarial Robustness](), CVPR 2018

Defending against adversarial examples

- Pre-process input images to disrupt adversarial perturbations



C. Guo, M. Rana, M. Cisse, L. van der Maaten, [Countering Adversarial Images Using Input Transformations](), ICLR 2018

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Adversarial examples for detection

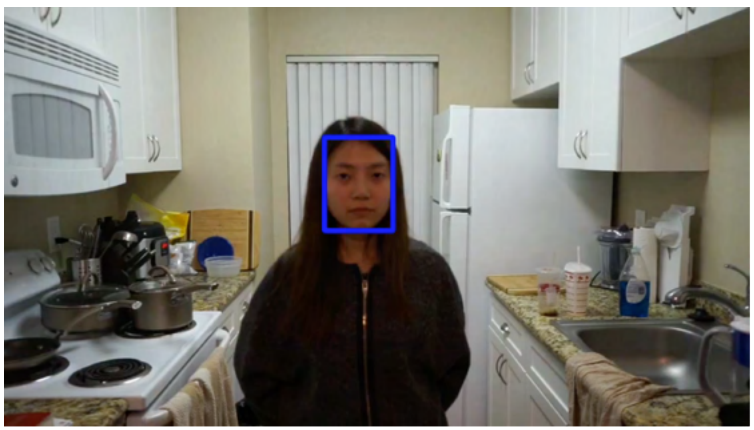
- TL;DR: It is much harder to fool a detector like Faster R-CNN or YOLO than a classifier; larger perturbations are required

J. Lu, H. Sibai, E. Fabry, [Adversarial examples that fool detectors](), arXiv 2018

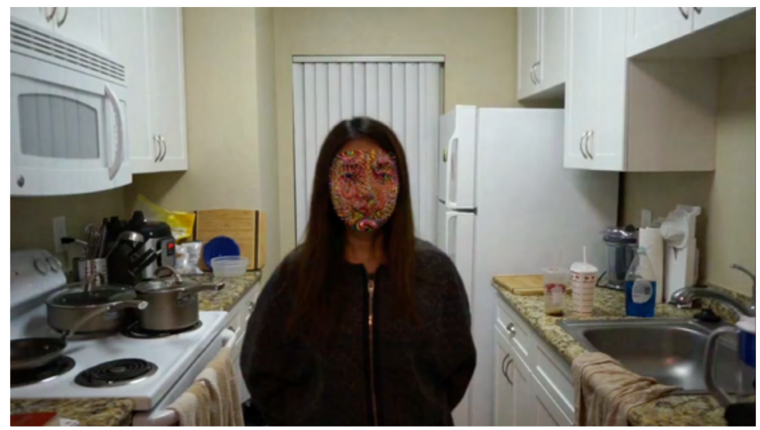
Adversarial examples for detection

- TL;DR: It is much harder to fool a detector like Faster R-CNN or YOLO than a classifier; larger perturbations are required

Original w/ Faster R-CNN detections



Attacked



J. Lu, H. Sibai, E. Fabry, [Adversarial examples that fool detectors](), arXiv 2018

Adversarial examples for detection

- TL;DR: It is much harder to fool a detector like Faster R-CNN or YOLO than a classifier; larger perturbations are required
- It is even harder to fool a detector with physical objects

"All three patterns reliably fool detectors when mapped into videos. However, physical instances of these patterns are not equally successful. The first two stop signs, as physical objects, only occasionally fool Faster RCNN; the third one, which has a much more extreme pattern, is more effective."

J. Lu, H. Sibai, E. Fabry, Adversarial examples that fool detectors, arXiv 2018

Adversarial examples for detection

- TL;DR: It is much harder to fool a detector like Faster R-CNN or YOLO than a classifier; larger perturbations are required
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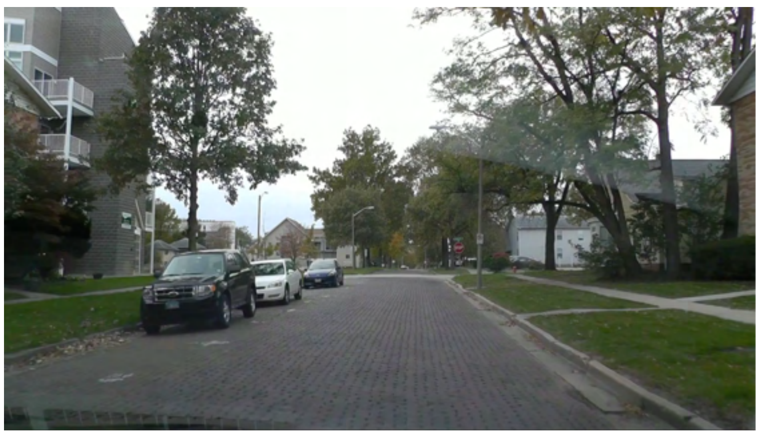
Original w/ Faster R-CNN detections



Digitally attacked

J. Lu, H. Sibai, E. Fabry, Adversarial examples that fool detectors, arXiv 2018

Adversarial examples for detection

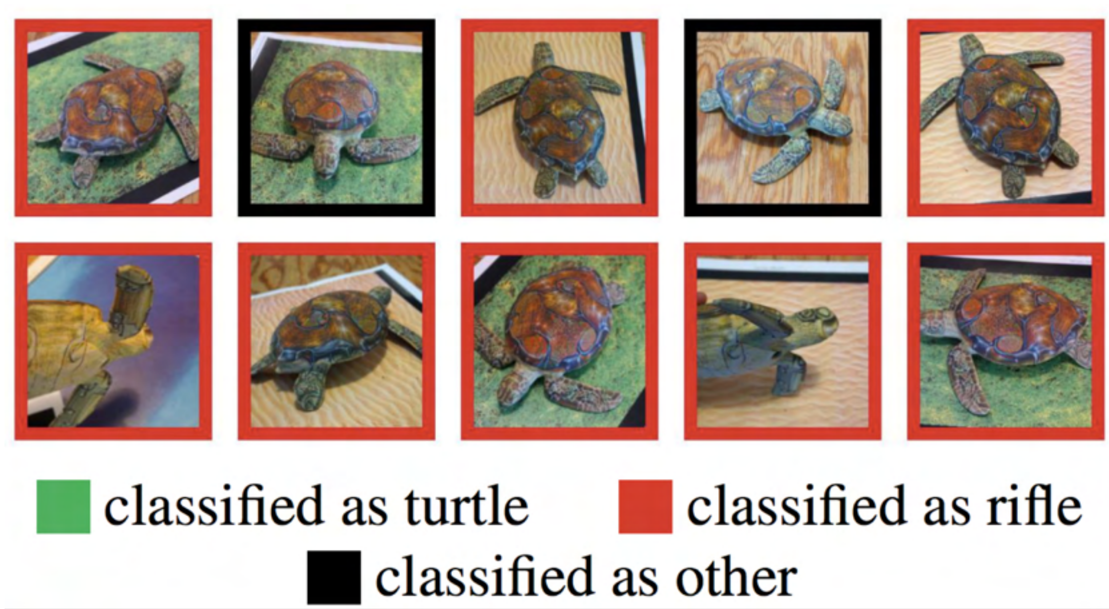
- TL;DR: It is much harder to fool a detector like Faster R-CNN or YOLO than a classifier; larger perturbations are required
- It is even harder to fool a detector with physical objects

Physical adversarial stop sign

J. Lu, H. Sibai, E. Fabry, [Adversarial examples that fool detectors](), arXiv 2018

Adversarial examples for 3D transformations

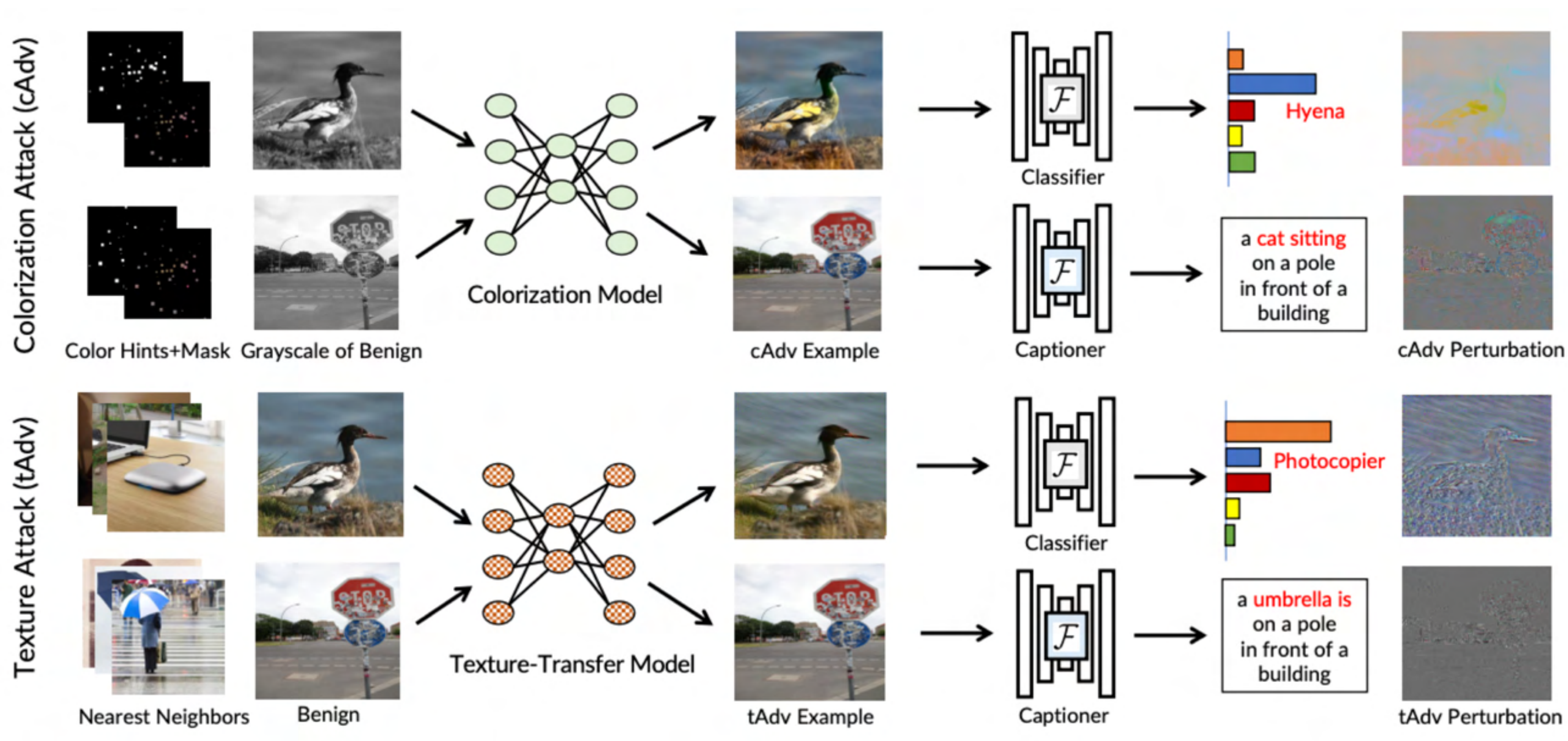
3D printed adversarial object (YouTube video)



https://blog.openai.com/robust-adversarial-inputs/

A. Athalye, L. Engstrom, A. Ilyas, K. Kwok, Synthesizing Robust Adversarial Examples, ICML 2018

Adversarial examples beyond the infinity-norm constraint



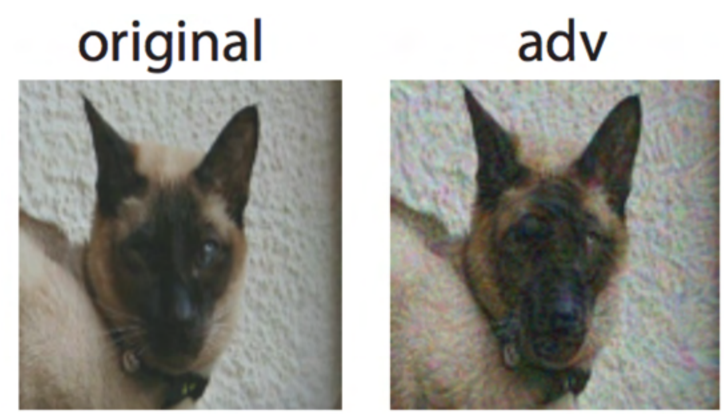
A. Bhattad, M.-J. Chong, K. Liang, B. Li, D. Forsyth. [Unrestricted adversarial examples via semantic manipulation](). ICLR 2020

Adversarial examples and humans

Image source

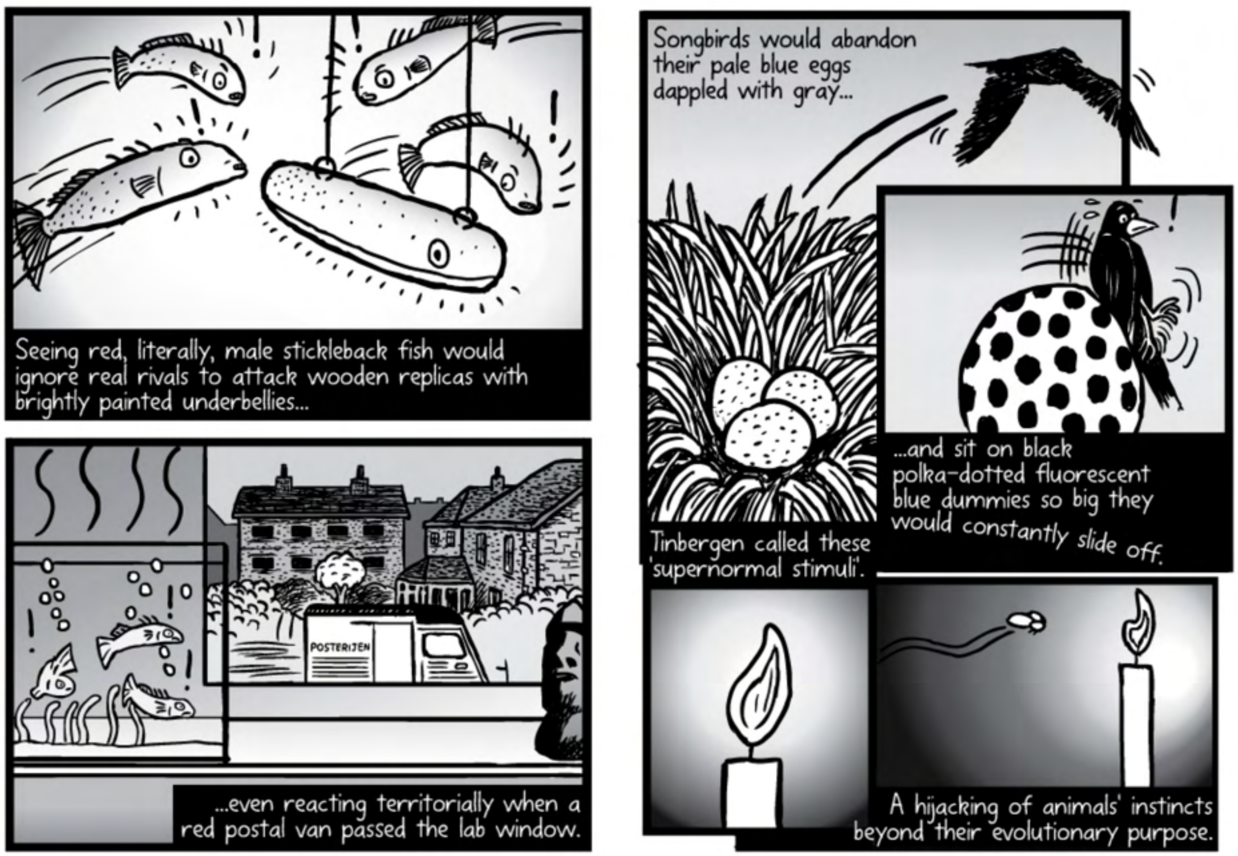
Adversarial examples and humans

- Adversarial examples that are designed to transfer across multiple architectures can also be shown to confuse the human visual system in rapid presentation settings



G. Elsayed et al., Adversarial Examples that Fool both Computer Vision and Time-Limited Humans, NeurIPS 2018

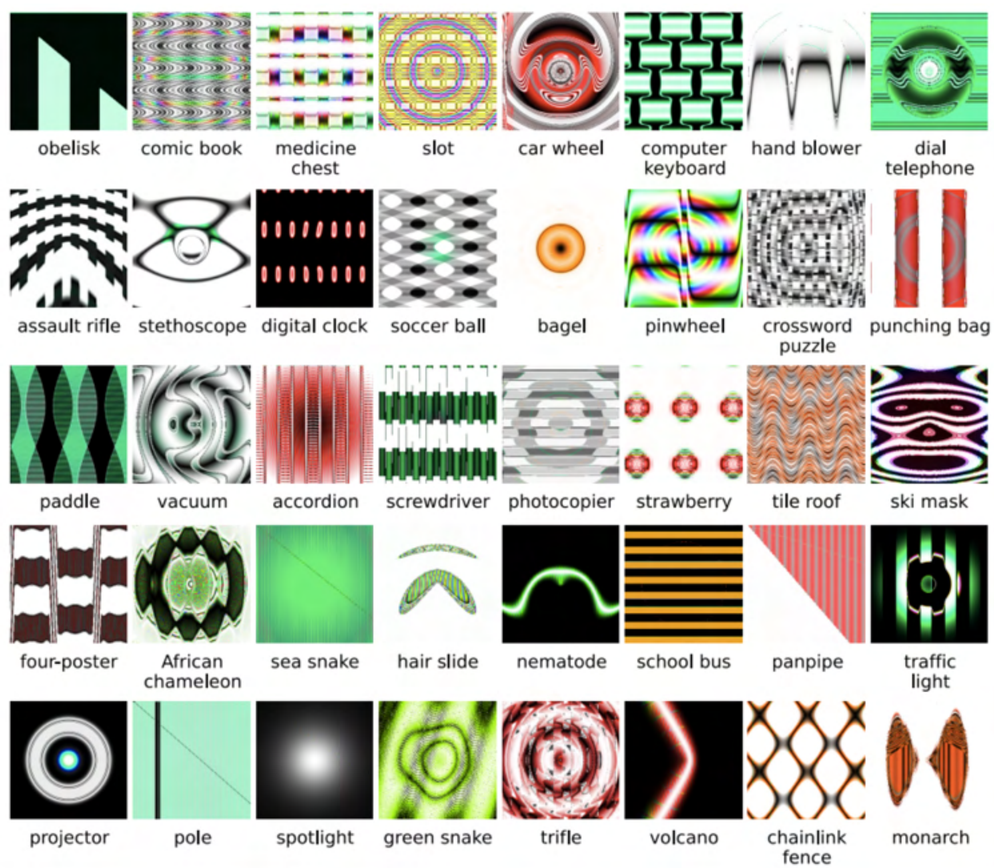
How robust is biological perception, really?



http://www.stuartmcmillen.com/comic/supernormal-stimuli/

https://en.wikipedia.org/wiki/Supernormal_stimulus

Recall: Generation of preferred inputs



A. Nguyen, J. Yosinski, J. Clune, [Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images](), CVPR 2015

Supernormal stimuli for humans?

https://en.wikipedia.org/wiki/Supernormal_stimulus

For further reading

- https://nicholas.carlini.com/writing/2019/all-adversarial-example-papers.html
- https://nicholas.carlini.com/writing/2018/adversarial-machine-learning-reading-list.html