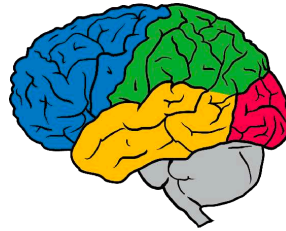


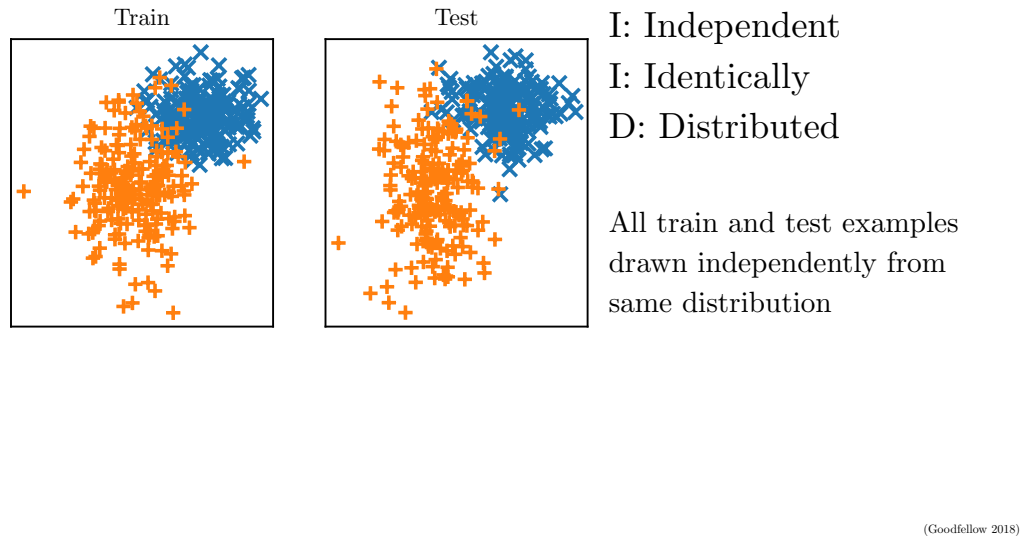
Defense Against the Dark Arts: An overview of adversarial example security research and future research directions

Ian Goodfellow, Staff Research Scientist, Google Brain
1st IEEE Deep Learning and Security Workshop, May 24, 2018



This document contains the slides for a keynote presentation at the 2018 IEEE Deep Learning and Security workshop, as well as lecture notes describing generally what the speaker planned to say. The notes are included so that readers can better understand the slides without attending the lecture and follow the accompanying references.

I.I.D. Machine Learning

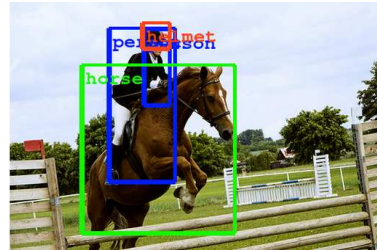


Traditionally, most machine learning work has taken place in the context of the I.I.D. assumptions.

“I.I.D.” stands for “independent and identically distributed”. It means that all of the examples in the training and test set are generated independently from each other, and are all drawn from the same data-generating distribution.

This diagram illustrates this with an example training set and test set sampled for a classification problem with 2 input features (one plotted on horizontal axis, one plotted on vertical axis) and 2 classes (orange plus versus blue X).

ML reached “human-level performance” on many IID tasks circa 2013



(Szegedy et al, 2014)

...recognizing objects
and faces....

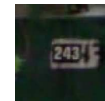


(Taigmen et al, 2013)



(Goodfellow et al, 2013)

...solving CAPTCHAS and
reading addresses...



(Goodfellow et al, 2013)

(Goodfellow 2018)

Until recently, machine learning was difficult, even in the I.I.D. setting.

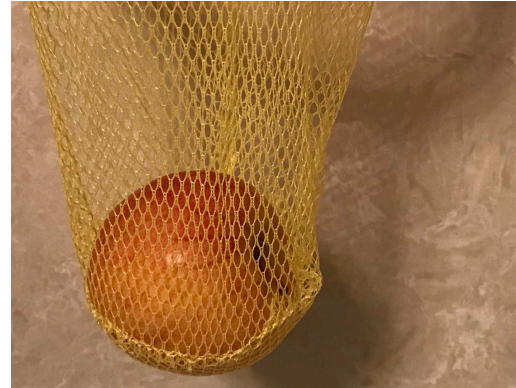
Adversarial examples were not interesting to most researchers because mistakes were the rule, not the exception.

In about 2013, machine learning started to reach human-level performance on several benchmark tasks (here I highlight vision tasks because they have nice pictures to put on a slide). These benchmarks are not particularly well-suited for comparing to humans, but they do show that machine learning has become quite advanced and impressive in the I.I.D. setting.

Caveats to “human-level” benchmarks



Humans are not very good
at some parts of the
benchmark



The test data is not very
diverse. ML models are fooled
by natural but unusual data.

(Goodfellow 2018)

When we say that a machine learning model has reached human-level performance for a benchmark, it is important to keep in mind that benchmarks may not be able to capture performance on these tasks realistically.

For example, humans are not necessarily very good at recognizing all of the obscure classes in ImageNet, such as this dhole (one of the 1000 ImageNet classes). Image from the Wikipedia article “dhole”.

Just because the data is I.I.D. does not necessarily mean it captures the same distribution the model will face when it is deployed. For example, datasets tend to be somewhat curated, with relatively cleanly presented canonical examples. Users taking photos with phones take unusual pictures. Here is a picture I took with my phone of an apple in a mesh bag. A state of the art vision model tags this with only one tag: “material”. My family wasn’t sure it was an apple, but they could tell it was fruit and apple was their top guess. If the image is blurred the model successfully recognizes it as “still life photography” so the model is capable of processing this general kind of data; the bag is just too distracting.

Security Requires Moving Beyond I.I.D.

- Not identical: attackers can use unusual inputs



(Eykholt et al, 2017)

- Not independent: attacker can repeatedly send a single mistake (“test set attack”)

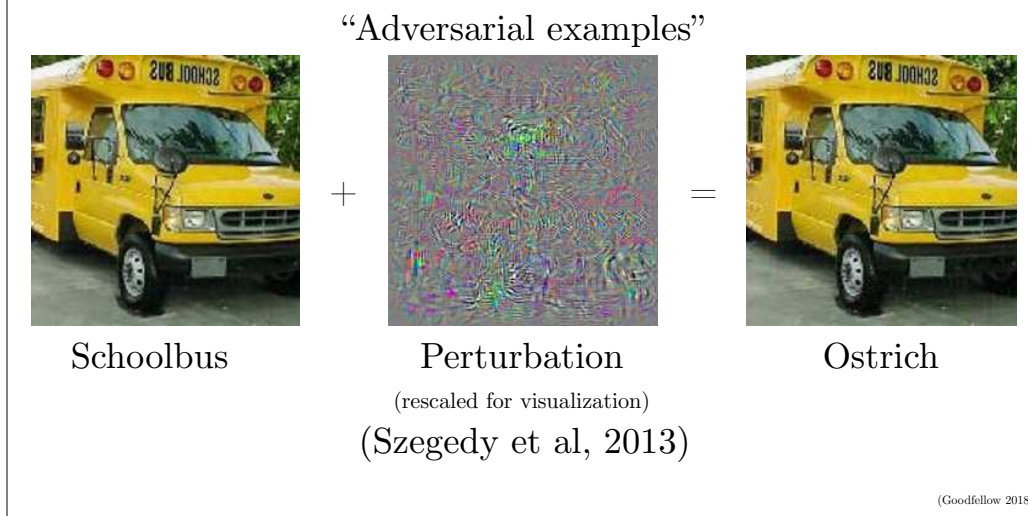
(Goodfellow 2018)

When we want to provide security guarantees for a machine learning system, we can no longer rely on the I.I.D. assumptions.

In this presentation, I focus on attacks based on modifications of the input at test time. In this context, the two main relevant violations of the I.I.D. assumptions are:

- 1) The test data is not drawn from the same distribution as the training data. The attacker intentionally shifts the distribution at test time toward unusual inputs such as this adversarial stop sign (<https://arxiv.org/abs/1707.08945>) that will be processed incorrectly.
- 2) The test examples are not necessarily drawn independently from each other. A real attacker can search for a single input that causes a mistake, and then send that input repeatedly, every time they interact with the system.

Good models make surprising mistakes in non-IID setting

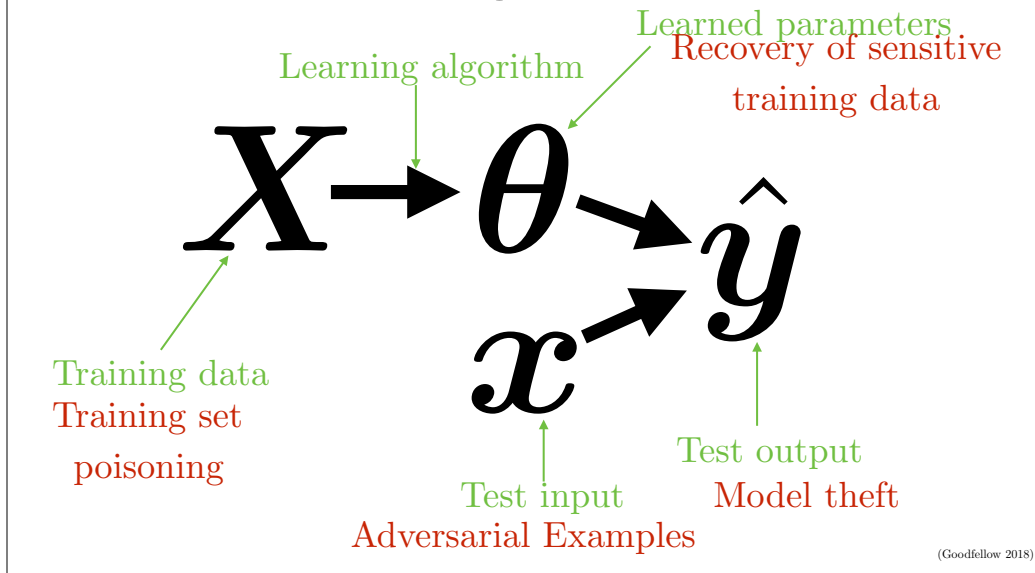


The deep learning community first started to pay attention to surprising mistakes in the non-IID setting when Christian Szegedy showed that even *imperceptible* changes of IID test examples could result in consistent misclassification.

The paper (<https://arxiv.org/abs/1312.6199>) introduced the term “adversarial examples” to describe these images. They were formed by using gradient-based optimization to perturb a naturally occurring image to maximize the probability of a specific class.

The discovery of these gradient-based attacks against neural networks was concurrent work happening at roughly the same time as work done by Battista Biggio et al (https://link.springer.com/chapter/10.1007%2F978-3-642-40994-3_25). Biggio et al’s work was published earlier in 2013 while Christian’s paper appeared on arxiv in late 2013. The first written record I personally have of Christian’s work is a 2012 e-mail from Yoshua Bengio.

Attacks on the machine learning pipeline



To define adversarial examples more clearly, we should consider some other security problems.

Many machine learning algorithms can be described as a pipeline that takes training data X , learns parameters θ , and then uses those parameters to process test inputs x to produce test outputs \hat{y} .

Attacks based on modifying the training data to cause the model to learn incorrect behaviors are called *training set poisoning*.

Attackers can study learned parameters θ to recover sensitive information from the training set (for example, recovering social security numbers from a trained language model as demonstrated by <https://arxiv.org/abs/1802.08232>).

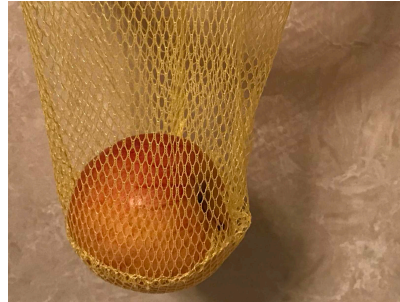
Attackers can send test inputs x and observe outputs \hat{y} to reverse engineer their model and train their own copy. This is known as a *model theft* attack. Model theft can then enable further attacks, like recovery of private training data or improved adversarial examples.

Adversarial examples are distinct from these other security concerns: they are inputs supplied at test time, intended to cause the model to make a mistake.

Definition

“Adversarial examples are inputs to machine learning models that an attacker has intentionally designed to cause the model to make a mistake”

(Goodfellow et al 2017)



(Goodfellow 2018)

There is no standard community-accepted definition of the term “adversarial examples” and the usage has evolved over time.

I personally coined the term “adversarial examples” while helping to write Christian’s paper (this was probably the most important thing I did, to be honest) so I feel somewhat within my rights to push a definition.

The definition that I prefer today was introduced in an OpenAI blog post and developed with my co-authors of that blog post.

There are three aspects of this definition I want to emphasize.

- 1) There is no need for the adversarial example to be made by applying a small or imperceptible perturbation to a clean image. That was how we used the term in the original paper, but its usage has evolved over time. In particular, the picture of the apple in the mesh bag counts. I went out of my way to find a strange context that would fool the model.
- 2) Adversarial examples are not defined in terms of deviation from human perception, but in terms of deviation from some absolute standard of correct behavior. In contexts like visual object recognition, human labelers might be the best approximation we have to the ground truth, but human perception is not the definition of truth. Humans are subject to mistakes and optical illusions too, and ideally we could make a machine learning system that is harder to fool than a human.
- 3) An adversarial example is *intended* to be misclassified, but the attacker does not necessarily succeed. This makes it possible to discuss “error rate on adversarial examples”. If adversarial examples were defined to be actually misclassified, this error rate would always be 1 by definition.

For a longer discussion see <https://arxiv.org/abs/1802.08195>

Define a game

- Define an action space for the defender
- Define an action space for an attacker
- Define cost function for defender
- Define cost function for attacker
 - Not necessarily minimax.
 - Targeted vs untargeted

(Goodfellow 2018)

To study machine learning in the adversarial setting, we must define a game, formally.

This means we must define an action space and cost function for both the attacker and the defender.

Usually, the defender's action space is to output a class ID, but we can also imagine other variants of the game, where the defender can output a confidence value or can refuse to classify adversarially manipulated inputs.

In the context of adversarial examples, the attacker's action space describes the kind of inputs that the attacker can present to the defender's model.

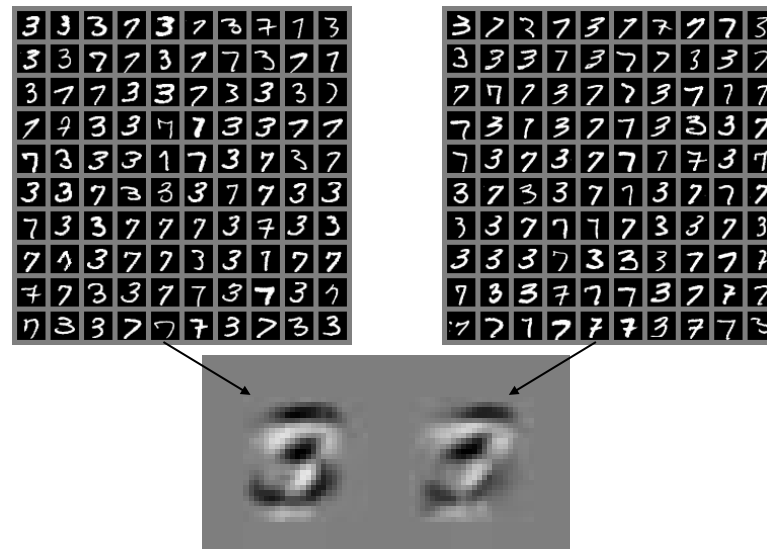
The defender's cost function, for the purpose of the game, is usually some kind of error rate. Note that this is different from the cost used to train the neural net, which is designed with other concerns like differentiability in mind. The cost for the purpose of the game should directly measure the actual performance of the defender.

Many people often think of adversarial settings as necessarily involving minimax games, but that is not always the case. In a minimax game, the attacker's cost is just the negative cost of the defender. Other cost functions for the attacker often make sense. For example, the defender may want to get as many examples correct as possible while the attacker may gain an advantage only from causing *specific* mistakes. An *untargeted* attacker just wants to cause mistakes, but a *targeted* attacker wants to cause an input to be recognized as coming from a specific class. For example, to sneak into a secure facility by fooling face recognition, it is not enough for the attacker to fool the face recognition system into guessing their identity incorrectly. The attacker must be recognized specifically as an individual who has access to the facility.

Fifty Shades of Gray Box Attacks

- Does the attacker go first, and the defender reacts?
 - This is easy, just train on the attacks, or design some preprocessing to remove them
- If the defender goes first
 - Does the attacker have full knowledge? This is “white box”
 - Limited knowledge: “black box”
 - Does the attacker know the task the model is solving (input space, output space, defender cost) ?
 - Does the attacker know the machine learning algorithm being used?
 - Details of the algorithm? (Neural net architecture, etc.)
 - Learned parameters of the model?
 - Can the attacker send “probes” to see how the defender processes different test inputs?
 - Does the attacker observe just the output class? Or also the probabilities?

Cross-model, cross-dataset generalization



(Goodfellow 2017)

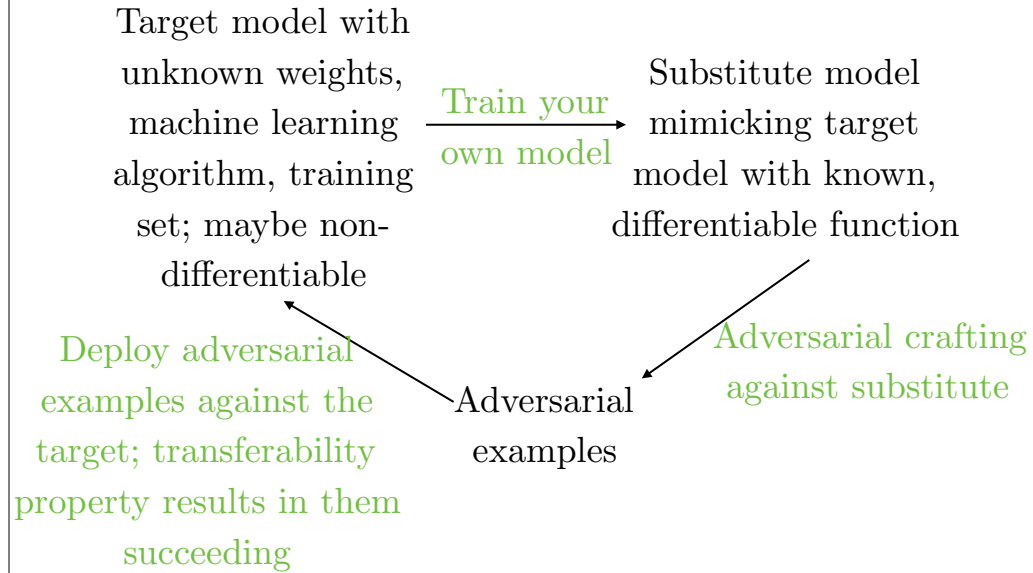
Cross-technique transferability

Source Machine Learning Technique	DNN	LR	SVM	DT	kNN	Ens.	
	DNN	38.27	23.02	64.32	79.31	8.36	20.72
	LR	6.31	91.64	91.43	87.42	11.29	44.14
	SVM	2.51	36.56	100.0	80.03	5.19	15.67
	DT	0.82	12.22	8.85	89.29	3.31	5.11
	kNN	11.75	42.89	82.16	82.95	41.65	31.92
		Target Machine Learning Technique					

(Papernot 2016)

(Goodfellow 2018)

Transfer Attack



(Goodfellow 2018)

Enhancing Transfer With Ensembles

	RMSD	ResNet-152	ResNet-101	ResNet-50	VGG-16	GoogLeNet
-ResNet-152	17.17	0%	0%	0%	0%	0%
-ResNet-101	17.25	0%	1%	0%	0%	0%
-ResNet-50	17.25	0%	0%	2%	0%	0%
-VGG-16	17.80	0%	0%	0%	6%	0%
-GoogLeNet	17.41	0%	0%	0%	0%	5%

Table 4: Accuracy of non-targeted adversarial images generated using the optimization-based approach. The first column indicates the average RMSD of the generated adversarial images. Cell (i, j) corresponds to the accuracy of the attack generated using four models except model i (row) when evaluated over model j (column). In each row, the minus sign “-” indicates that the model of the row is not used when generating the attacks. Results of top-5 accuracy can be found in the appendix (Table 14).

(Liu et al, 2016)

(Goodfellow 2018)

Norm Balls: A Toy Game

- How to benchmark performance on points that are not in the dataset and not labeled?
- Propagate labels from nearby labeled examples
- Attacker action:
 - Given a clean example, add a norm-constrained perturbation to it
- The *drosophila* of adversarial machine learning
- Interesting for *basic research* purposes because of its clarity and difficulty
- Not relevant for most practical purposes: not a *current, applied* security problem
- In my view, this shouldn't be primarily about human perception

(Goodfellow 2018)

Most adversarial example research today is based on a specific toy game in the context of visual object recognition.

We want to evaluate the performance of a classifier on arbitrary inputs, since in most scenarios the attacker is not constrained to supply naturally occurring data as input. Unfortunately, for visual object recognition, it is not straightforward to evaluate the classifier on arbitrary inputs. We rely on human labelers to obtain ground truth labels, and it is slow and expensive to include a human in the loop to label all attack images.

To obtain an inexpensive and automated evaluation, we can propagate labels from nearby points (<https://arxiv.org/abs/1412.6572>). This suggests that for research purposes, a convenient game to study is one where the attacker's action space is to take a clean test image and modify it by adding a norm-constrained perturbation. The size *epsilon* of this perturbation is chosen to ensure that the resulting adversarial examples have the same class as the clean examples. Epsilon should be made as large as possible while still preserving classes in order to benchmark performance on as large a subset of the input space as possible.

These games have gained a lot of attention because, despite their simplicity, it has been extremely difficult for a defender to win such a game.

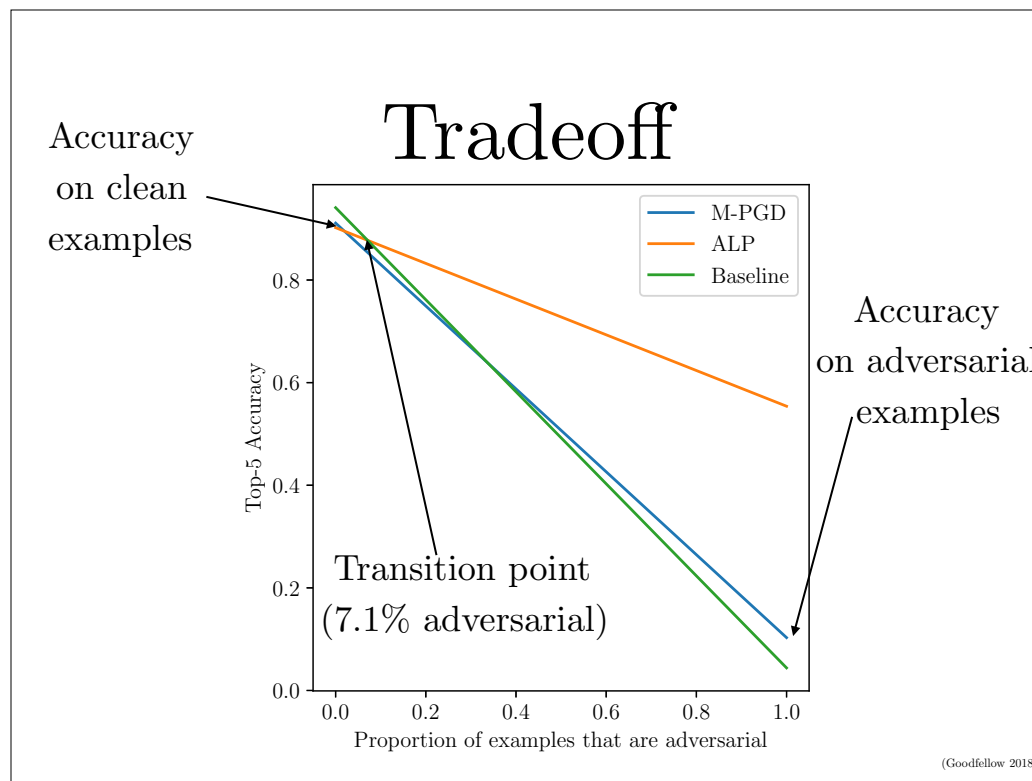
However, it is important to emphasize that these games are primarily tools for basic research, and not models of real-world security scenarios. One of the best things that one could do for adversarial machine learning research is to devise a practical means of benchmarking performance in more realistic scenarios.

Who goes first?

- Attacker goes first:
 - Defender trains on the attacks. Usually the defender wins.
 - Not much more interesting than standard dataset augmentation
- Defender goes first:
 - Attacker is *adaptive* / *reactive*
 - Extremely difficult. Main reason this topic is unsolved.

(Goodfellow 2018)

An example of where the person trying to fool the neural net goes first is text CAPTCHAs. Text-based CAPTCHAs have been broken since 2013. <https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42241.pdf>



In some cases, defenses against adversarial examples act as a regularizer and actually improve accuracy on the test set (<https://arxiv.org/abs/1412.6572>). p p

In most of the recent literature, the strongest defenses against adversarial examples tend to decrease accuracy on the clean test set.

To choose a specific model to use on a particular task, we should p pd consider the cost it will incur when it is actually used in practice. To simplify the discussion, assume all errors are equally costly. If we believe a model will always receive adversarial examples, we should choose the model with the highest accuracy in the adversarial setting. If we believe it will receive only clean examples, then we should choose the model with the highest accuracy on the clean test set. In many settings, we probably expect the model to come under attack a certain percentage of the time. If we assume that this percentage is independent of the choice of model (in reality, models with greater vulnerability may be attacked more often) we should choose the model that performs the best on a test set consisting of this proportion of adversarial examples.

For example, this plot shows the accuracy of an undefended baseline and two defenses, M-PGD and ALP (<https://arxiv.org/abs/1803.06373>) on the ImageNet test set. The ALP model is more robust to adversarial examples, but at the cost of accuracy on the clean test set. For the ALP model to be preferable to the baseline, we need to expect that the model will face adversarial examples about 7.1% of the time on the test set. Another interesting thing we see from this plot is that it shows us some tradeoffs are just not worth it: M-PGD might look like it offers complementary advantages and disadvantages relative to ALP because it has higher accuracy on the clean test set, but there is actually never any point on the curve where M-PGD has the highest accuracy. We can optimally navigate the tradeoff with only ALP and the undefended baseline as our two choices.

The choice between these two models is complicated by the fact that accuracies in the adversarial setting are usually upper bounds, based on testing the defense against a particular attack algorithm. A smarter attack algorithm or an attack using a different threat model could bring the accuracy of either model even lower in the adversarial setting, so there is uncertainty about the true tradeoff.

Of course, for the purposes of basic research, it still makes sense to study how to obtain better accuracy in the completely adversarial setting, but we must not lose sight of the need to retain good performance on clean data.

Gradient Masking

- Some defenses look like they work because they break gradient-based white box attacks
- But then they don't break black box attacks (e.g., adversarial examples made for other models)
- The defense denies the attacker access to a useful gradient but does not actually make the *decision boundary* secure
- This is called *gradient masking*

(Goodfellow 2018)

For further reading:











<https://arxiv.org/abs/1602.02697>

<https://arxiv.org/abs/1705.07204>

<https://arxiv.org/abs/1802.00420>

Why not to use L2

Experiments excluding MNIST 1s, many of which look like 7s

	Pair	Diff	L_0	L_1	L_2	L_∞
Nearest L_0			63	35.0	4.86	1.0
Nearest L_1			91	19.9	3.21	.996
Nearest L_2			110	21.7	2.83	1.0
Nearest L_∞			121	34.0	3.82	.76
Clipped Random uniform			784	116.0	4.8	.3

(Goodfellow 2018)

To propagate labels from points in the dataset with known labels to nearby off-dataset points with unknown labels, we need some way to measure distance. In most current work on adversarial examples, this is done with the L_∞ norm, advocated by <https://arxiv.org/abs/1412.6572>

This is intended to be a way of guaranteeing that the label is known on new test points. Ideally we would like to propagate labels to as large a volume of space as possible. (A common misconception is that we want to keep the perturbations small, to be imperceptible—actually we would like to benchmark on all of R^n if we had a way of labeling it)

Norms are convenient to implement and to study mathematically, but some norms are better than others for propagating labels. This is of course highly application-specific. The L_∞ norm is relevant primarily for visual object recognition tasks. For other tasks like malware detection, we would be interested in transformations of code that preserve its function.

In this example, we see that if we want to add large uniform noise (within the confines of the unit hypercube), the L_∞ norm is the best at assigning larger distances to noisy perturbations than to perturbations that change the class. L_0 , L_1 , and L_2 all assign smaller distances to examples that lie in different classes than to noisy versions of the example shown. The L_∞ does not do this. We also see that if we constraint the input using the L_∞ norm, we can get relatively large perturbations in terms of the other norms. Our L_∞ -constrained uniform perturbation has an L_2 norm larger than most of the class-changing perturbations shown here. Intuitively, restricting the perturbation using the L_∞ makes sure that the adversary cannot focus the whole perturbation on a small number of pixels, to completely erase or completely draw in ink that changes the MNIST digit.

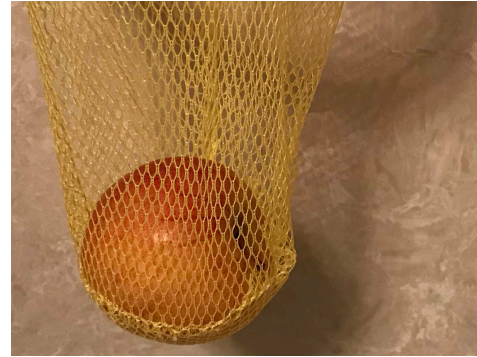
The example of uniform noise makes L_0 , L_1 , and L_2 all look bad, but L_0 and L_1 can perform better in other examples. It is mostly L_2 that I intend to discourage here.

It would be great if researchers could find an improved method of reliably propagating labels to more points in space than this norm-ball approach allows. It is important to remember that the goal to an improved evaluation should either be to label more points or to more realistically model an actual security threat. In particular, the goal is not to find a good model of human perceptual distance, unless that helps with either of the preceding goals.

Real Attacks Will not be in the Norm Ball



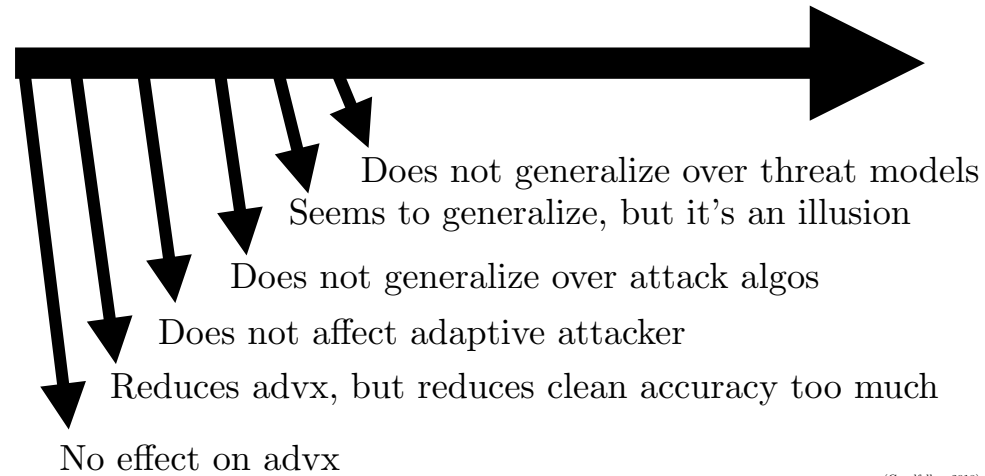
(Eykholt et al, 2017)



(Goodfellow 2018)

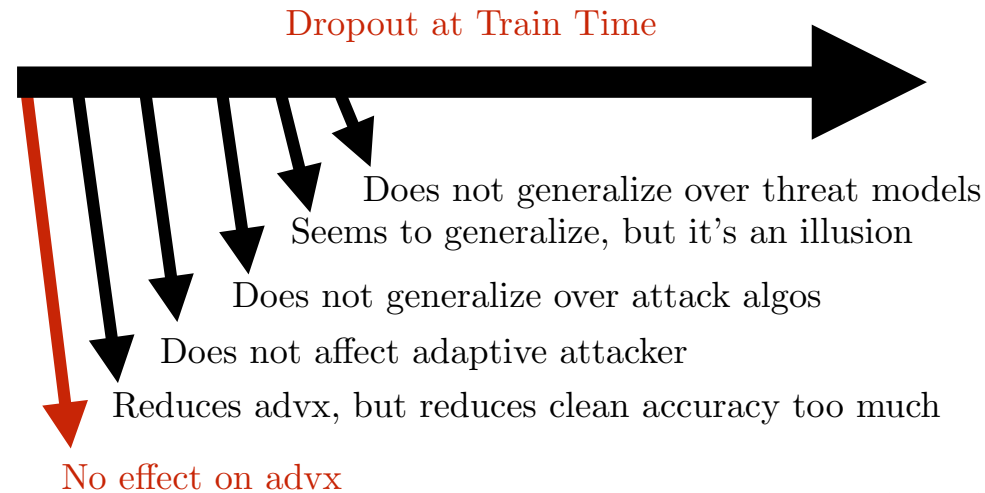
The norm ball is a nice way of formalizing games for basic research purposes. We must remember though that the norm ball is not the real game.

Pipeline of Defense Failures



(Goodfellow 2018)

Pipeline of Defense Failures

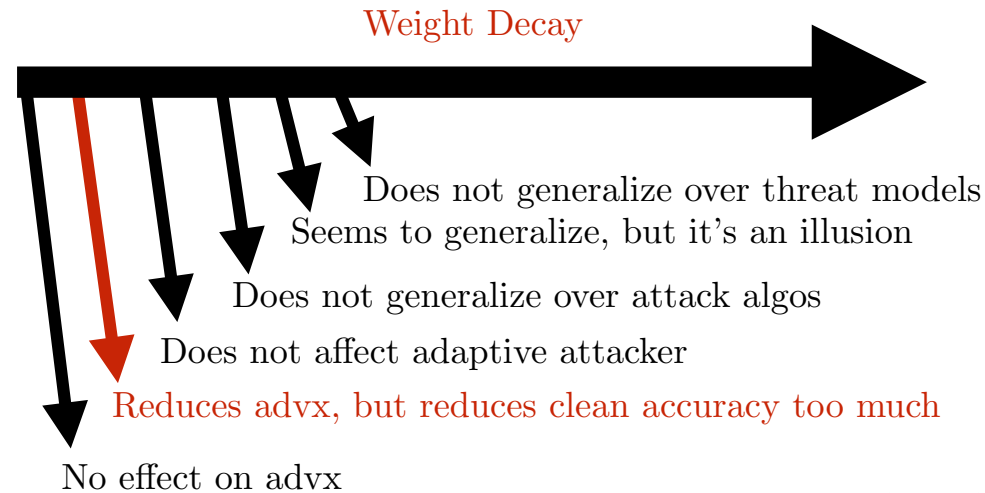


(Goodfellow 2018)

Many of the networks tested in early work on adversarial examples were trained with dropout: <https://arxiv.org/abs/1312.6199>
<https://arxiv.org/abs/1412.6572>

Dropout is a good regularizer, but does not seem to offer any adversarial robustness.

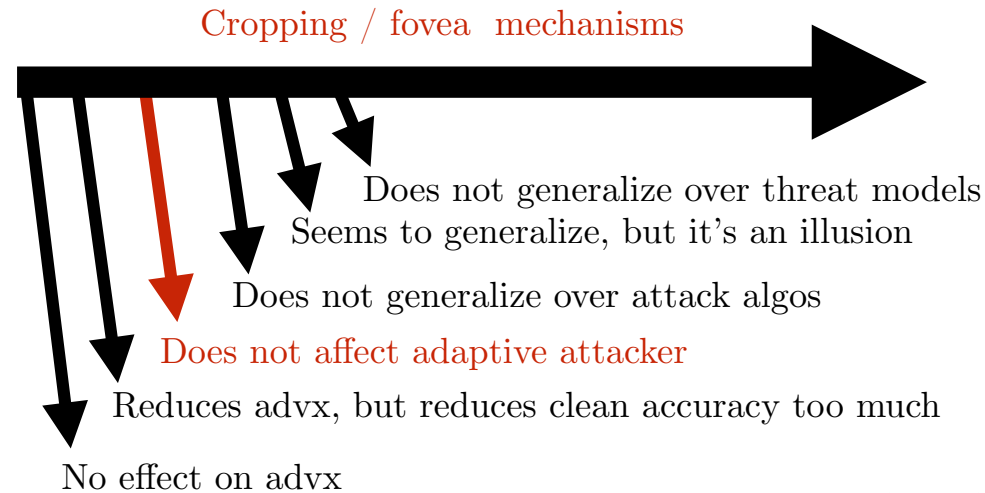
Pipeline of Defense Failures



Early work on adversarial examples explored the effect of both $L1$ and squared $L2$ weight decay: <https://arxiv.org/abs/1312.6199>
<https://arxiv.org/abs/1412.6572>

For large enough weight decay coefficients weight decay does eventually make the weights small enough that the model becomes robust to adversarial examples, but it also makes the accuracy on clean data become relatively bad. Such claims are of course problem-dependent.

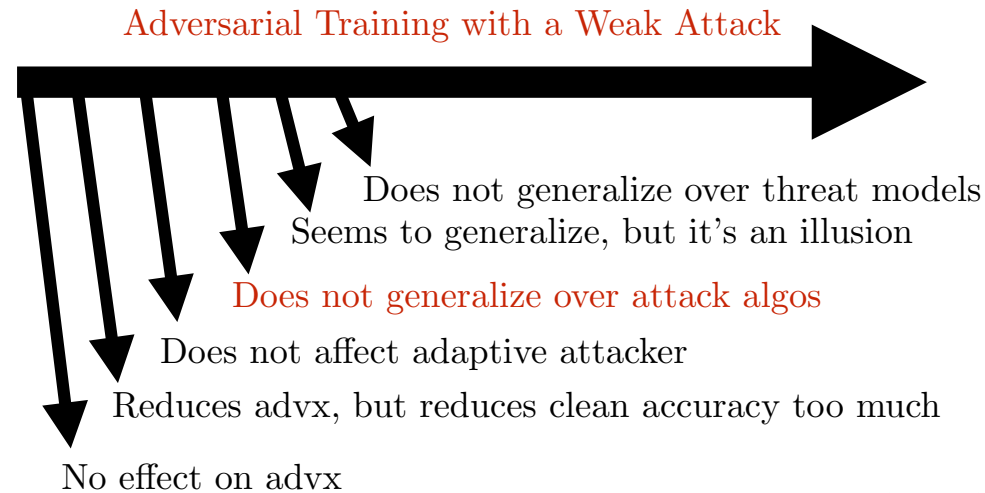
Pipeline of Defense Failures



(Goodfellow 2018)

Cropping and fovea mechanisms have been repeatedly proposed as defenses. Generating adversarial examples and then cropping them sometimes reduces error rate. The latest evaluations show that an attacker aware of the mechanism can defeat it. <https://arxiv.org/pdf/1802.00420.pdf>

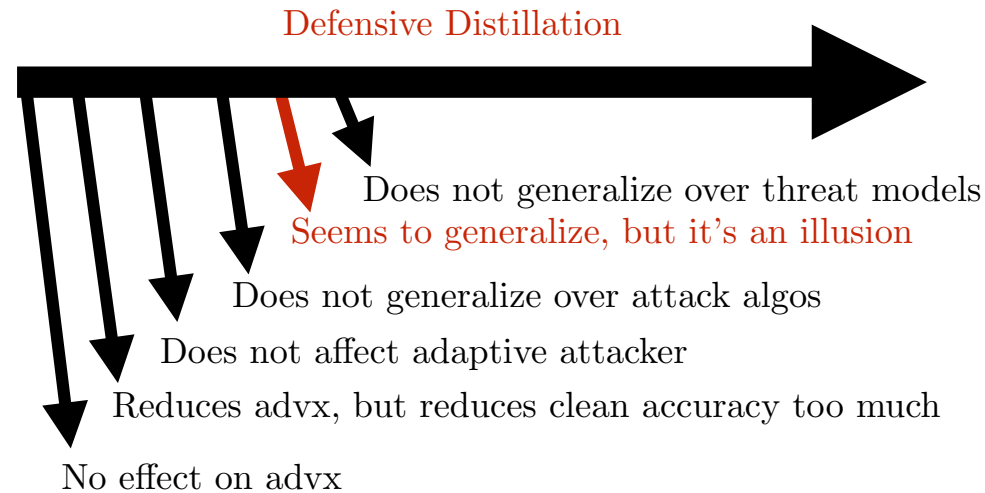
Pipeline of Defense Failures



(Goodfellow 2018)

One of the first successes in the defense literature was adversarial training, approximating the minimax optimization using a fast approximation for the adversarial example construction process to generate adversarial examples on the fly in the inner loop of training. This resulted in a model that was robust to adversarial examples made using the same attack algorithm but could be broken by other attack algorithms that used more computation. <https://arxiv.org/abs/1412.6572>

Pipeline of Defense Failures



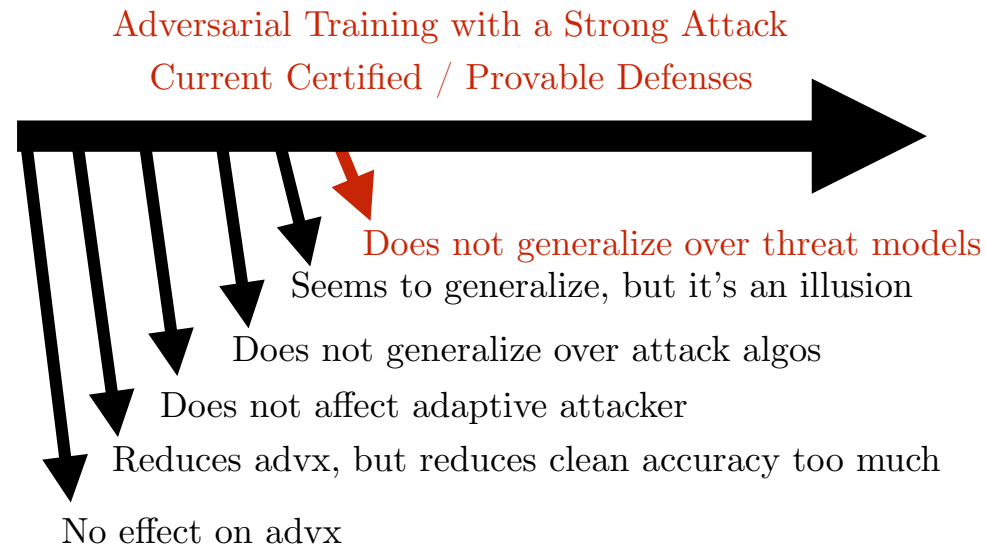
(Goodfellow 2018)

Many defense algorithms seem to perform well against multiple adaptive attack algorithms, but then are later broken. This usually means that their apparent success was an illusion, for example due to gradient masking. In many cases, such broken defenses are still useful contributions to the literature, because they help to develop the stronger attacks that are used to reveal the illusion.

<https://arxiv.org/abs/1511.04508>

<https://arxiv.org/abs/1607.04311>

Pipeline of Defense Failures



The current state of the art defense (<https://arxiv.org/abs/1803.06373>) is based on using a strong attack (<https://arxiv.org/abs/1706.06083>) for adversarial training (<https://arxiv.org/abs/1412.6572> <https://arxiv.org/abs/1611.01236>).

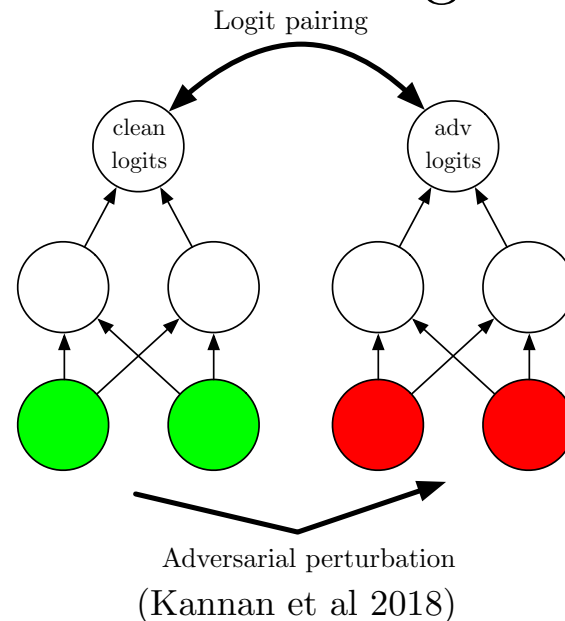
On MNIST in particular, Madry et al's model is regarded as highly robust, after being subject to public scrutiny for several months.

However, this robustness holds only within the L_∞ ball. It is possible to break this model by switching to a different threat model, even one that seems conceptually similar, such as the L_1 ball: <https://arxiv.org/abs/1709.04114>

This problem even applies to all existing certified defenses, because the certificates are specific to a particular norm ball: <https://arxiv.org/abs/1801.09344> <https://arxiv.org/abs/1803.06567> <https://arxiv.org/abs/1711.00851>

A late-breaking result is that GAN-based models can also produce adversarial examples that appear *unperturbed* to a human

Adversarial Logit Pairing (ALP)

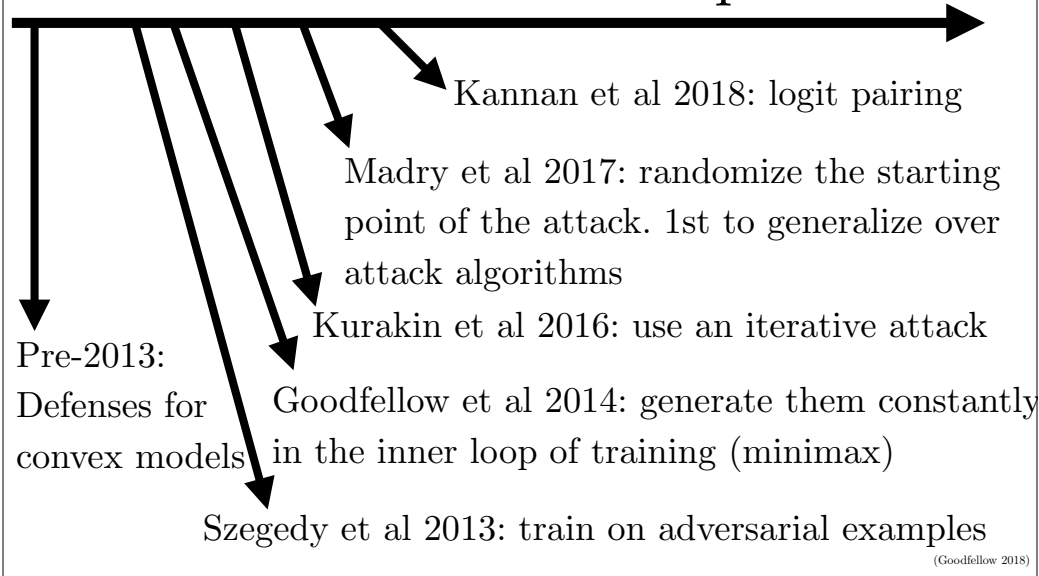


First approach
to achieve $>50\%$
top-5 accuracy
against iterative
adversarial examples
on ImageNet
Current state
of the art

(Goodfellow 2018)

For more information, see <https://arxiv.org/abs/1803.06373>

Timeline of Defenses Against Adversarial Examples



2013: <https://arxiv.org/abs/1312.6199>

2014: <https://arxiv.org/abs/1412.6572>

2016: <https://arxiv.org/abs/1611.01236>

2017: <https://arxiv.org/abs/1706.06083>

2018: <https://arxiv.org/abs/1803.06373>

(There has also been earlier work on securing convex models, which is very different from securing neural nets, e.g.: <https://homes.cs.washington.edu/~pedrod/papers/kdd04.pdf> https://cs.nyu.edu/~roweis/papers/robust_icml06.pdf)

Disappointing outcome of toy game

- My hope: something simple (Bayesian deep nets?) will solve the adversarial example problem, do well on the points we can measure via norm ball label propagation, also do well on points that are hard to measure
- Outcome so far: best results are obtained by directly optimizing the performance measure. Both for empirical and for certified approaches. Defenses do not generalize out of the norm ball.

Future Directions: Indirect Methods

- Do not just optimize the performance measure exactly
- Best methods so far:
 - Logit pairing (non-adversarial)
 - Label smoothing
 - Logit squeezing
- Can we perform a lot better with other methods that are similarly indirect?

(Goodfellow 2018)

[https://books.google.com/books?](https://books.google.com/books?hl=en&lr=&id=F4c3DwAAQBAJ&oi=fnd&pg=PA311&dq=info:J1EtPob5tcoJ:scholar.google.com&ots=idBTNGuyP8&sig=HMrjcmrn_fs2-kyaAo-XNr1Expo#v=onepage&q&f=false)

[hl=en&lr=&id=F4c3DwAAQBAJ&oi=fnd&pg=PA311&dq=info:J1EtPob5tcoJ:scholar.google.com&ots=idBTNGuyP8&sig=HMrjcmrn_fs2-kyaAo-XNr1Expo#v=onepage&q&f=false](https://books.google.com/books?hl=en&lr=&id=F4c3DwAAQBAJ&oi=fnd&pg=PA311&dq=info:J1EtPob5tcoJ:scholar.google.com&ots=idBTNGuyP8&sig=HMrjcmrn_fs2-kyaAo-XNr1Expo#v=onepage&q&f=false) observed that label smoothing helps resist adversarial examples.

<https://arxiv.org/abs/1803.06373> observed that a few non-adversarial methods of regularizing the logits of a model help it to resist adversarial examples.

So far, these are the only methods of resisting adversarial examples I know of that are not based on directly optimizing some definition of adversarial error rate. I think an important research direction is to find other methods that are similarly indirect and yet perform well. These methods seem most likely to generalize beyond a specific attack model, because they do not involve optimizing directly for performance under that specific attack.

Future Directions: Better Attack Models

- Add new attack models other than norm balls
- Study messy real problems in addition to clean toy problems
- Study certification methods that use other proof strategies besides local smoothness
- Study more problems other than vision

Future Directions: Security Independent from Traditional Supervised Learning

- Until recently, both adversarial example research and traditional supervised learning seemed fully aligned: just make the model better
- They still share this goal
- It is now clear security research must have some independent goals.
For two models with the same error volume, for reasons of security we prefer:
 - The model with lower confidence on mistakes
 - The model whose mistakes are harder to find
 - A stochastic model that does not repeatedly make the same mistake on the same input
 - A model whose mistakes are less valuable to the attacker / costly to the defender
 - A model that is harder to reverse engineer with probes
 - A model that is less prone to transfer from related models

Some Non-Security Reasons to Study Adversarial Examples

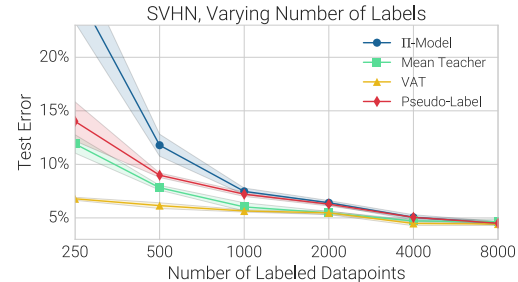
Improve Supervised Learning
(Goodfellow et al 2014)

Understand Human Perception



Gamaleldin et al 2018

Improve Semi-Supervised Learning
(Miyato et al 2015)



(Oliver+Odena+Raffel et al, 2018)

(Goodfellow 2018)

My recommendations today have mostly focused on how to make machine learning secure.

This is distinct from the question of what research should be done regarding adversarial examples.

Studying adversarial examples has improved supervised learning temporarily in the past (<https://arxiv.org/abs/1412.6572>) and may make a more lasting improvement to supervised learning in the future. Studying adversarial examples has certainly made a significant contribution to semi-supervised learning: virtual adversarial training (<https://arxiv.org/abs/1507.00677>) was the best performing method in a recent exhaustive benchmark (<https://arxiv.org/abs/1804.09170>).

Studying adversarial examples may also help to understand the human brain (<https://arxiv.org/abs/1802.08195>).

Besides these applications, many other applications such as model-based optimization seem possible.

Clever Hans



(“Clever Hans,
Clever
Algorithms,”
Bob Sturm)



(Goodfellow 2018)

Get involved!

<https://github.com/tensorflow/cleverhans>



(Goodfellow 2018)