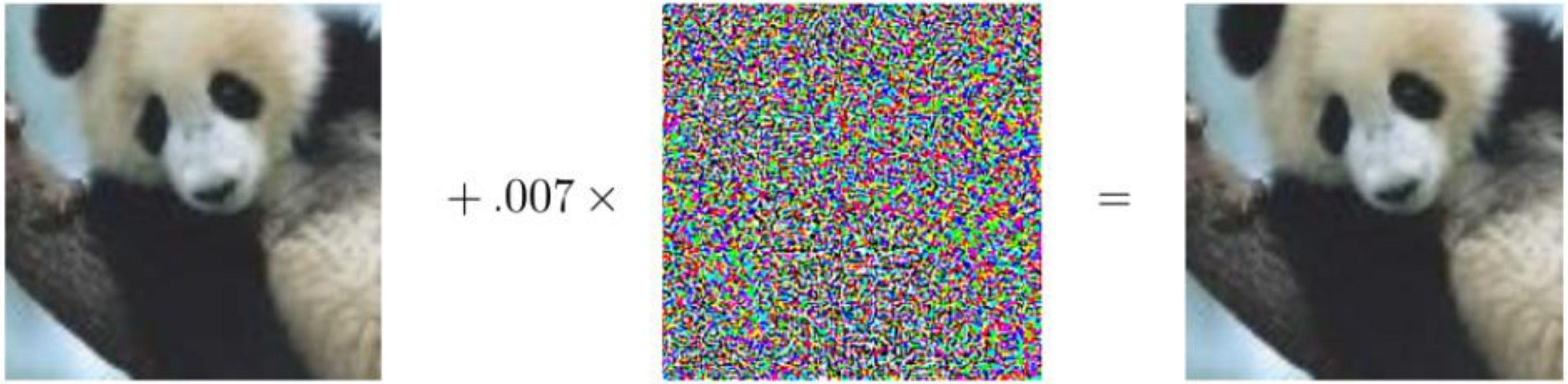
CS231n
Lecture 16. Adversarial Examples and Adversarial Training

Tobig's 14기 서아라

Overview

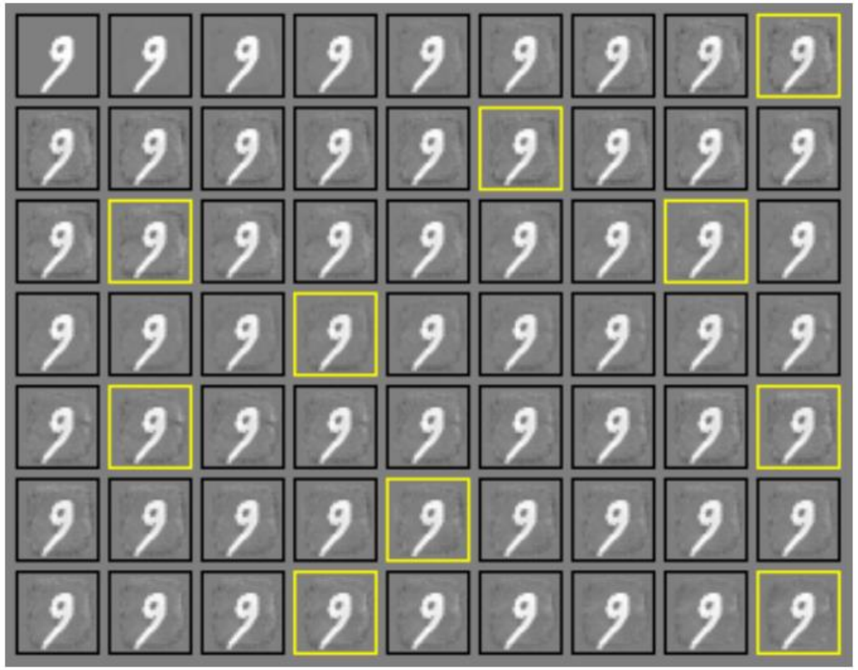
- What are adversarial examples?
- Why do they happen?
- How can they be used to compromise machine learning systems?
- What are the defenses?
- How to use adversarial examples to improve machine learning, even when there is no adversary

Adversarial Examples

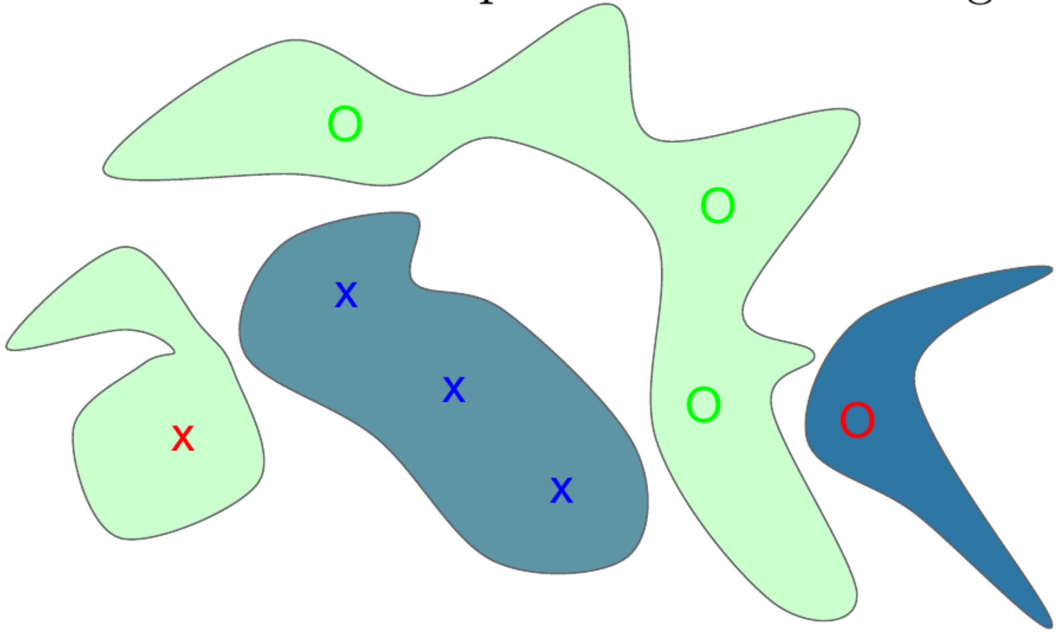


Turning Objects into "Airplanes"

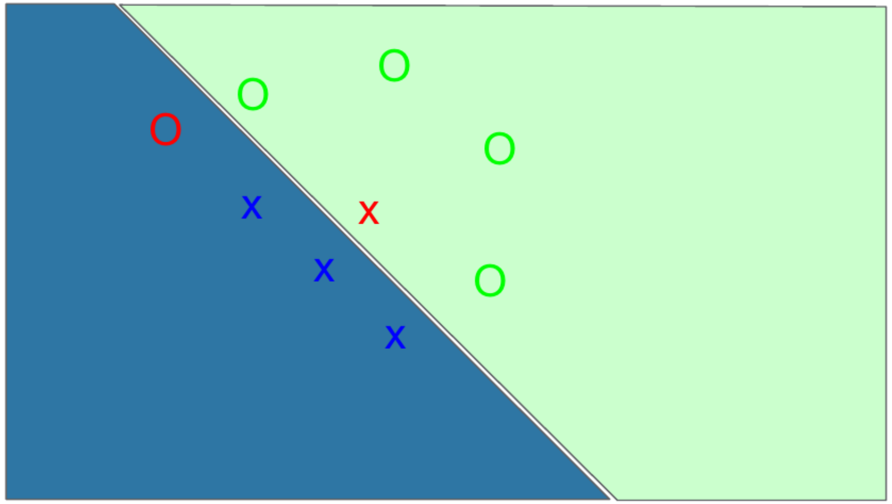
Attacking a Linear Model



Adversarial Examples from Overfitting

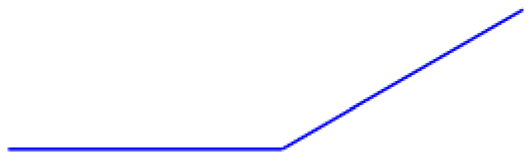


Adversarial Examples from Excessive Linearity

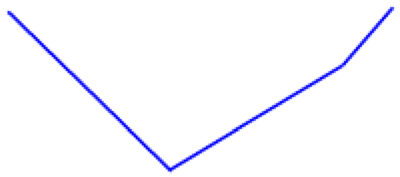


Modern deep nets are very piecewise linear

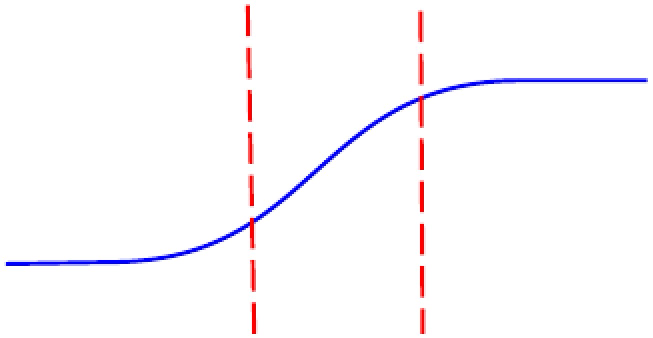
Rectified linear unit



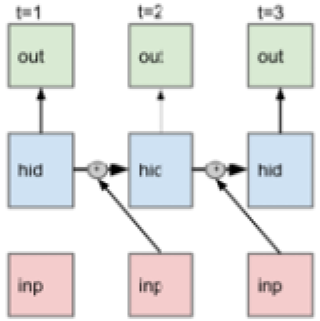
Maxout



Carefully tuned sigmoid

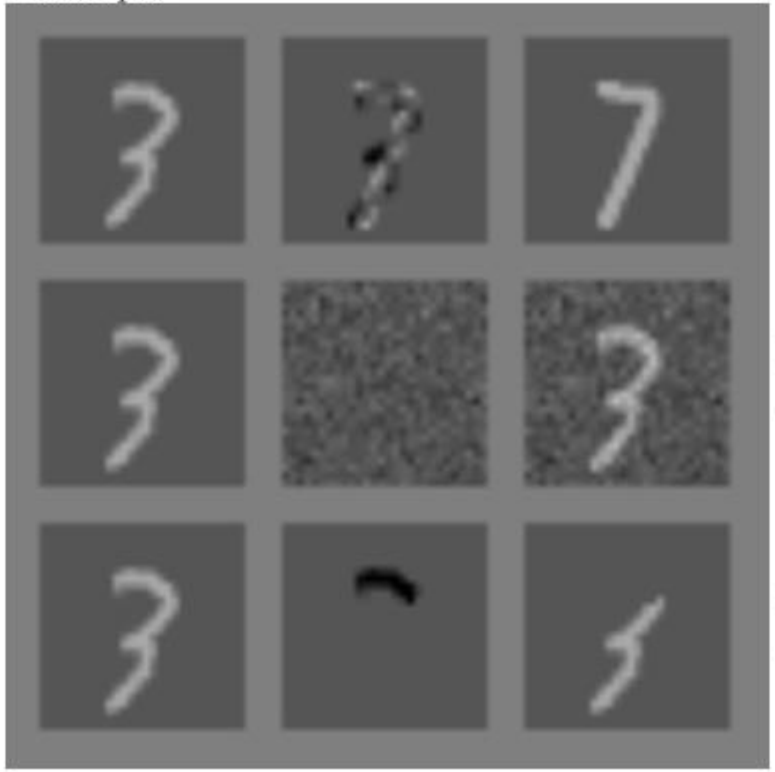


LSTM



Small inter-class distances

Clean example | Perturbation | Corrupted example



Perturbation changes the true class

Random perturbation does not change the class

Perturbation changes the input to “rubbish class”

All three perturbations have L2 norm 3.96

This is actually small. We typically use 7!

The Fast Gradient Sign Method

$$J(\tilde{\boldsymbol{x}}, \boldsymbol{\theta}) \approx J(\boldsymbol{x}, \boldsymbol{\theta}) + (\tilde{\boldsymbol{x}} - \boldsymbol{x})^\top \nabla_{\boldsymbol{x}} J(\boldsymbol{x}).$$

Maximize

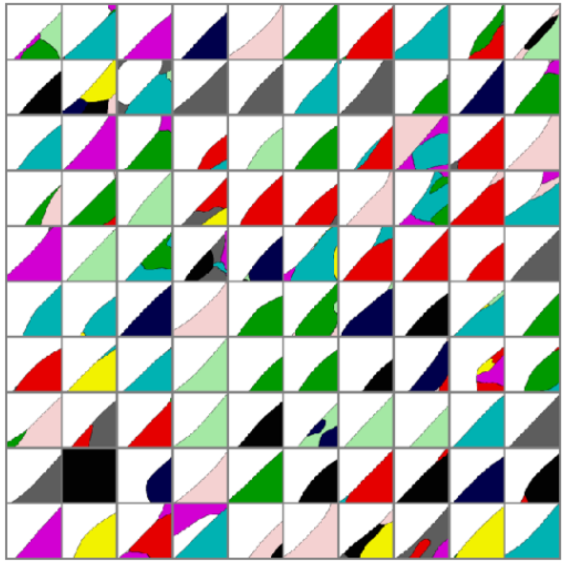
$$J(\boldsymbol{x}, \boldsymbol{\theta}) + (\tilde{\boldsymbol{x}} - \boldsymbol{x})^\top \nabla_{\boldsymbol{x}} J(\boldsymbol{x})$$

subject to

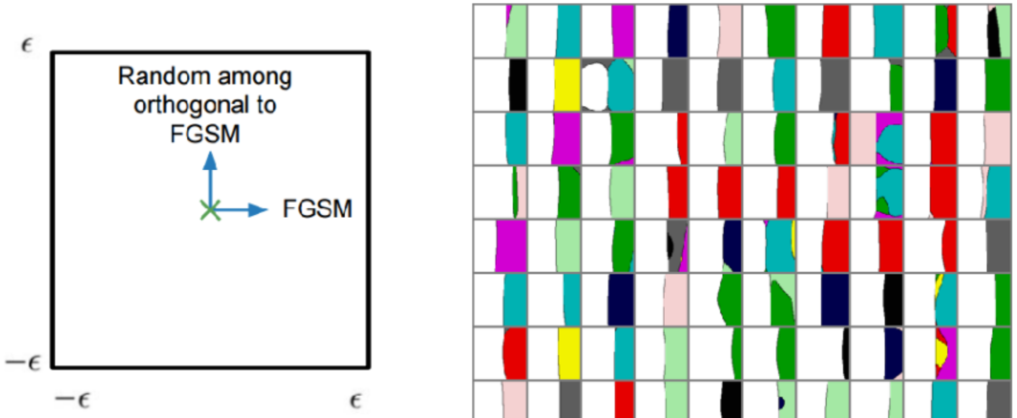
$$||\tilde{\boldsymbol{x}} - \boldsymbol{x}||_\infty \leq \epsilon$$

$$\Rightarrow \tilde{\boldsymbol{x}} = \boldsymbol{x} + \epsilon \mathrm{sign}\left(\nabla_{\boldsymbol{x}} J(\boldsymbol{x})\right).$$

Maps of Adversarial Cross-Sections

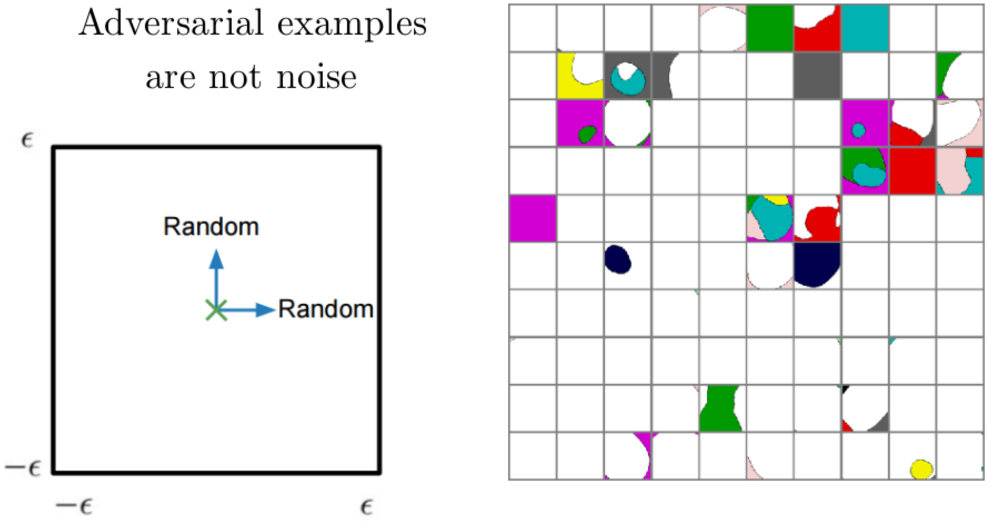


Maps of Adversarial and Random Cross-Sections

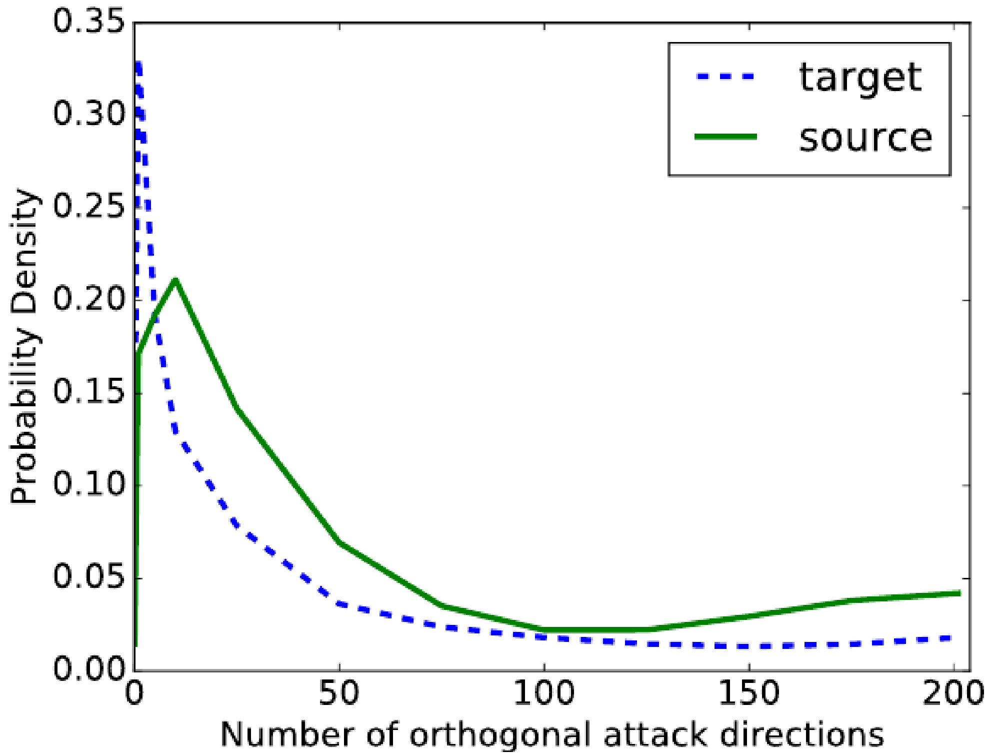


Maps of Random Cross-Sections

Adversarial examples
are not noise



Estimating the Subspace Dimensionality

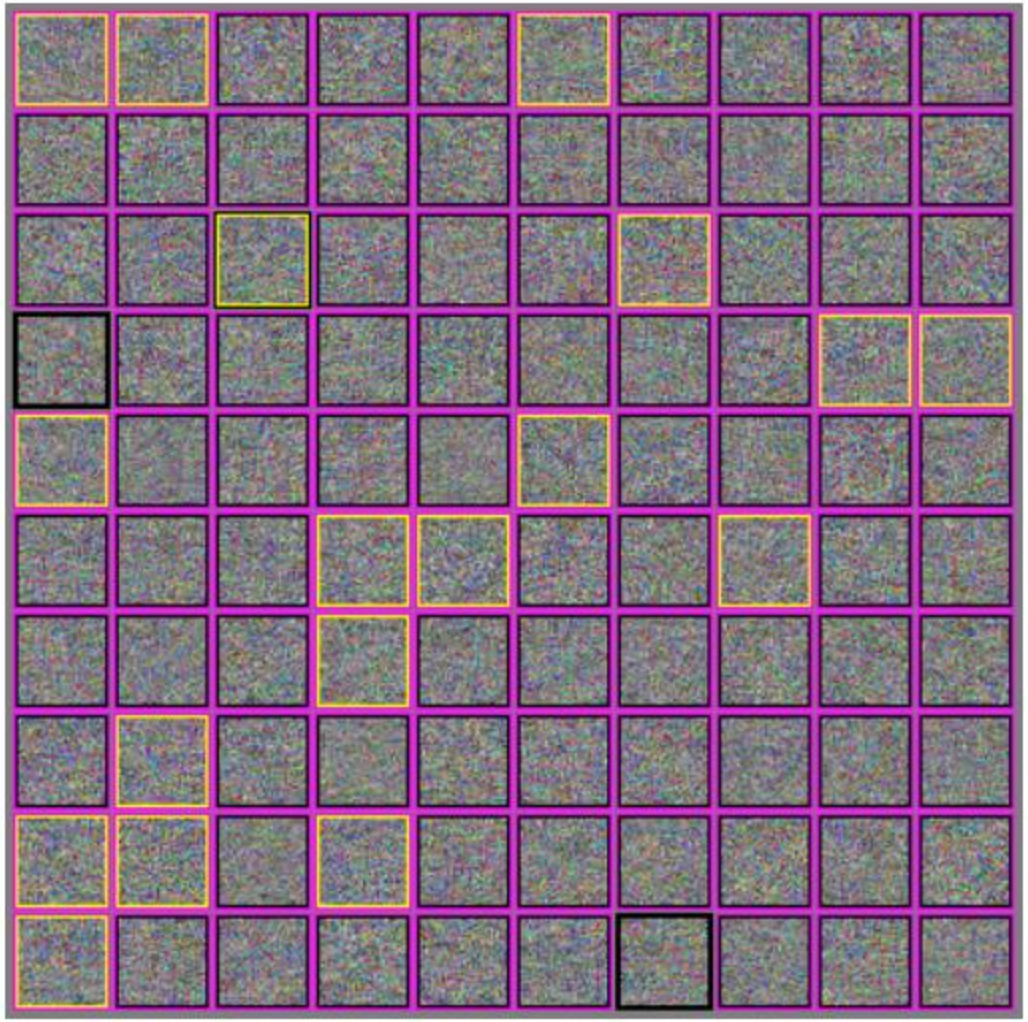


(Tramèr et al, 2017)

Clever Hans

("Clever Hans, Clever Algorithms," Bob Sturm)

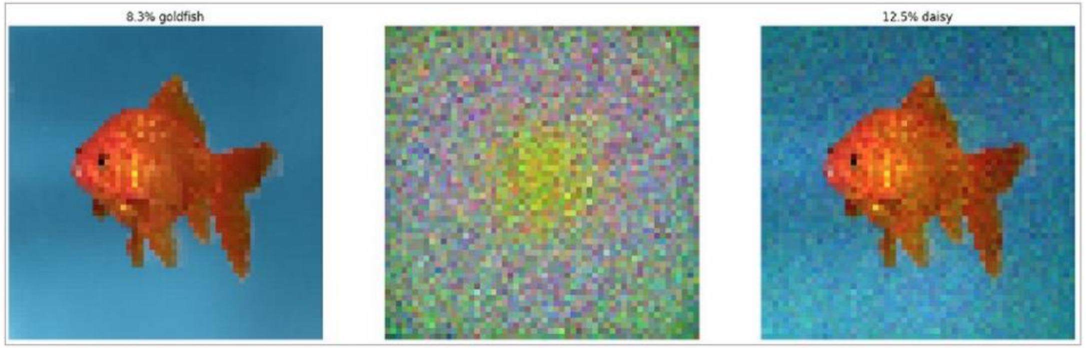
Wrong almost everywhere



Adversarial Examples for RL

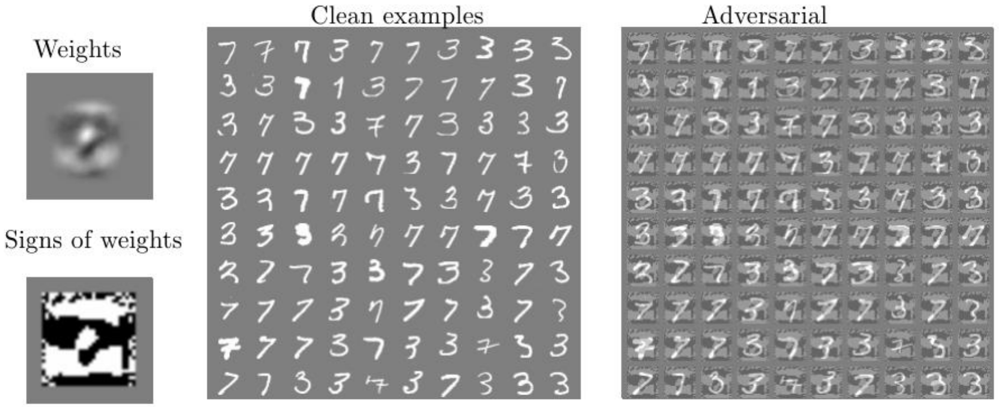
(Huang et al., 2017)

Linear Models of ImageNet

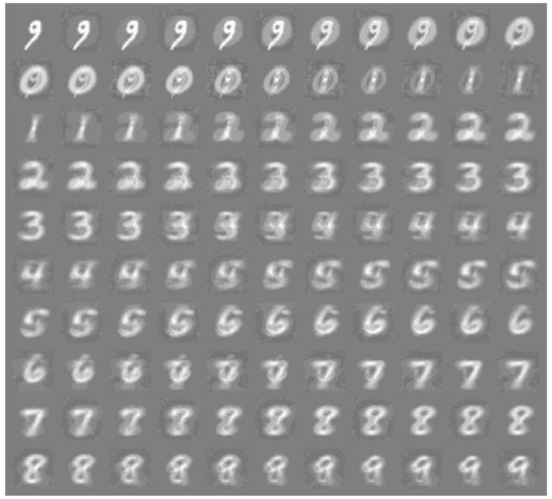


(Andrej Karpathy, "Breaking Linear Classifiers on ImageNet")

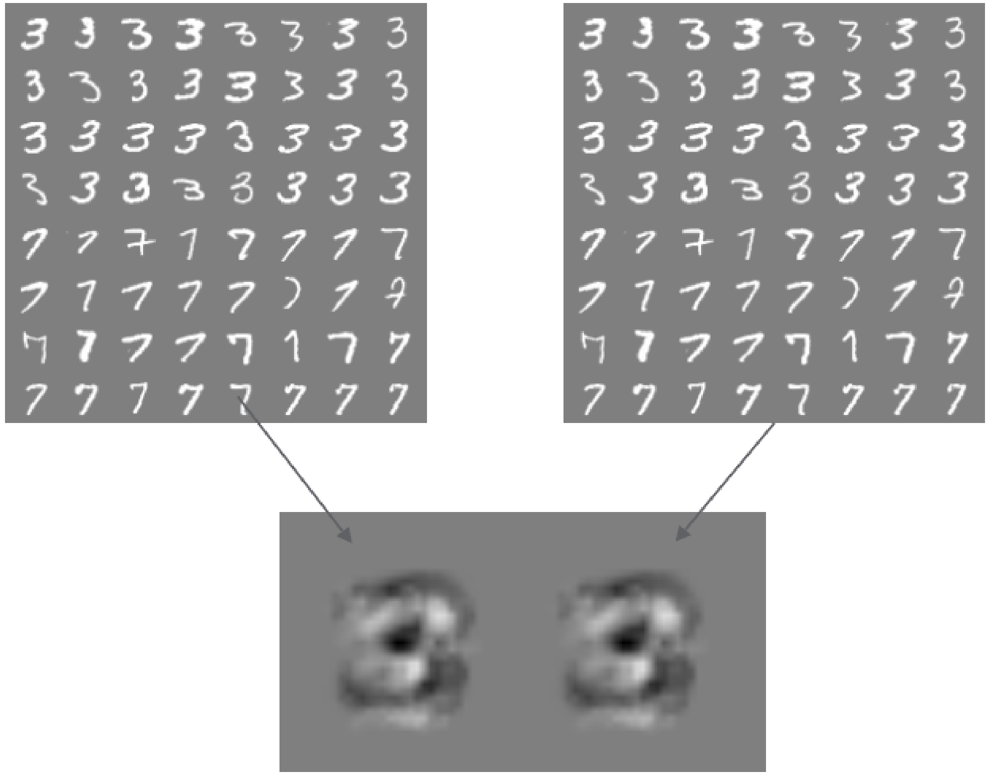
High-Dimensional Linear Models



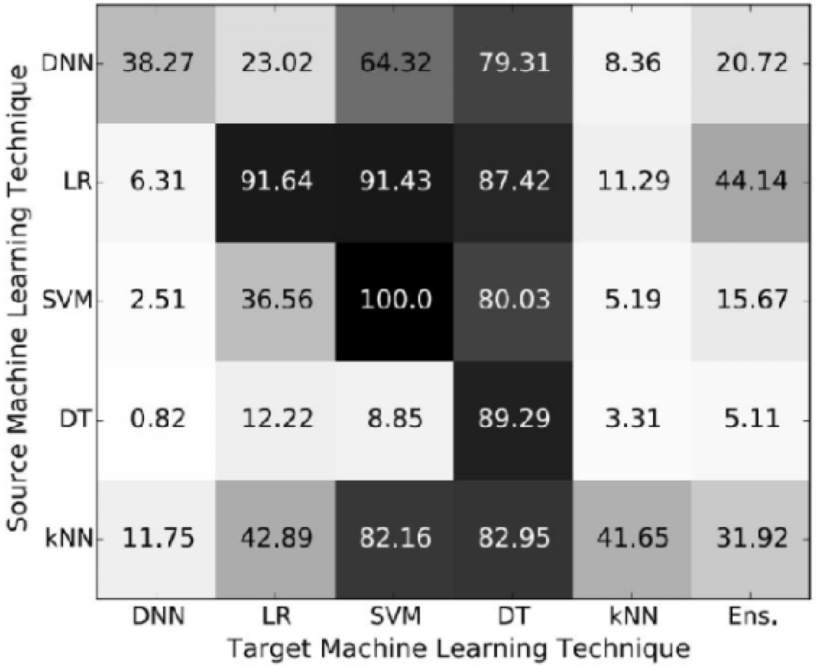
RBFs behave more intuitively



Cross-model, cross-dataset generalization



Cross-technique transferability



(Papernot 2016)

Transferability Attack

Target model with unknown weights, machine learning algorithm, training set; maybe non-differentiable

Train your own model

Substitute model mimicking target model with known, differentiable function

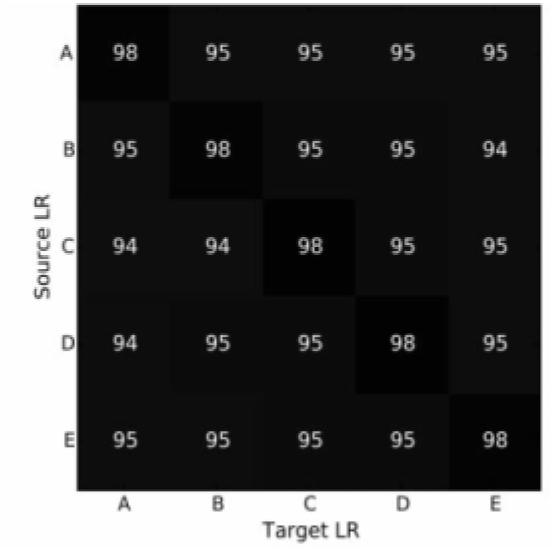
Adversarial crafting against substitute

Adversarial examples

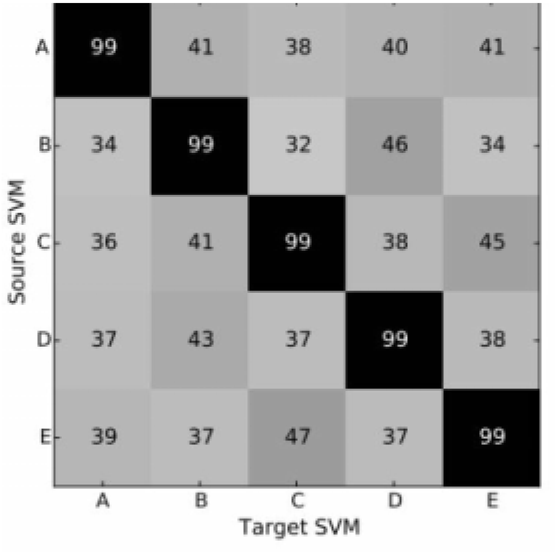
Deploy adversarial examples against the target; transferability property results in them succeeding

(Goodfellow 2016)

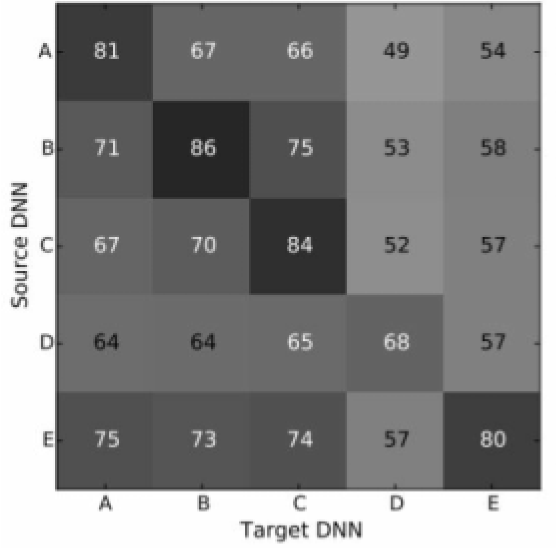
Cross-Training Data Transferability



Strong



Weak



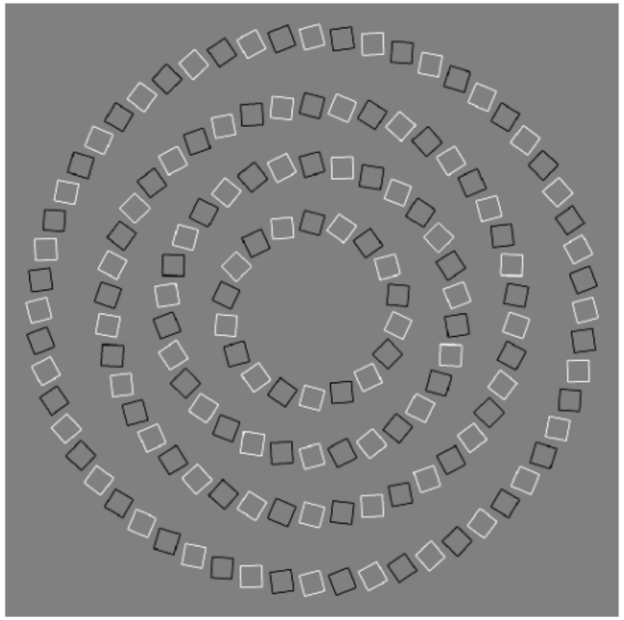
Intermediate

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).

Adversarial Examples in the Human Brain

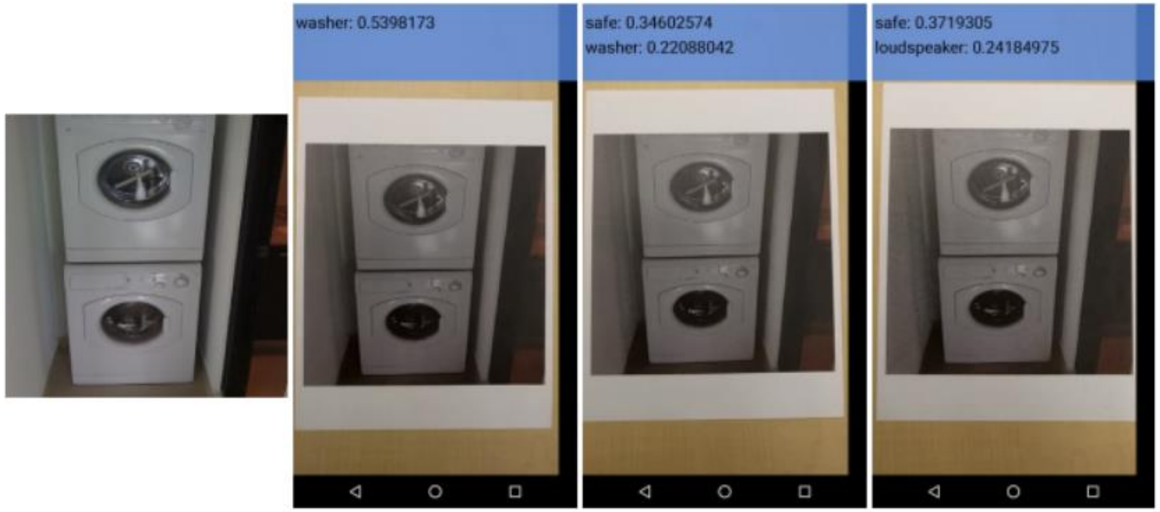


These are concentric circles, not intertwined spirals.

Practical Attacks

- Fool real classifiers trained by remotely hosted API (MetaMind, Amazon, Google)
- Fool malware detector networks
- Display adversarial examples in the physical world and fool machine learning systems that perceive them through a camera

Adversarial Examples in the Physical World



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

Failed defenses

Generative pretraining

Removing perturbation with an autoencoder

Adding noise at test time

Ensembles

Confidence-reducing perturbation at test time

Error correcting codes

Multiple glimpses

Weight decay

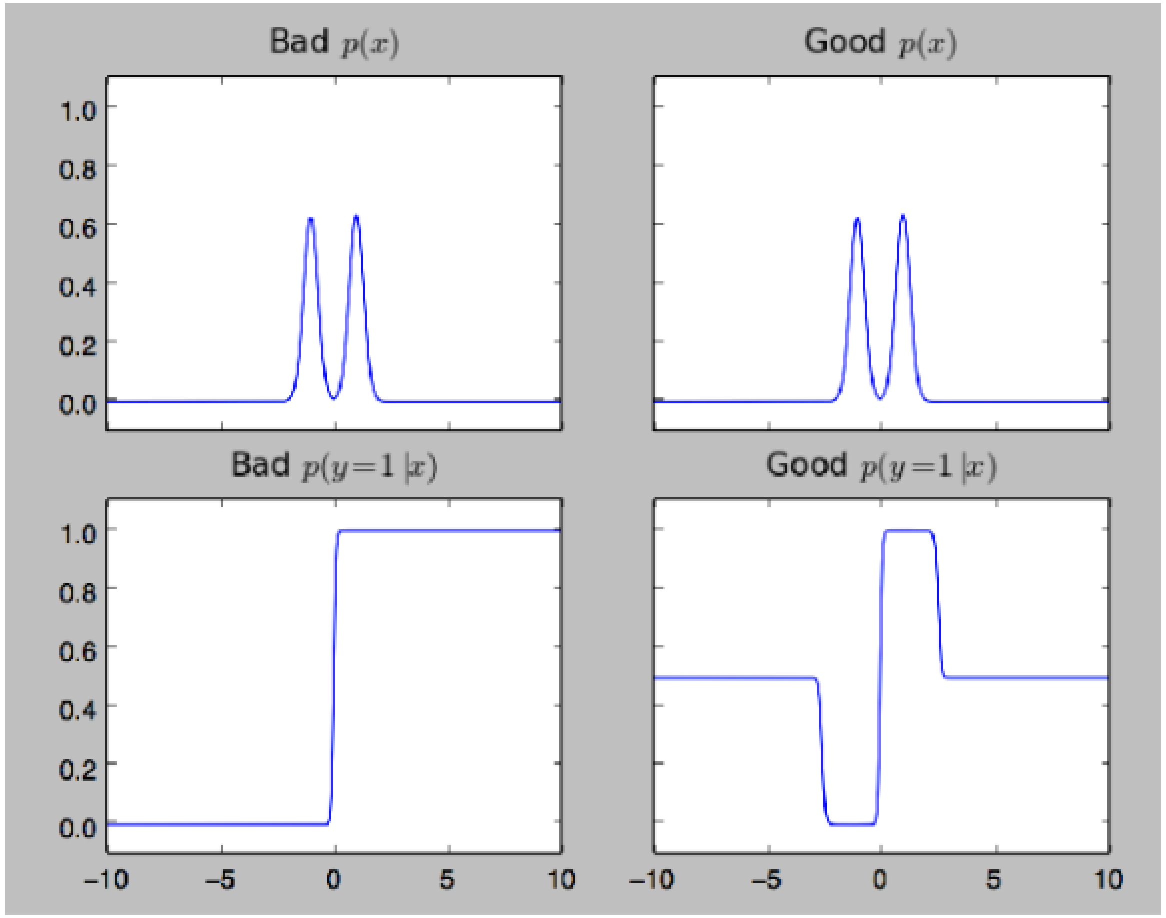
Double backprop

Adding noise at train time

Various non-linear units

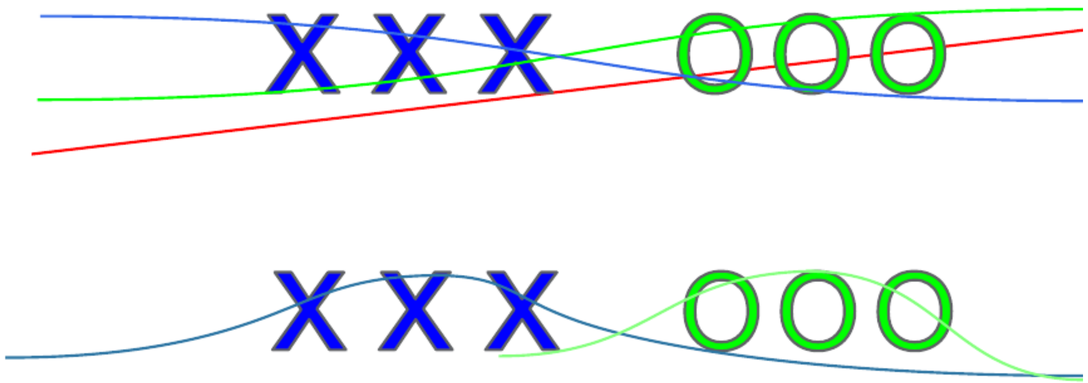
Dropout

Generative Modeling is not Sufficient to Solve the Problem



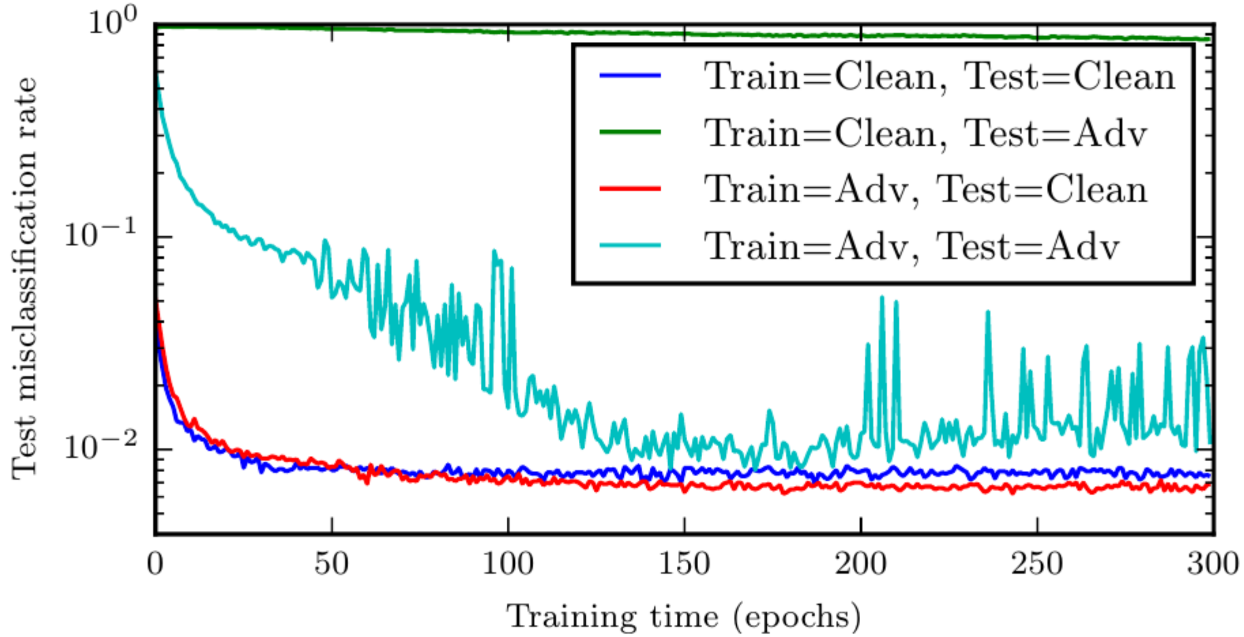
Universal approximator theorem

Neural nets can represent either function:



Maximum likelihood doesn't cause them to learn the right function. But we can fix that...

Training on Adversarial Examples



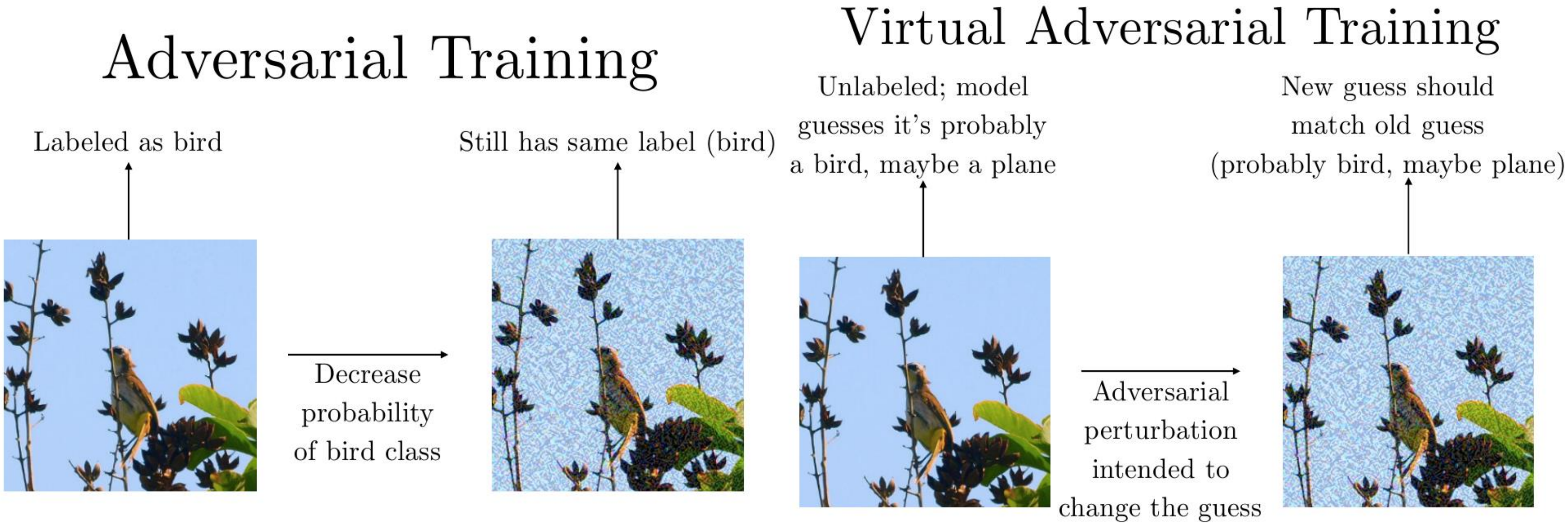
Adversarial Training of other Models

- Linear models: SVM / linear regression cannot learn a step function, so adversarial training is less useful, very similar to weight decay

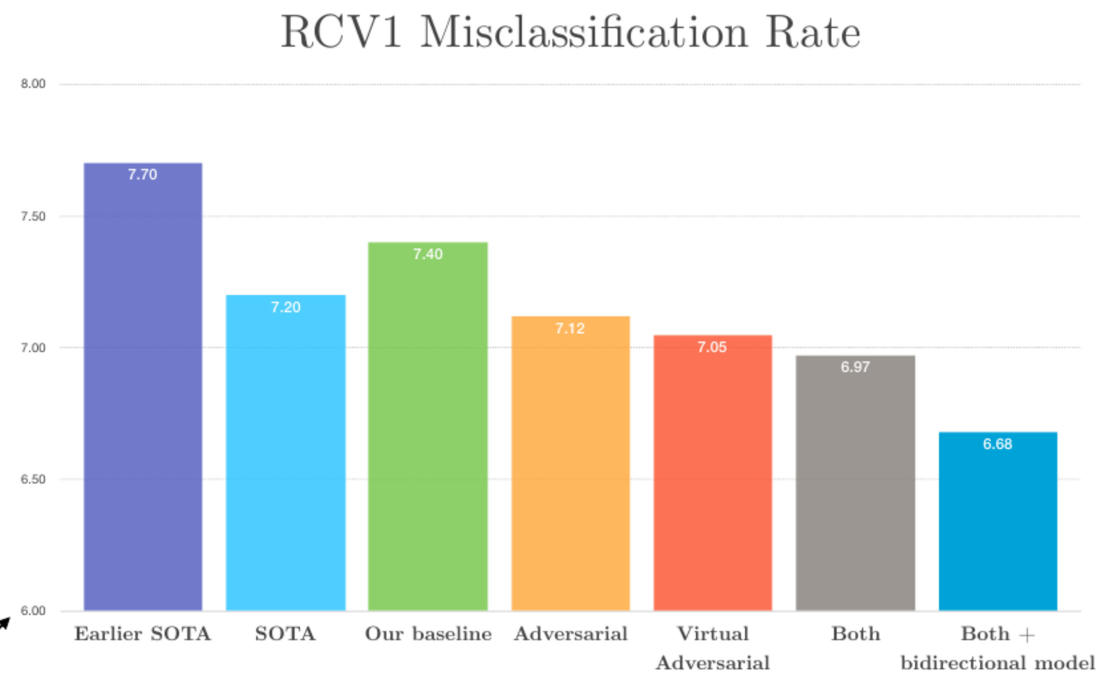
- k-NN: adversarial training is prone to overfitting.

- Takeway: neural nets can actually become more secure than other models. *Adversarially trained neural nets have the best empirical success rate on adversarial examples of any machine learning model.*

Weaknesses Persist

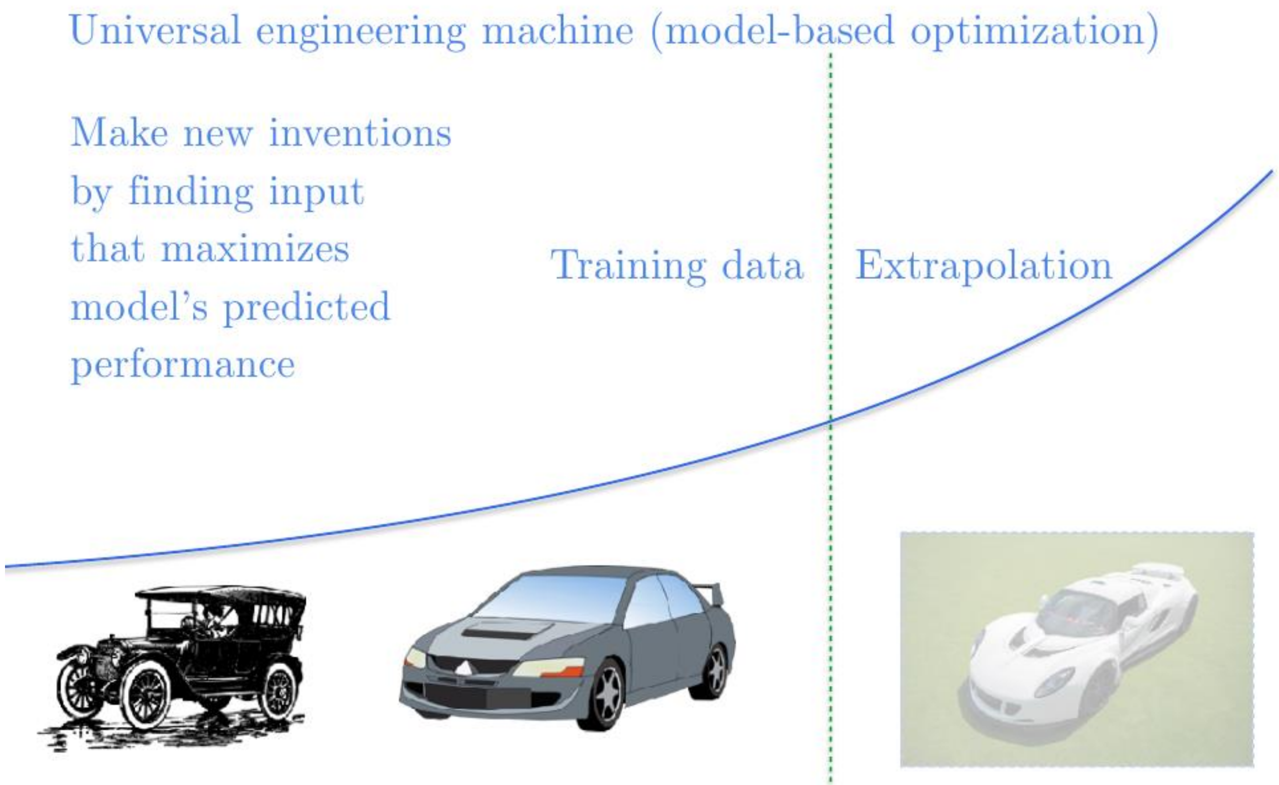

Adversarial Training
Labeled as bird
Decrease probability of bird class
Still has same label (bird)
Virtual Adversarial Training
Unlabeled; model guesses it's probably a bird, maybe a plane
Adversarial perturbation intended to change the guess
New guess should match old guess (probably bird, maybe plane)

Text Classification with VAT



Zoomed in for legibility

(Goodfellow 2016)



Conclusion

- Attacking is easy
- Defending is difficult
- Adversarial training provides regularization and semi-supervised learning
- The out-of-domain input problem is a bottleneck for model-based optimization generally

- 감사합니다☺!