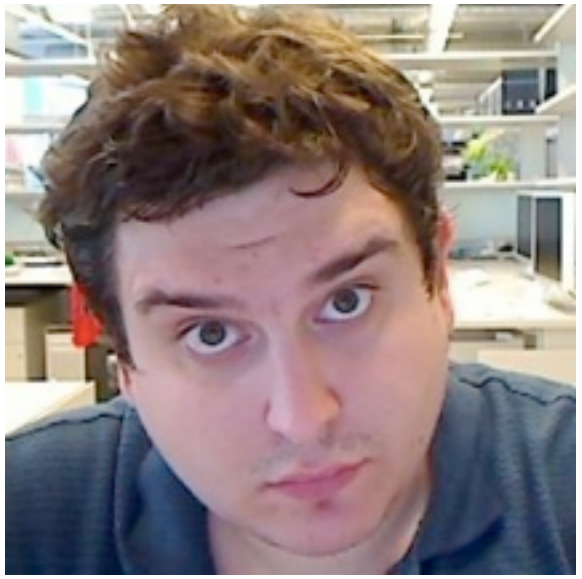
Adversarial Examples and Adversarial Training

Ian Goodfellow, OpenAI Research Scientist
NIPS 2016 Workshop on Reliable ML in the Wild
2016-12-9

In this presentation

- “Intriguing Properties of Neural Networks” Szegedy et al, 2013

- “Explaining and Harnessing Adversarial Examples” Goodfellow et al 2014



- “Adversarial Perturbations of Deep Neural Networks” Warde-Farley and Goodfellow, 2016

In this presentation

- "Transferability in Machine Learning: from Phenomena to Black-Box Attacks using Adversarial Samples" Papernot et al 2016

- "Practical Black-Box Attacks against Deep Learning Systems using Adversarial Examples" Papernot et al 2016

- "Adversarial Perturbations Against Deep Neural Networks for Malware Classification" Grosse et al 2016 **(not my own work)**

In this presentation

- "Adversarial Examples in the Physical World" Kurakin et al 2016

- Also be sure to check out Takeru Miyato et al's work on *virtual* adversarial training.

(Goodfellow 2016)

Overview

- What are adversarial examples?

- Why do they happen?

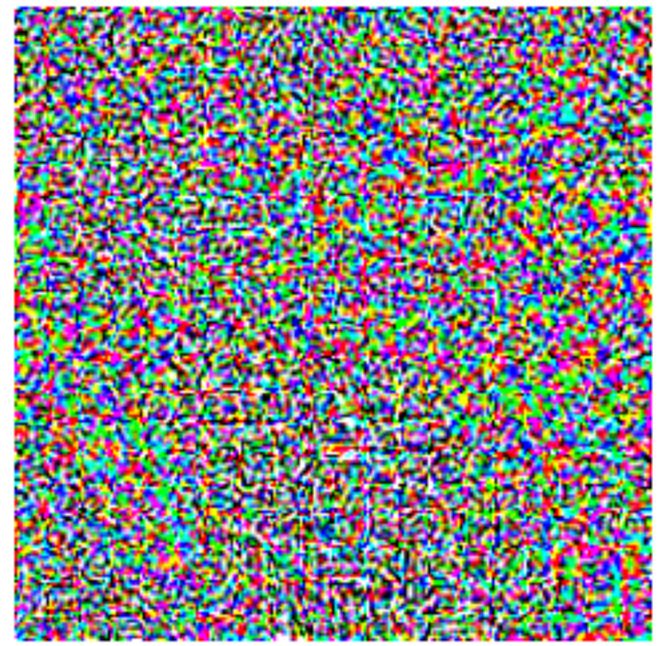
- How can they be used to compromise machine learning systems?

- What are the defenses?

- How to use adversarial examples to improve machine learning, even when there is no adversary

Adversarial Examples

$+ .007 \times$



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Timeline:

"Adversarial Classification" Dalvi et al 2004: fool spam filter

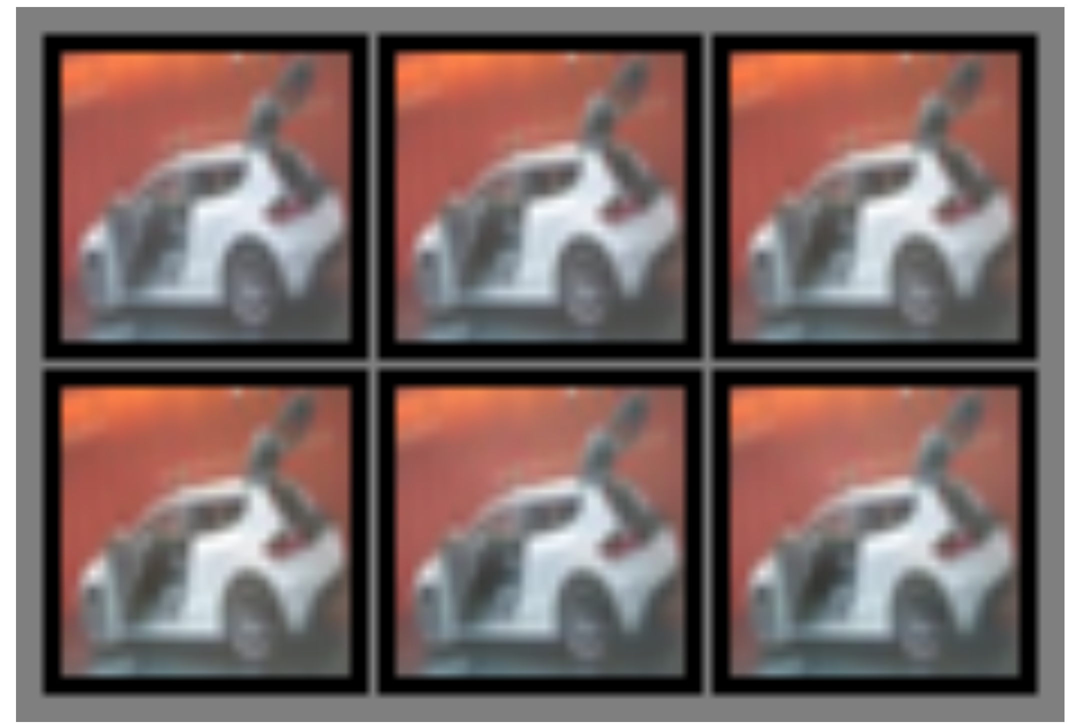
"Evasion Attacks Against Machine Learning at Test Time"

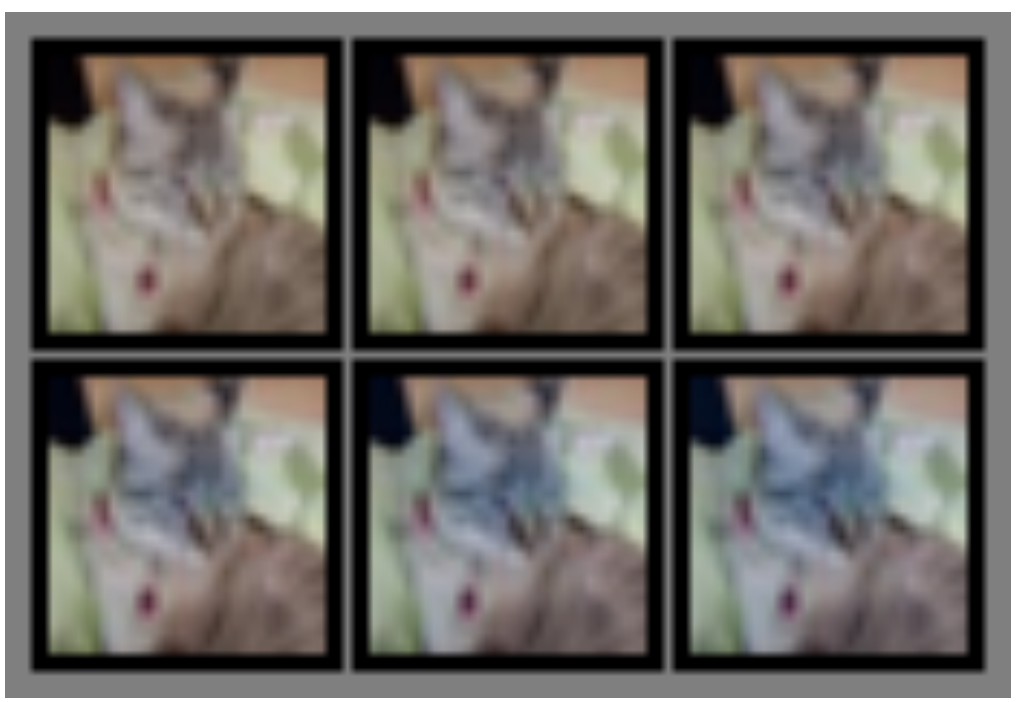
Biggio 2013: fool neural nets

Szegedy et al 2013: fool ImageNet classifiers imperceptibly

Goodfellow et al 2014: cheap, closed form attack

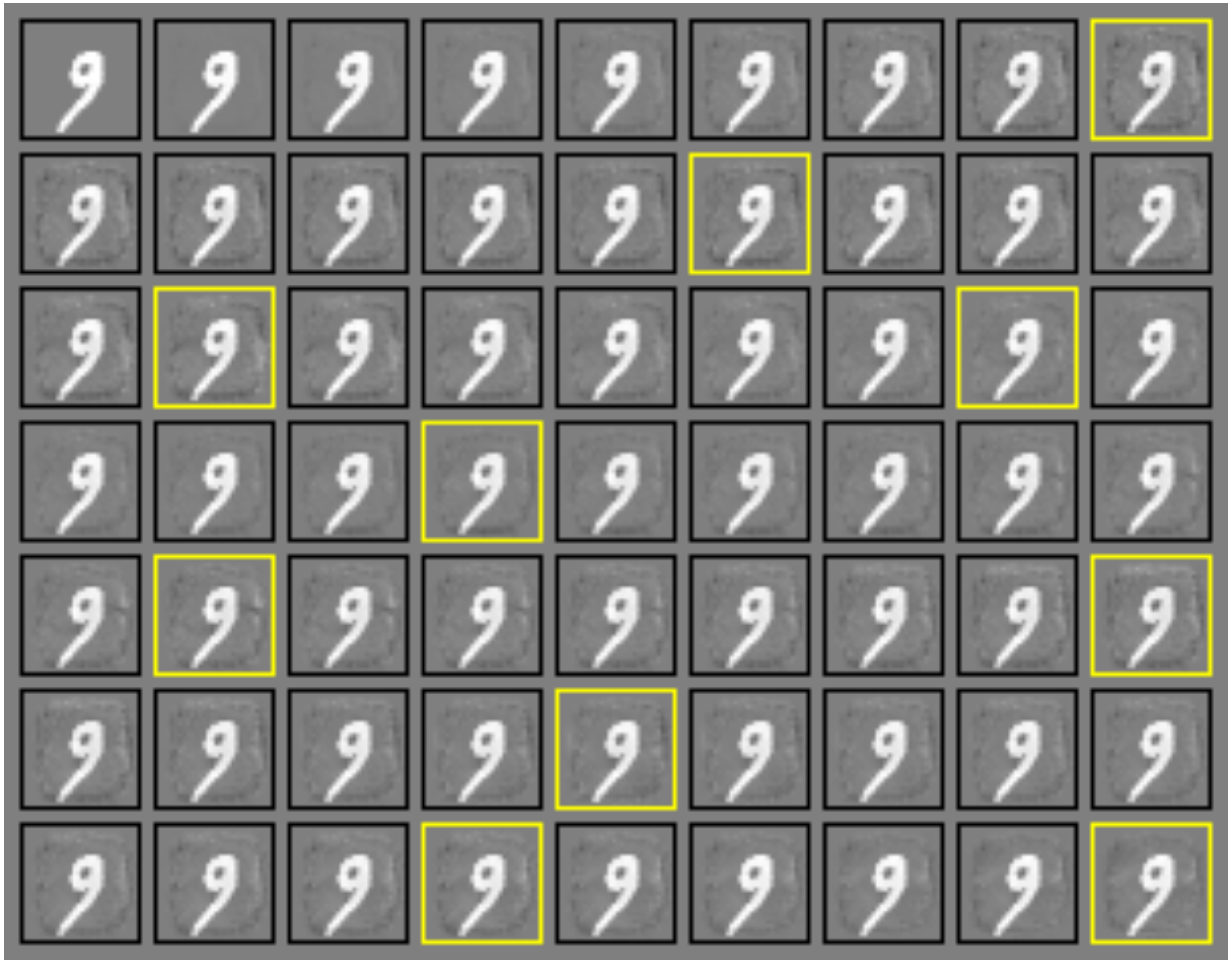
Turning Objects into “Airplanes”





(Goodfellow 2016)

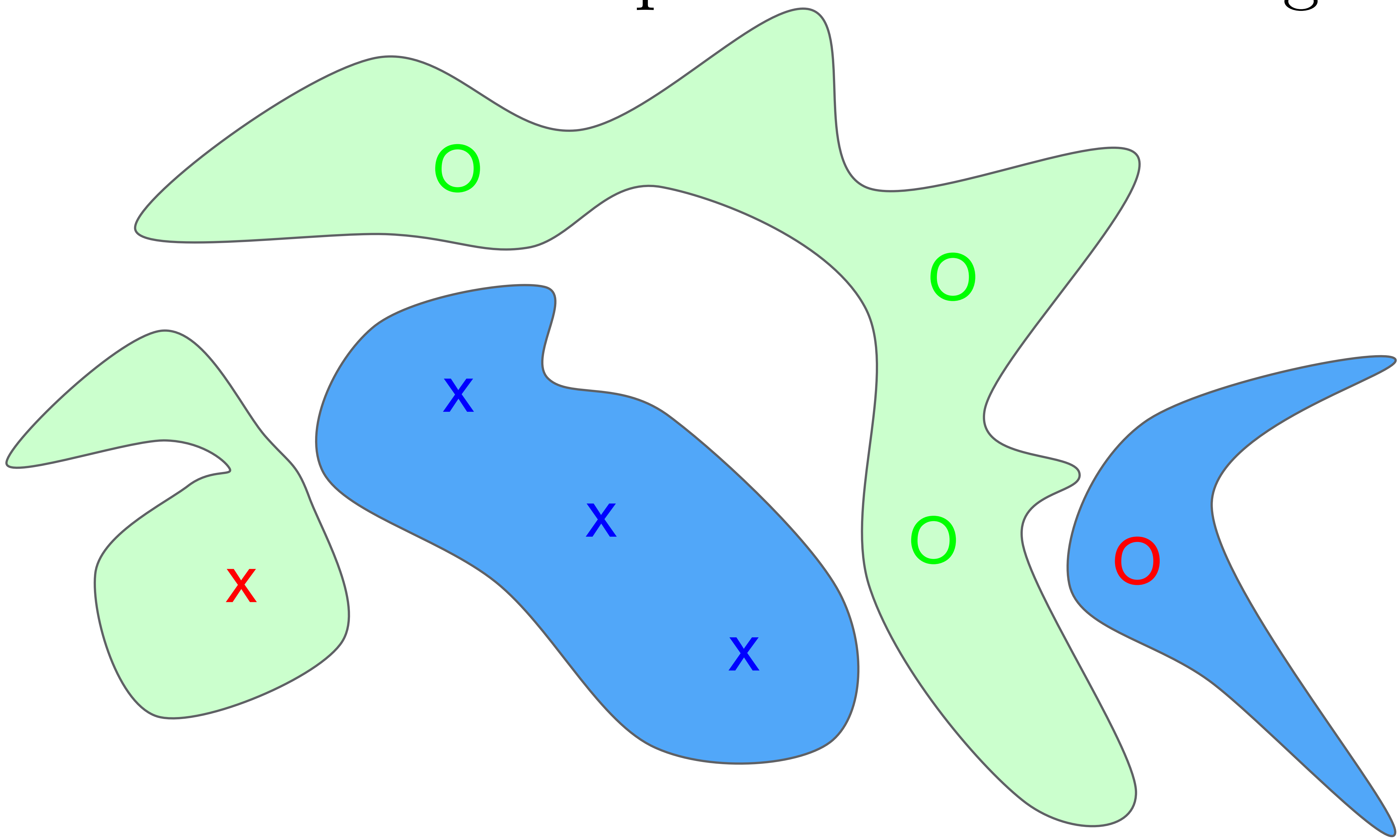
Attacking a Linear Model



Not just for neural nets

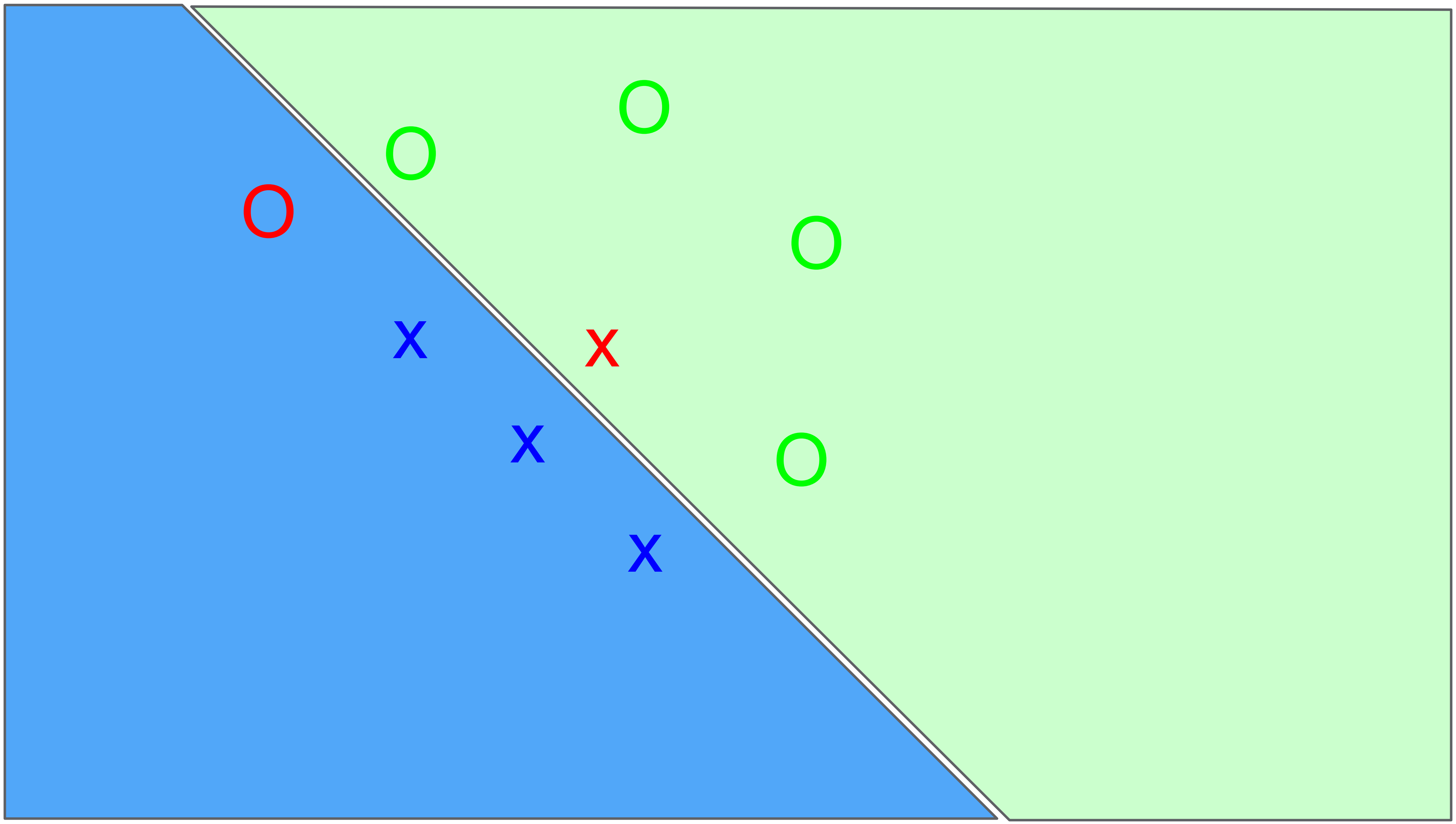
- Linear models
  - Logistic regression
  - Softmax regression
  - SVMs
- Decision trees
- Nearest neighbors

Adversarial Examples from Overfitting



(Goodfellow 2016)

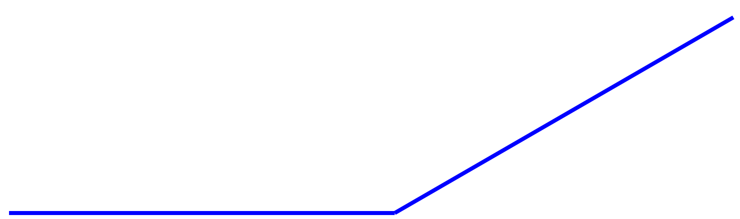
Adversarial Examples from Excessive Linearity



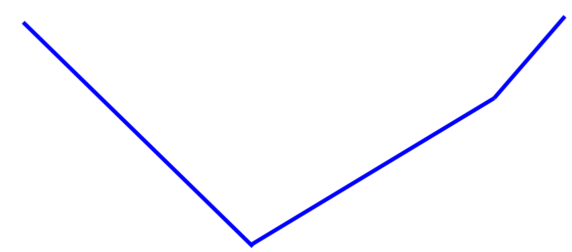
(Goodfellow 2016)

Modern deep nets are very piecewise linear

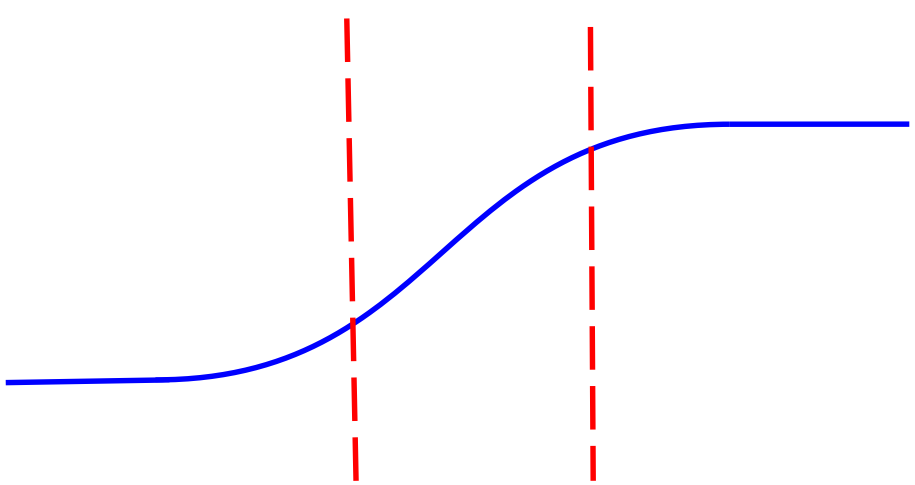
Rectified linear unit



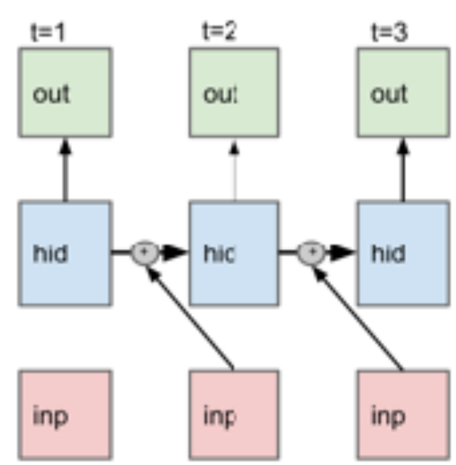
Maxout



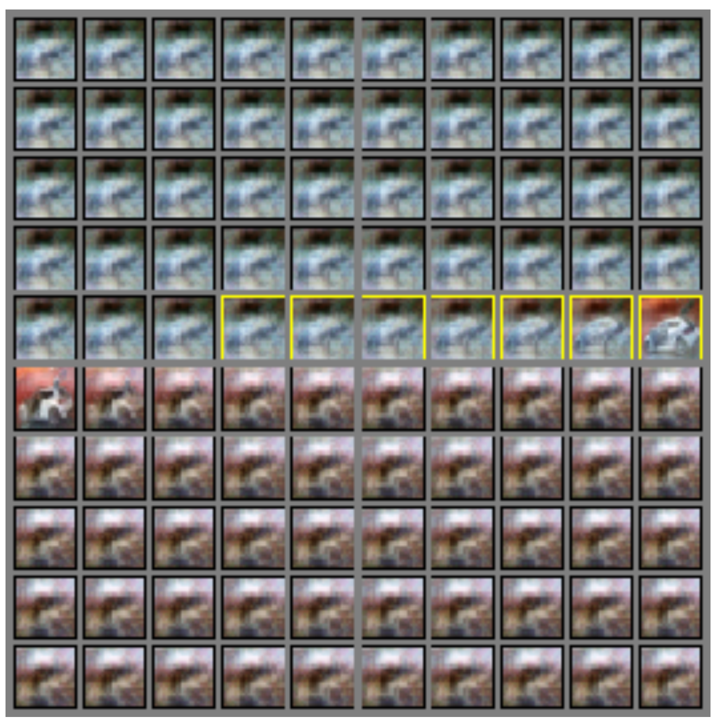
Carefully tuned sigmoid

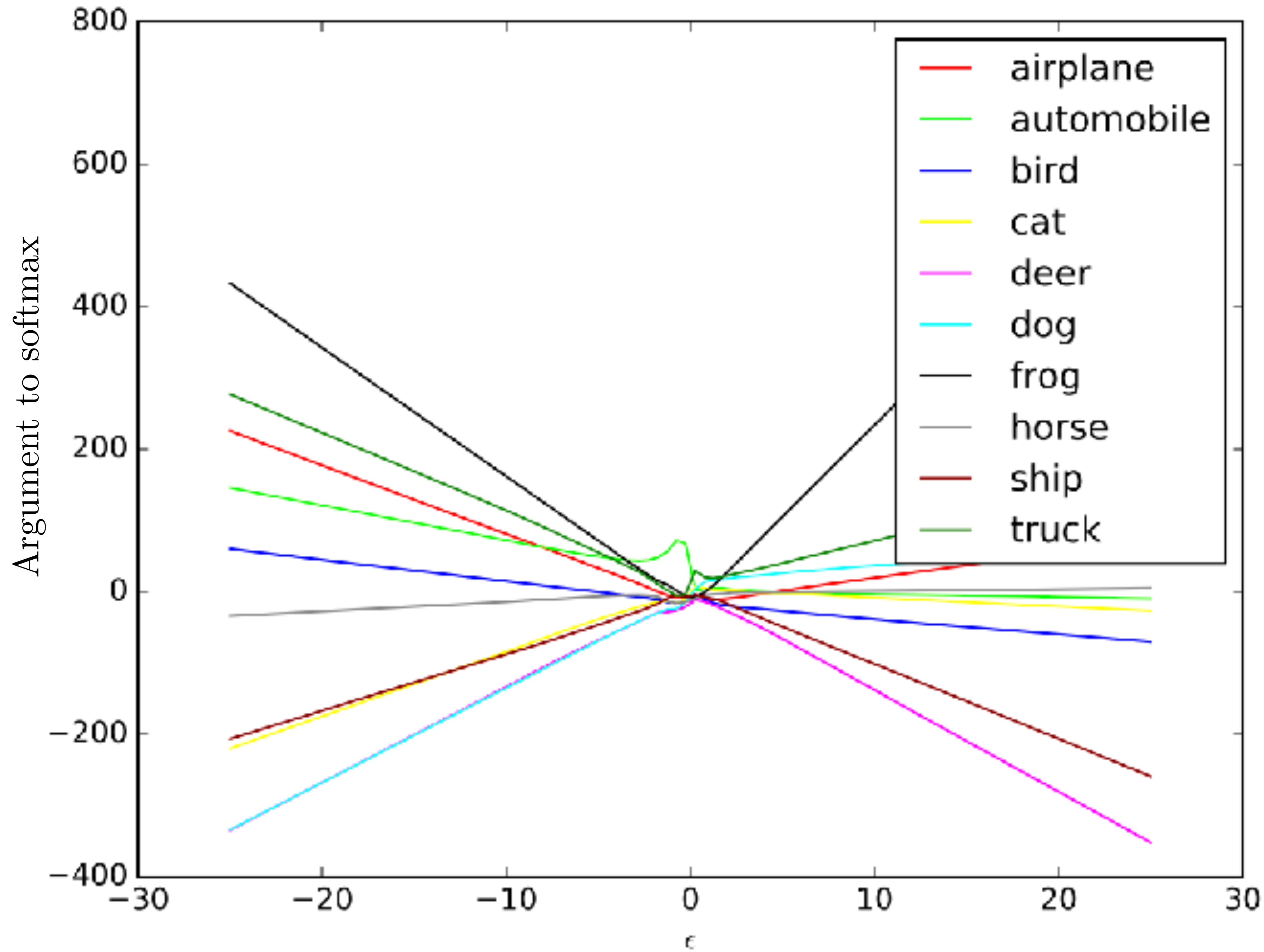


LSTM



Nearly Linear Responses in Practice

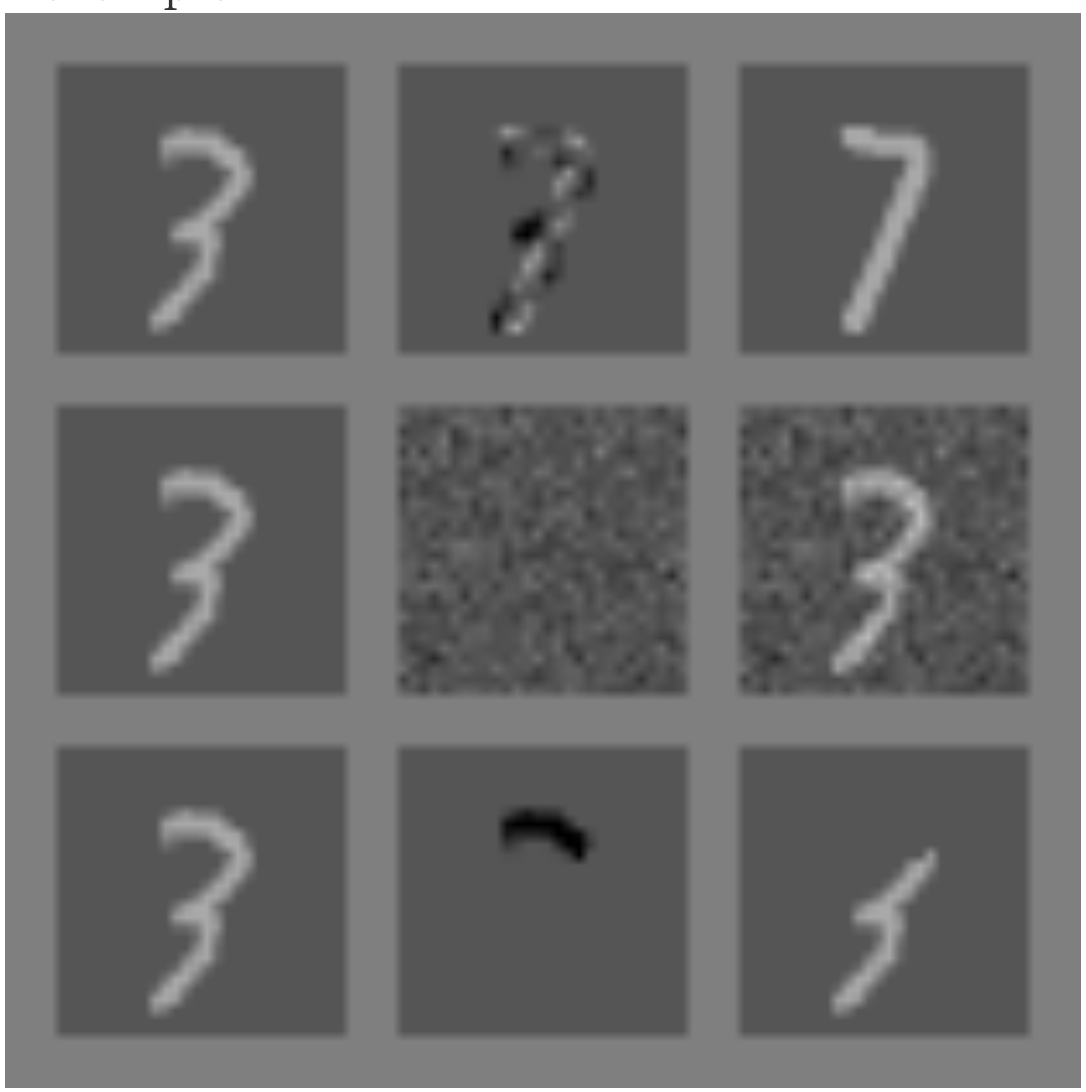




(Goodfellow 2016)

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!

(Goodfellow 2016)

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

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

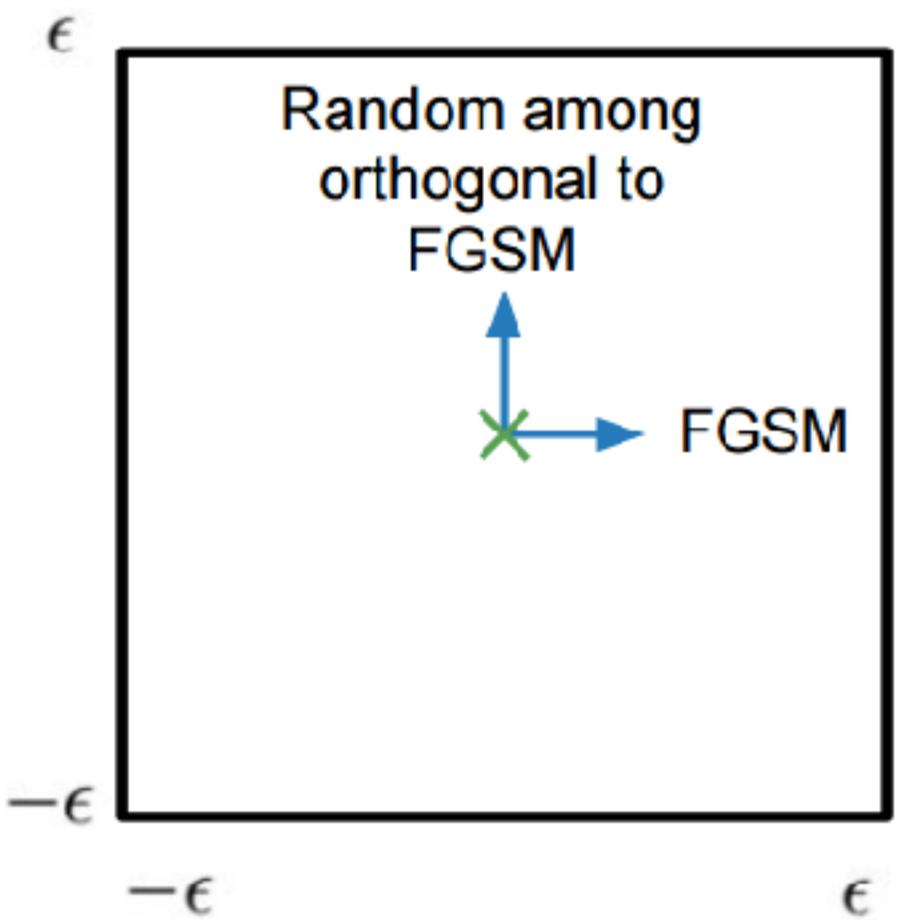
subject to

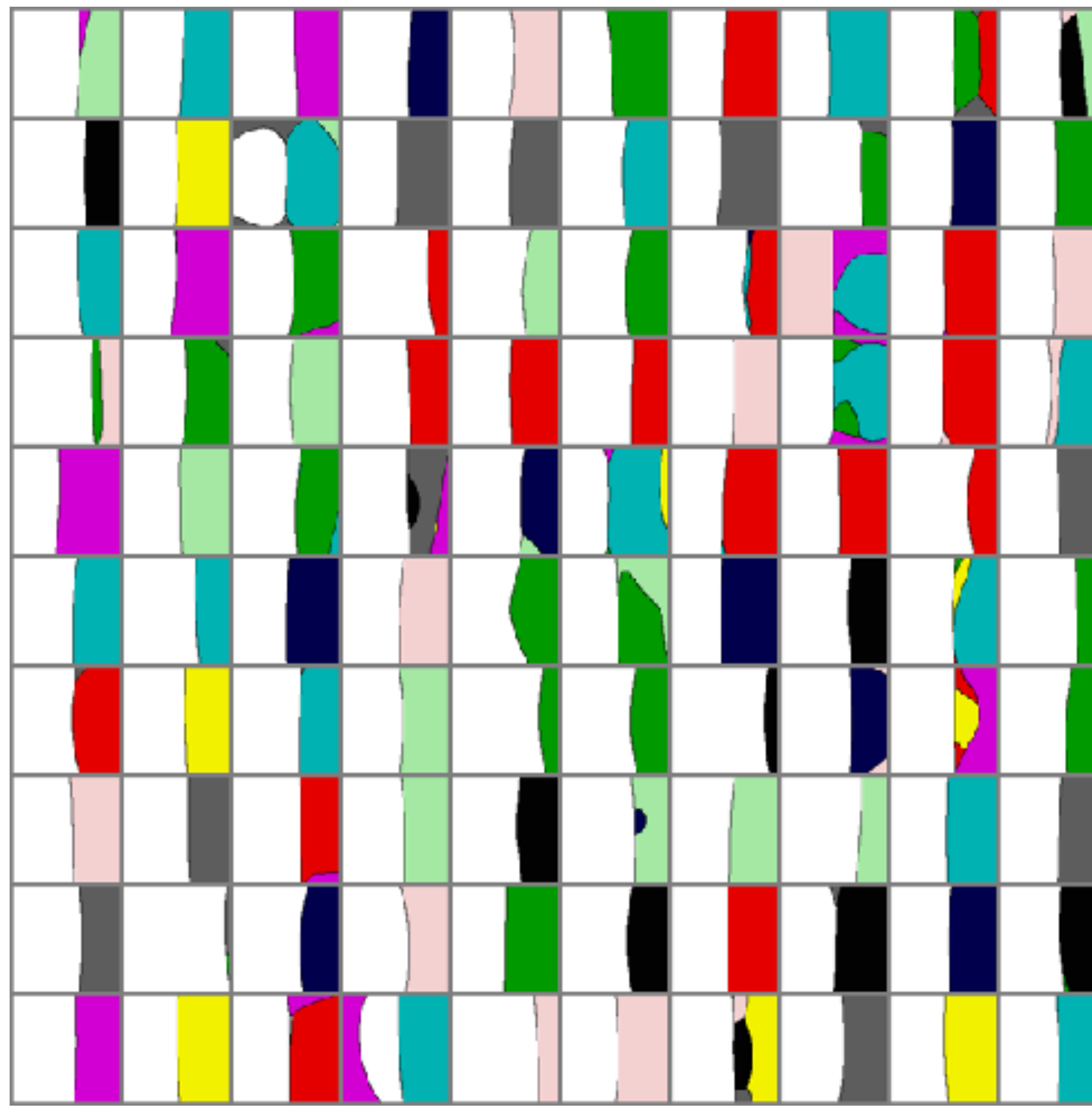
$$||\tilde{\boldsymbol{x}} - \boldsymbol{x}||_\infty \leq \epsilon$$

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

(Goodfellow 2016)

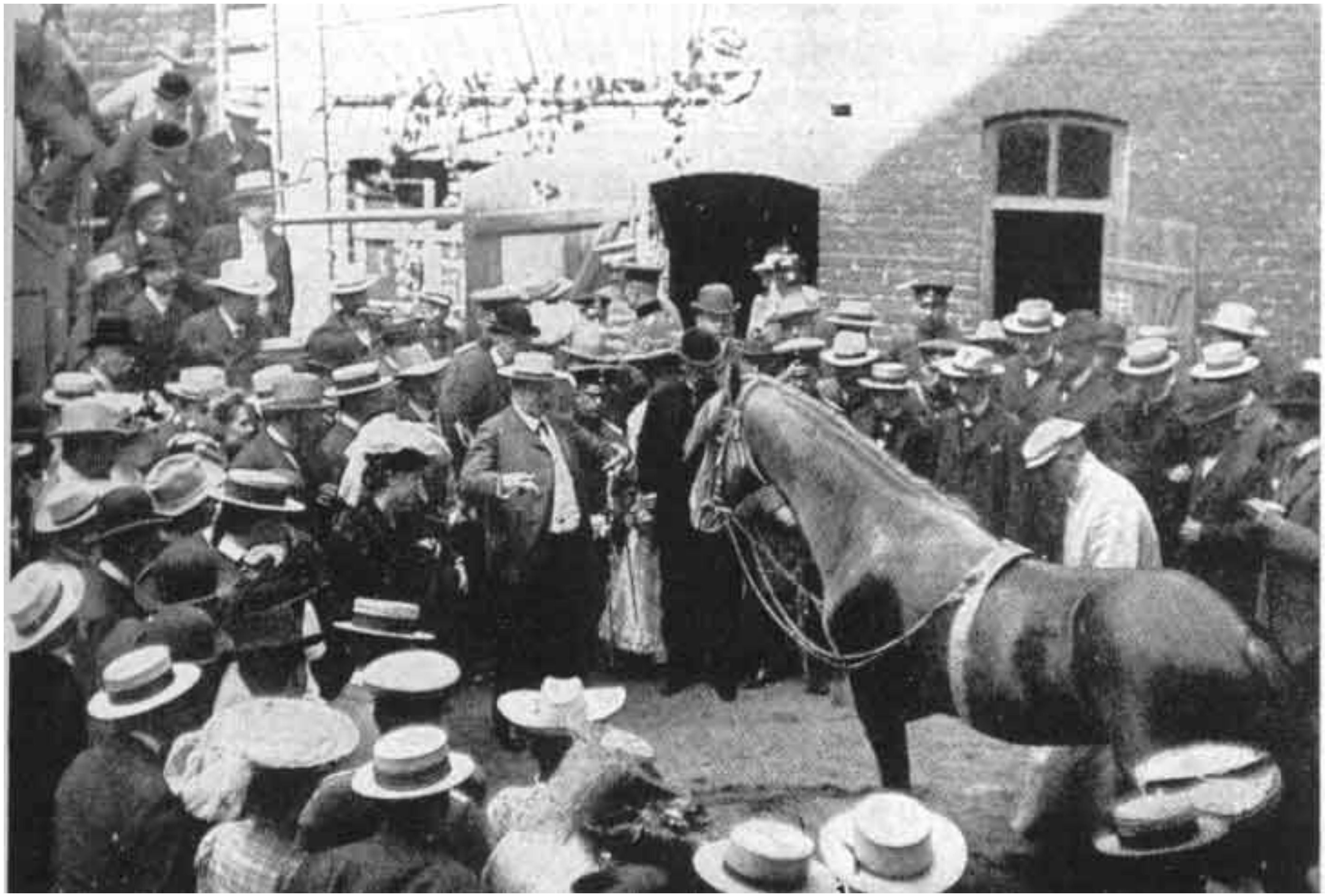
Maps of Adversarial and Random Cross-Sections





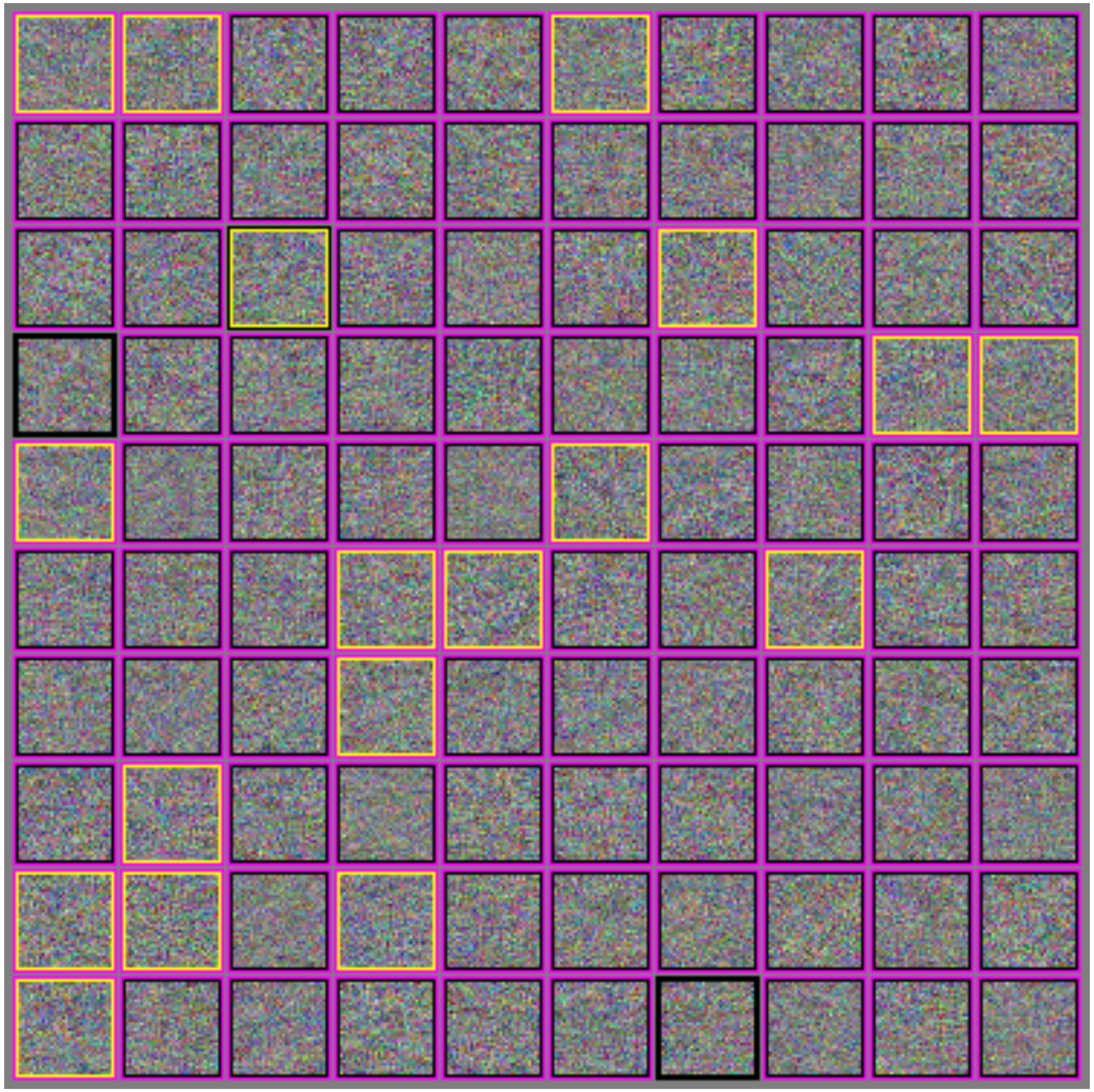
(collaboration with David Warde-Farley and Nicolas Papernot)

Clever Hans



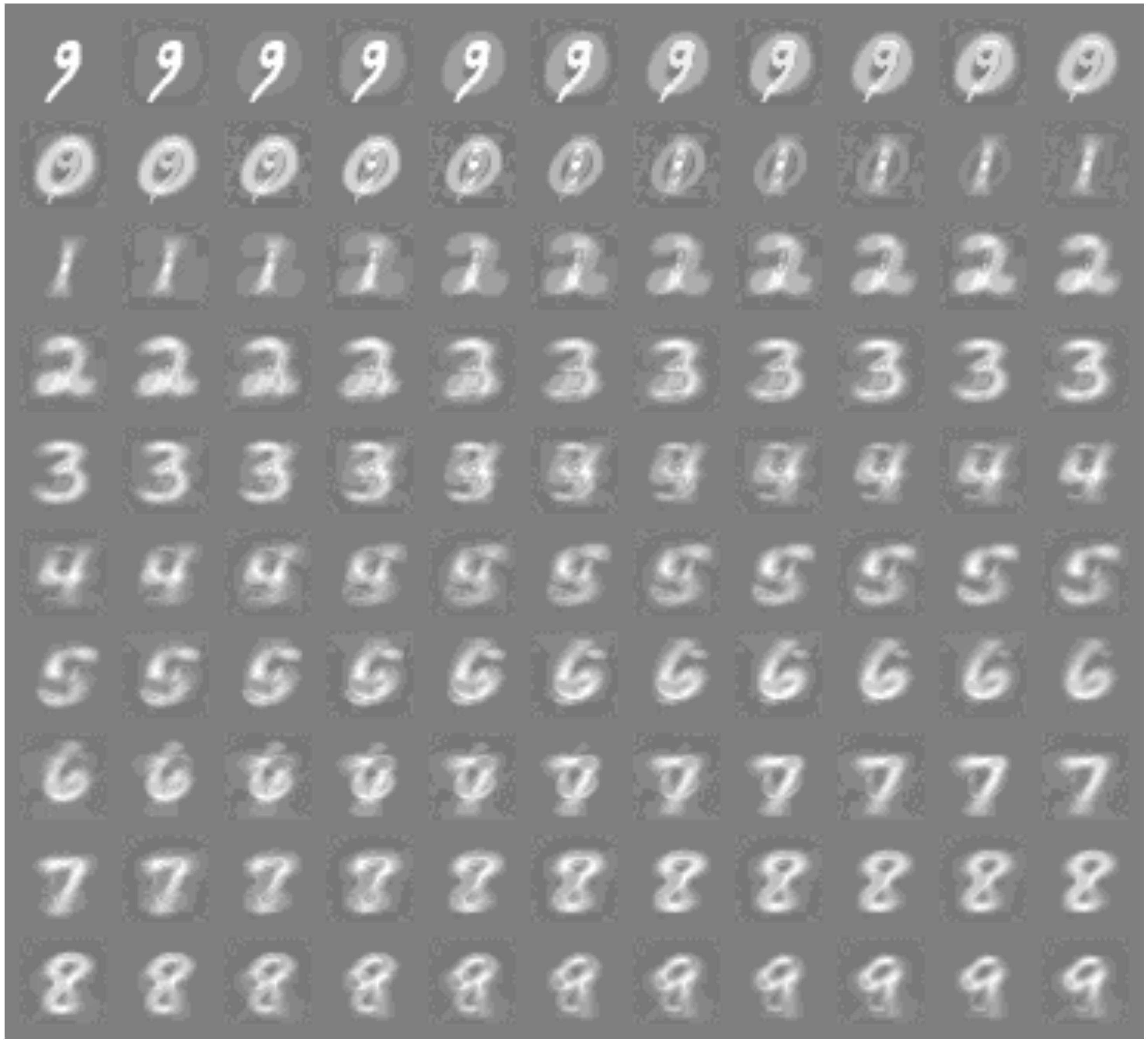
("Clever Hans, Clever Algorithms," Bob Sturm)

Wrong almost everywhere



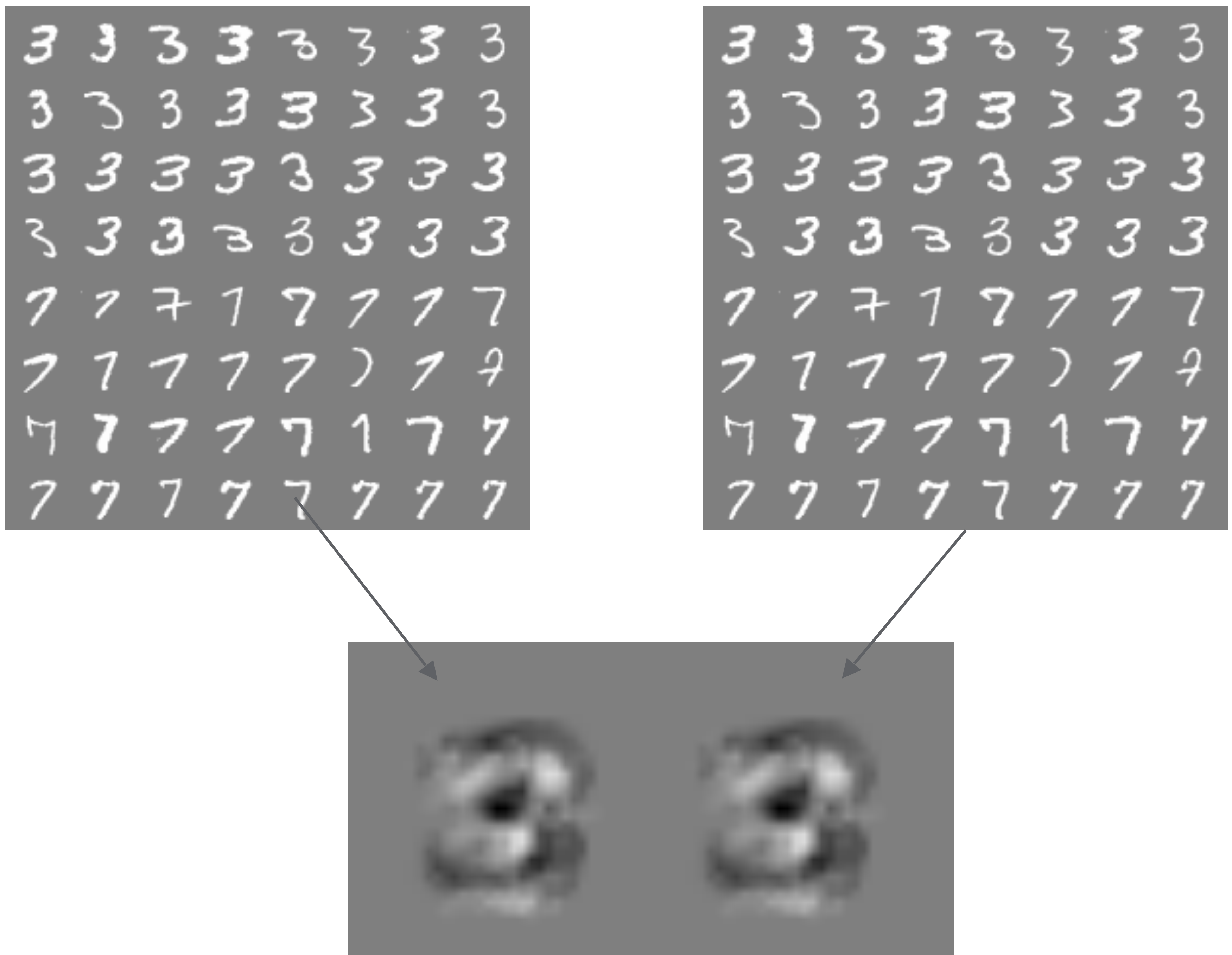
(Goodfellow 2016)

RBFs behave more intuitively



(Goodfellow 2016)

Cross-model, cross-dataset, cross-technique generalization



(Goodfellow 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

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) Printout (b) Photo of printout (c) Cropped image

(Goodfellow 2016)

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

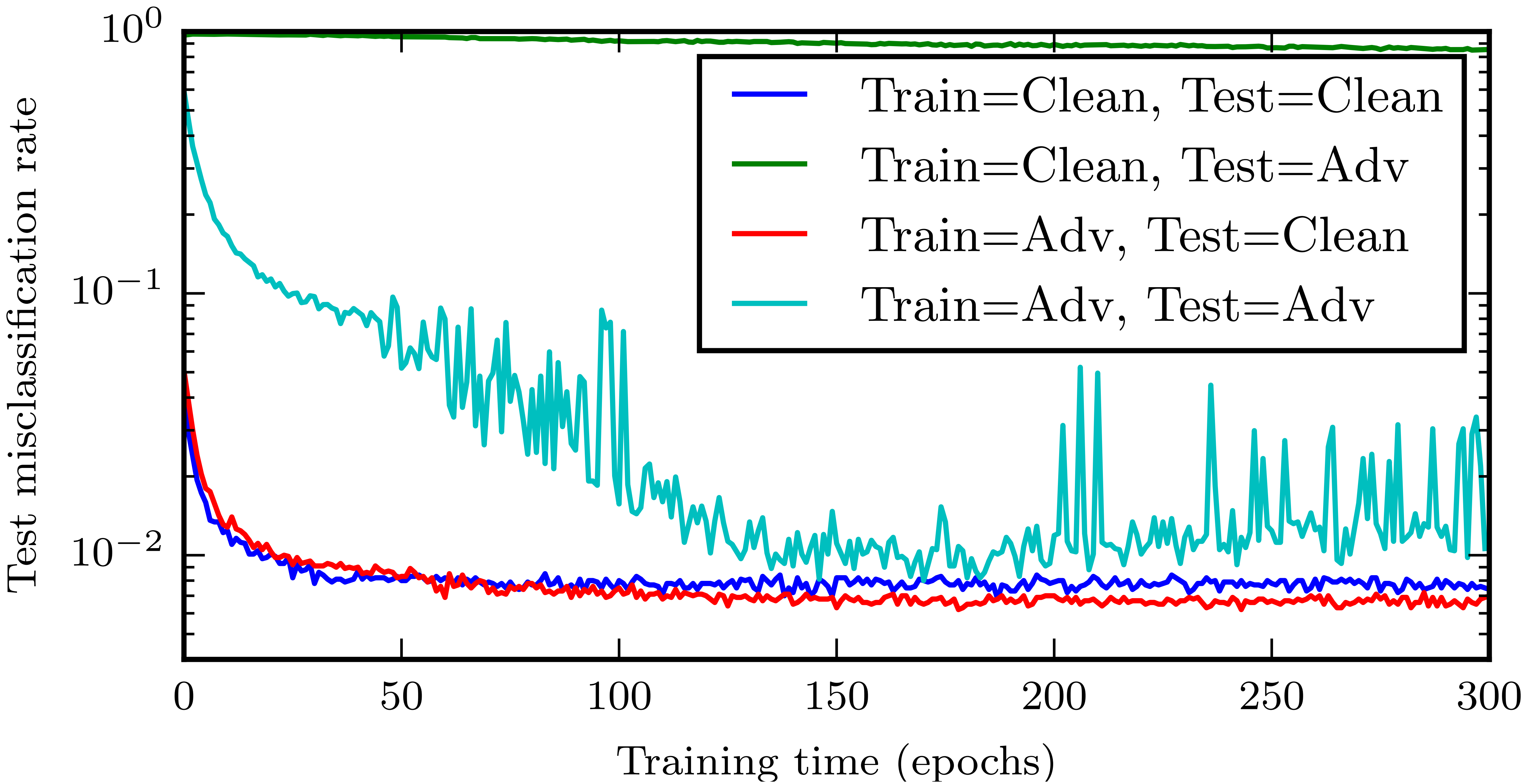
Adding noise at train time

Various non-linear units

Dropout

(Goodfellow 2016)

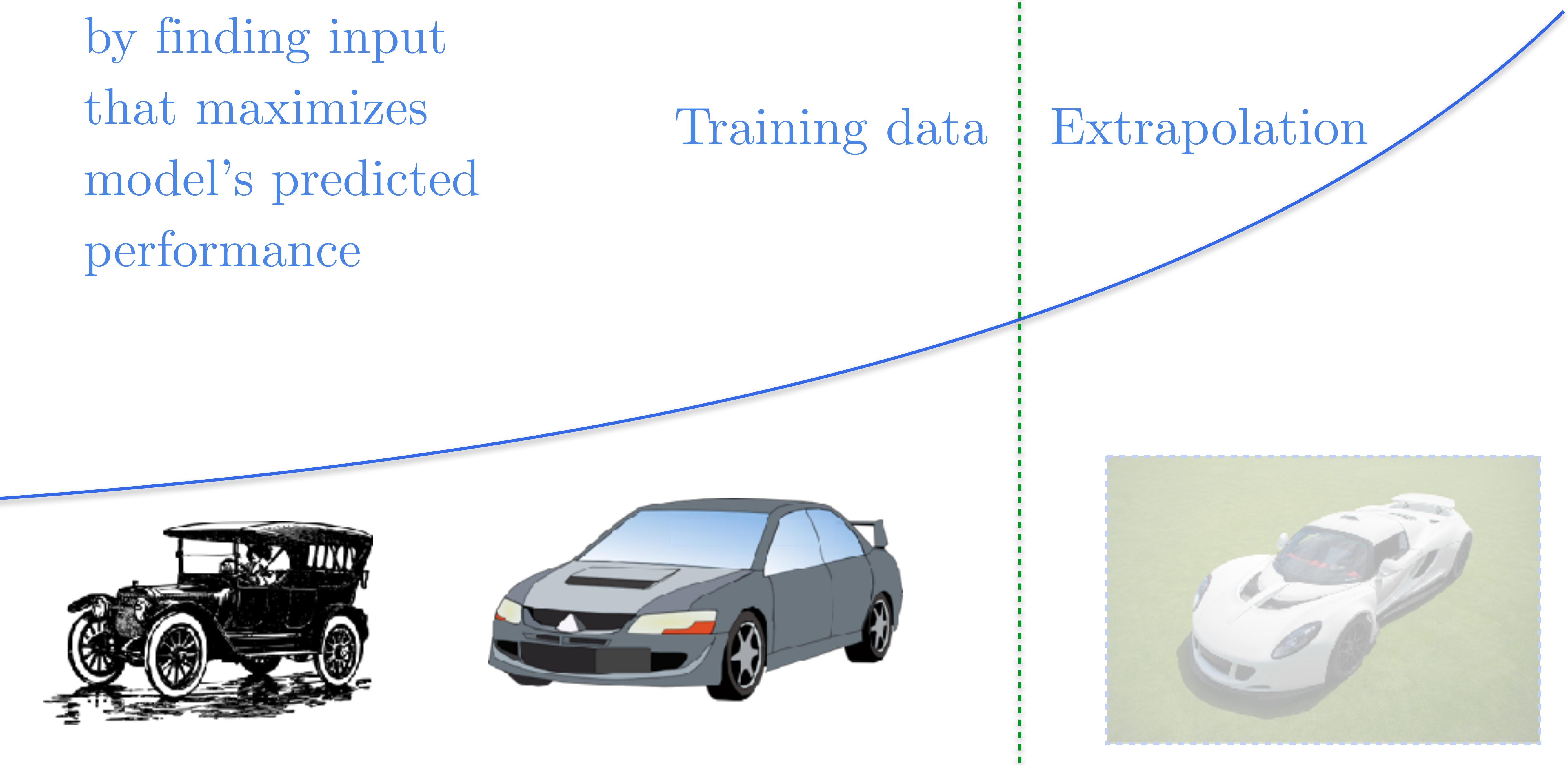
Training on Adversarial Examples



(Goodfellow 2016)

Universal engineering machine (model-based optimization)

Make new inventions by finding input that maximizes model's predicted performance



(Goodfellow 2016)

Conclusion

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

cleverhans

Open-source library available at:

https://github.com/openai/cleverhans

Built on top of TensorFlow (Theano support anticipated)

Standard implementation of attacks, for adversarial training and reproducible benchmarks

cleverhans

(Goodfellow 2016)