Deep Neural Networks are easily fooled

High Confidence Predictions for Unrecognizable Images

a paper of Anh Nguyen, Jason Yosinski, Jeff Clune

presented by Nils Wenzler
General idea: Fooling neural networks

from “Intriguing properties of neural networks” by Szegedy et al.
General idea:
Generate pictures that AI can “see” but humans not

What is this?
I’m sure it’s an electric guitar!
But why?

Original goal:

- Visualize DNN perception
- Explain to what kind of features DNNs react to

Extended goal:

- Explain why DNNs are so easily fooled
- Research how to possibly improve resilience and robustness
Structure

Chapter 1: How to create fooling pictures?
Chapter 2: How do nowadays networks “see”?  
Chapter 3: How to defend against adversarial pictures?  
Chapter 4: Lessons learned
Chapter 1: How to create fooling pictures?

Data sets:

MNIST

ImageNet
Chapter 1: How to create fooling pictures?

3 approaches:

direct model

indirect model

gradient ascend
Direct model

Learn all pixels with evolutionary algorithm

Results:

- 99,9% confidence that images are numbers (MNIST)
- Performance in ImageNet classification not very convincing
Direct model - ImageNet classification
Indirect model

Evolve on compositional pattern-producing networks (CPPN)
Indirect model

Results:

- 99.9% confidence that images are numbers (MNIST)
Indirect model - ImageNet classification
Gradient ascend

Whitebox approach which mathematically optimizes input image

Works but not further considered because:

- Visualization is hard to understand
- Danger of being very network specific
Chapter 2: How do neural networks “see”?  

They “see” differently than human beings
Feature size

5 times a 99.9% confidence remote control:

Tend to react to medium sized features but not whole structures
Adversarial images generalize to other networks

Some adversarial images trained for a DNN can fool another DNN as well. Some images will only fool one of them.

⇒ DNNs tend to observe similar features
Repeated instances

Several instances seem to improve confidence
Dogs are hard to differentiate
Chapter 3: How do defend against adversarial pictures?

Just add adversarial pictures to training set with adversarial class?

- still easily fooled for MNIST digit recognition task
- learned to classify CPPN pictures for ImageNet (no exhaustive defense)
What’s the problem?

Image classification has a very high input space but significantly lower intrinsic dimensionality

If you create a random picture, how would it look like?
Discriminative versus Generative approaches

\[ p(y|X) \text{ versus } p(y, X) \]
Chapter 4: Lessons learned

Neural networks currently

- learn medium sized features
- can easily be fooled
- become more confident through feature repetition
Chapter 4: Lessons learned

Adversarial images

- can be hidden in perfectly normal pictures
- can be abstract images
- can generalize to other networks
- can not be dealt with by adding them to the training set
Chapter 4: Lessons learned

Furthermore,

- natural images have lower intrinsic dimensionality
- generative models may be more robust than discriminative models
- bigger and more diverse training sets make fooling harder
Neural networks as artists?
Thanks for your attention

Let’s discuss the paper:

● natural images have lower intrinsic dimensionality
● generative models may be more robust than discriminative models
● bigger and more diverse training sets make fooling harder