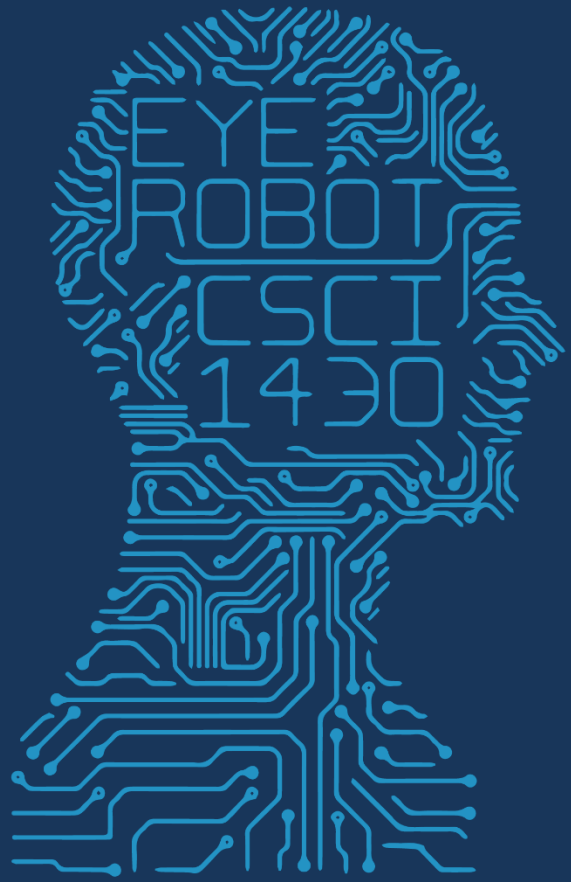
1950

Future Vision



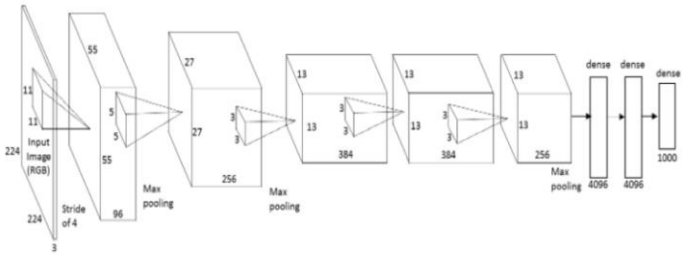
2020

Computer Vision

Russell, 2009

Simultaneous contrast

Training Neural Networks



- Build network architecture and define loss function
- Pick hyperparameters – learning rate, batch size
- Initialize weights + bias in each layer randomly

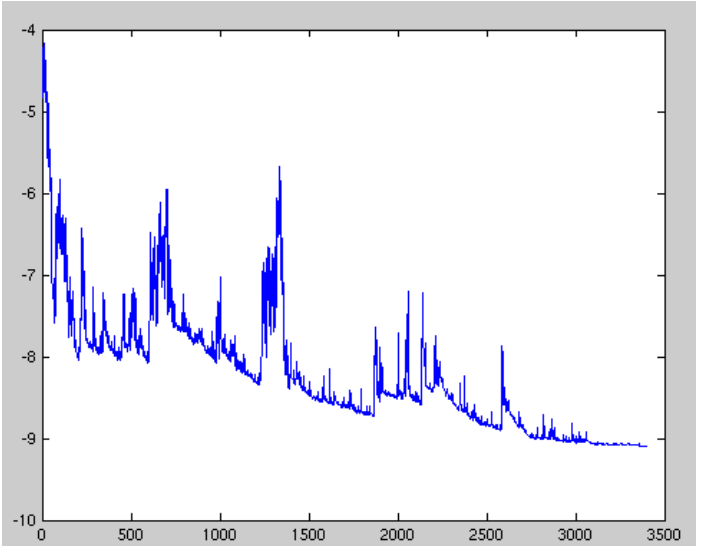
- While loss still decreasing
  - Shuffle training data
  - For each data point *i=1…n (maybe as mini-batch)*
    - *Gradient descent*
  - Check validation set loss

"Epoch"

Stochastic Gradient Descent

Try to speed up processing with random training subsets

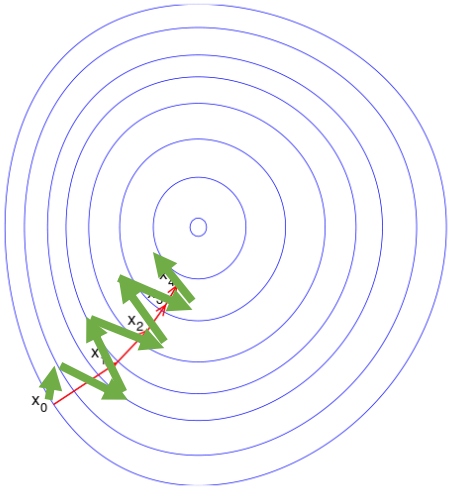
Loss will not always decrease (locally) as training data point is random, but converges over time.



Momentum

Gradient descent step size is weighted combination over time to dampen ping pong.

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \gamma\left(\alpha\left[\frac{\partial L}{\partial \boldsymbol{\theta}}\right]_{t-1} + \left[\frac{\partial L}{\partial \boldsymbol{\theta}}\right]_t\right)$$



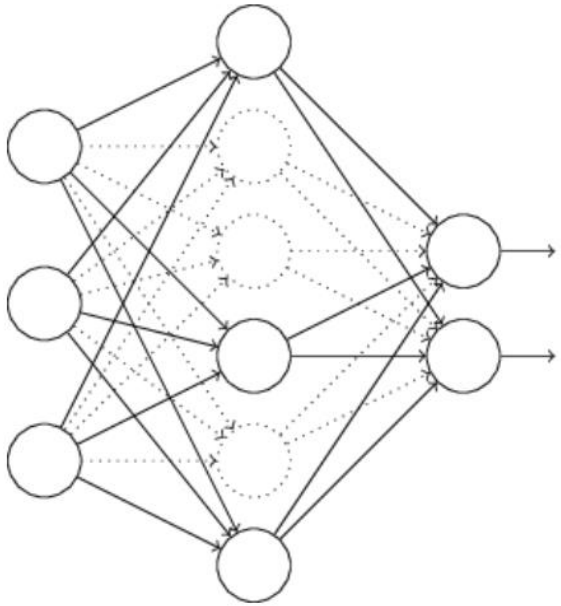
Wikipedia

Regularization

- Penalize weights for simpler solution
  - Occam's razor

$$C = C_0 + \lambda \sum_w w^2,$$

- Dropout half of neurons for each minibatch
  - Forces robustness



But James…

…I thought we were going to treat machine learning like a black box? I like black boxes.

Deep learning is:
- a black box
- *also a black art*.

- Grad student
  gradient descent : (

http://www.isrtv.com/

Why do we initialize the weights randomly?

What if we set zero weights?

Setting zero weights makes all neurons equivalent as there is no difference in the gradient computed across neurons. Called “symmetric updates”.

Setting zero bias is OK.
Typically, we *standardize* the data beforehand by subtracting the mean and dividing by std. dev.

$$x' = \frac{x - \bar{x}}{\sigma}$$

Where $\bar{x}$ is the mean *of the input feature across the dataset* (not spatially across the image)

Thus, a zero bias is a good initialization.

Why do we initialize the weights randomly?

What if we set zero weights?

Wx = 0 for the layer output

-> produces uniform softmax output (each class equally probable; i.e., on MNIST, 0.1)

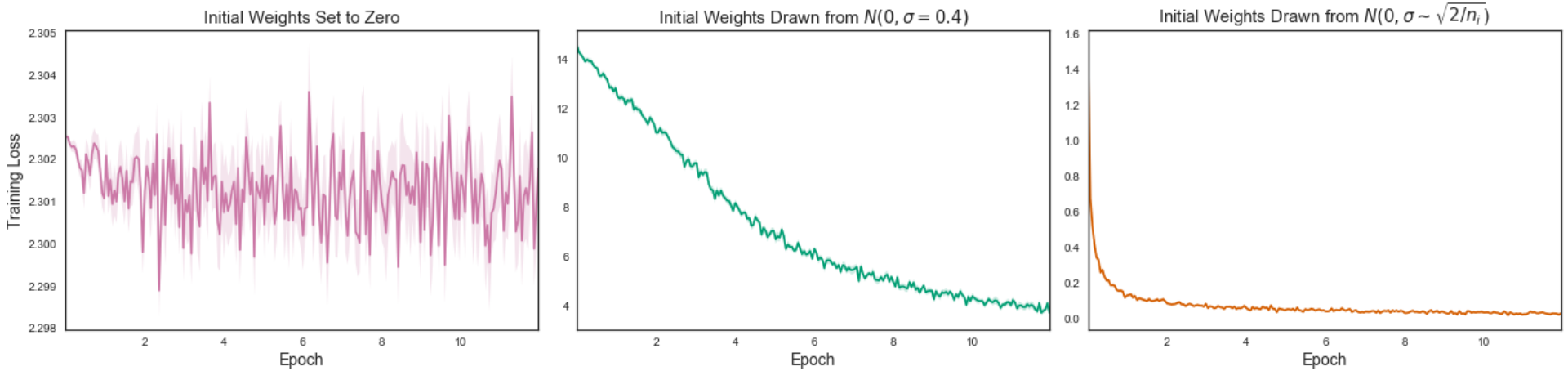
Gradient update rule and supervision label y_j still provides the right signal

p_j *vs* $1 - p_j$

…but all neurons not of class j receive same gradient update.

So what is a good initialization of the weights?

In general, initialization is very important.



Good strategy: He et al. 2015:

For ReLU, draw random weights from Gaussian distribution with variance = 2 / # inputs to layer

[Image Andre Perunicic]

What is activation function for?

To allow multiple layers; to avoid resulting composition of linear functions collapsing to a single layer.

Difference between CNN and convolution in feature extraction?

No difference! Same operation [correlation/convolution]

Why do we shave off pixels?

We only use the valid region of convolution; typically no padding.

Some recent works special case these edge convolutions.

Why multidimensional kernels?

We wish to convolve over the outputs of many other learned kernels -> ‘integrating’ information via weighted sum of previous layer outputs.

How to know which kernels to use in 2nd+ convolution layers?

Gradient descent + back propagation learns them.

How to set weights on fully connected layers?

Gradient descent + back propagation learns them.

What even is back propagation again?

Computing the (change in) contribution of each neuron to the loss as the parameters vary.

Project 4 written has some good references.

How do we decide the parameters for network architecture?
For less complicated situations, we can use 'trial and error'.
Is there any other method?

'Grid search' -> trial and error

'Bayesian optimization' -> meta-learning; optimize the hyperparameters

General strategy:

Bottleneck -> extract information (kernel) and learn to squeeze representation into a smaller number of parameters.

But James – I happen to have a thousand GPUs:
Neural Architecture Search!

I've heard about many more terms of jargon!

Skip connections

Residual connections

Batch normalization

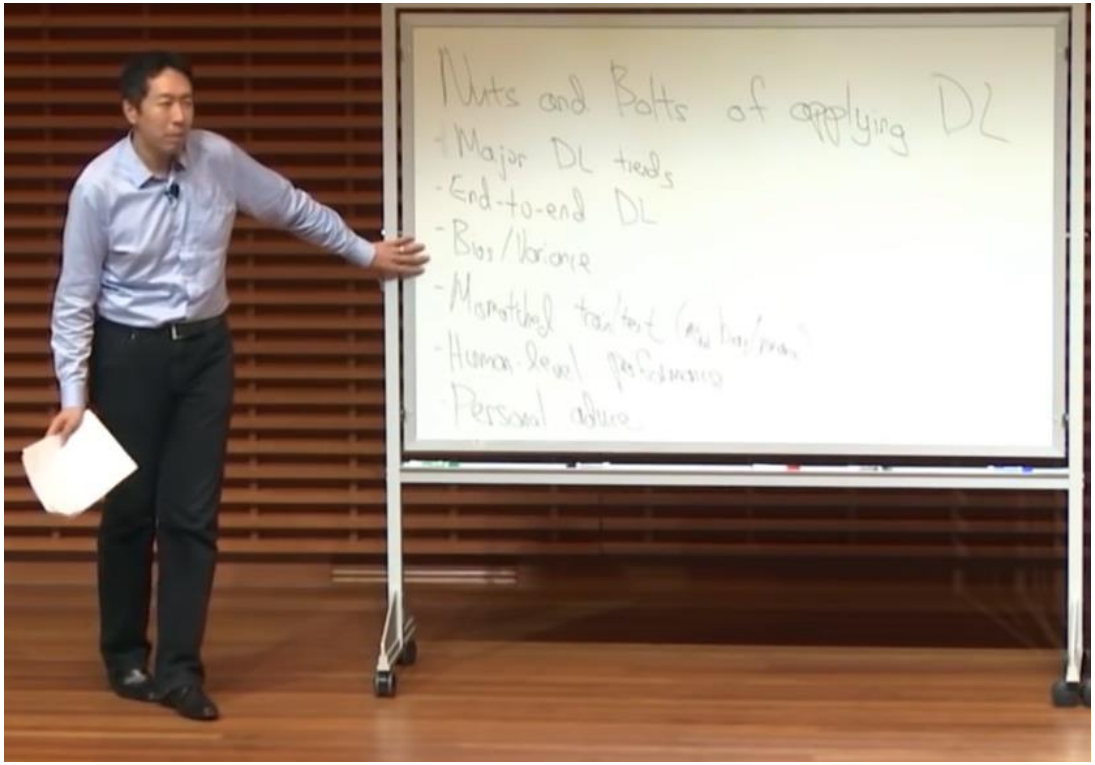
…we'll get to these in a little while.

When something is not working…

…how do I know what to do next?

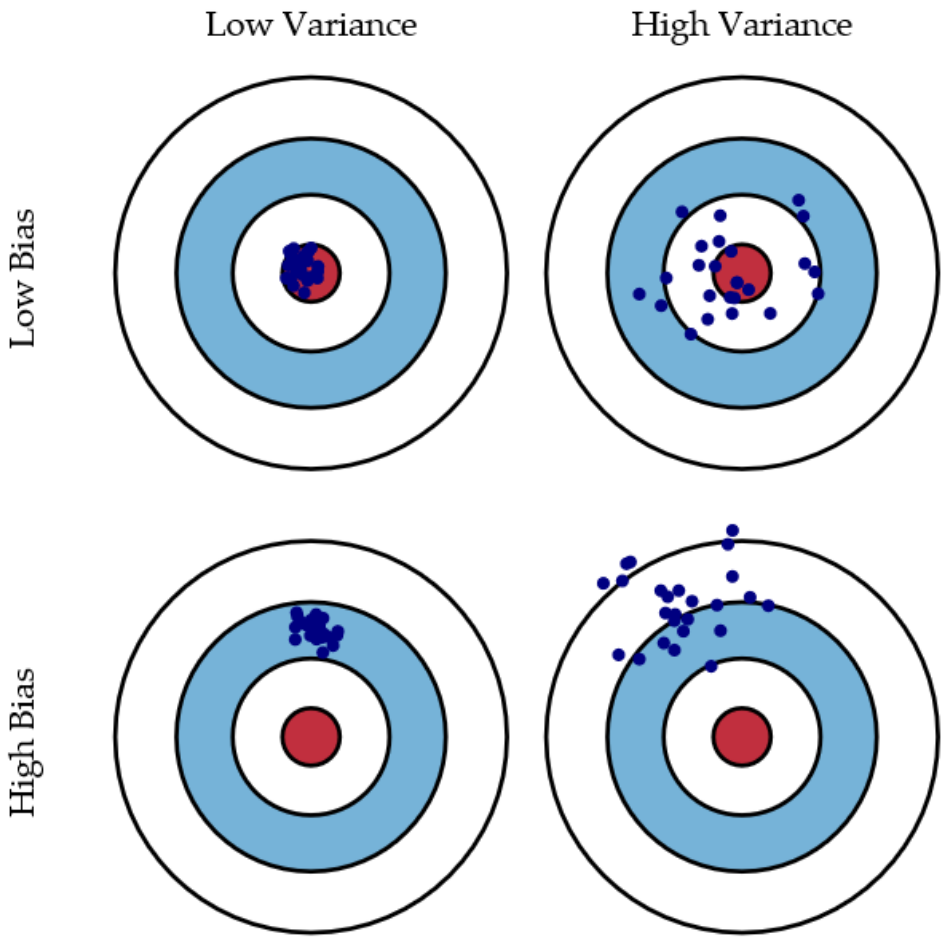
The Nuts and Bolts of Building Applications using Deep Learning

- Andrew Ng - NIPS 2016
- https://youtu.be/F1ka6a13S9I

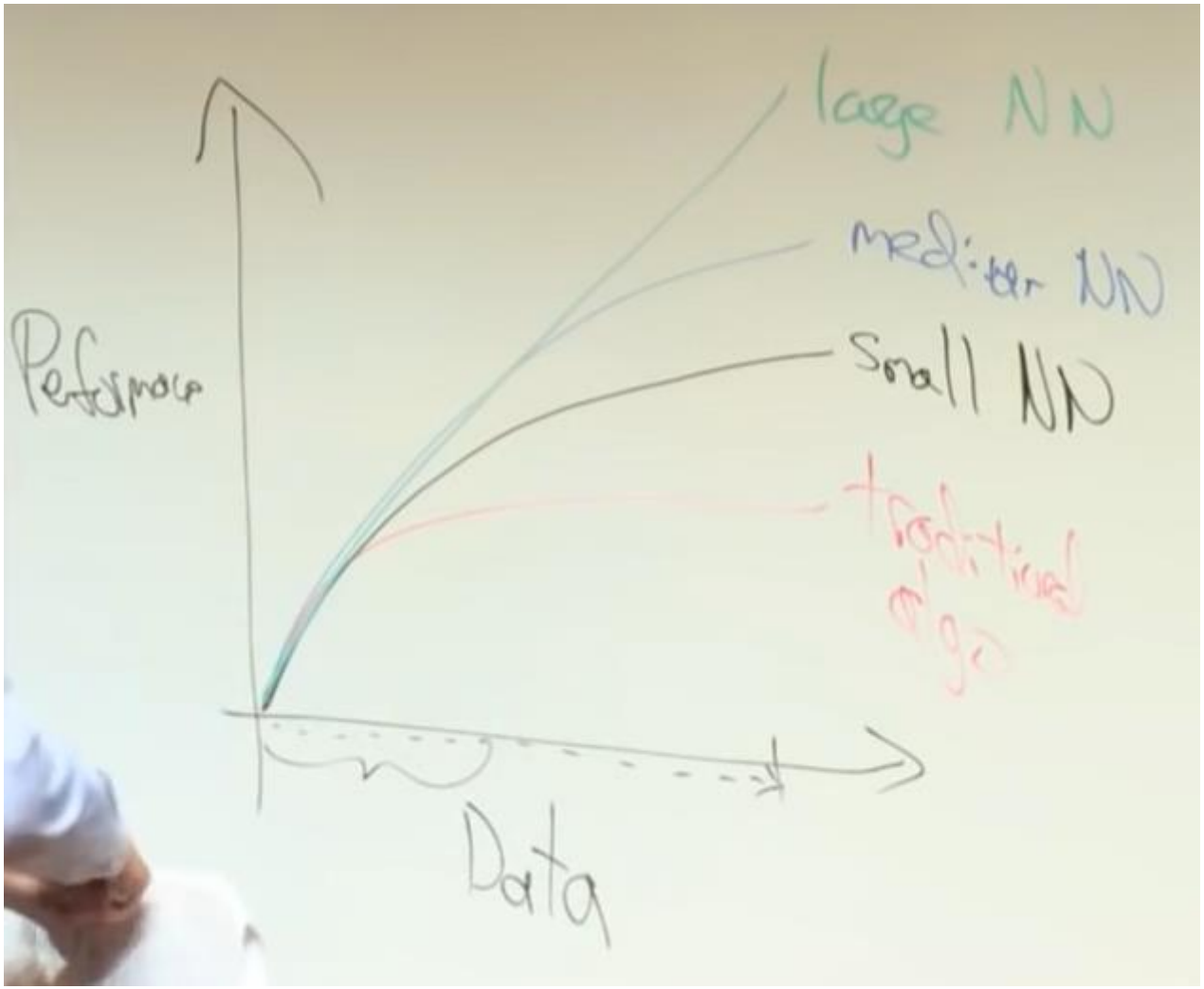


Bias/variance trade-off

"It takes surprisingly long time to grok bias and variance deeply, but people that understand bias and variance deeply are often able to drive very rapid progress." *--Andrew Ng*



Bias = accuracy
Variance = precision


large NN
medium NN
Small NN
traditional algo
Performance
Data

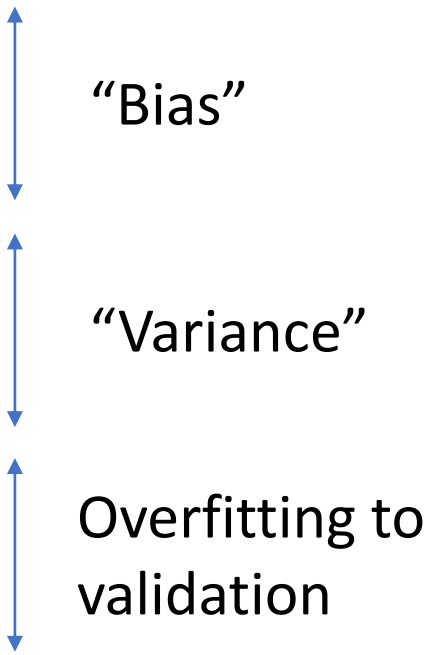
Go collect a dataset

- Most important thing:
  - Training data must represent target application!

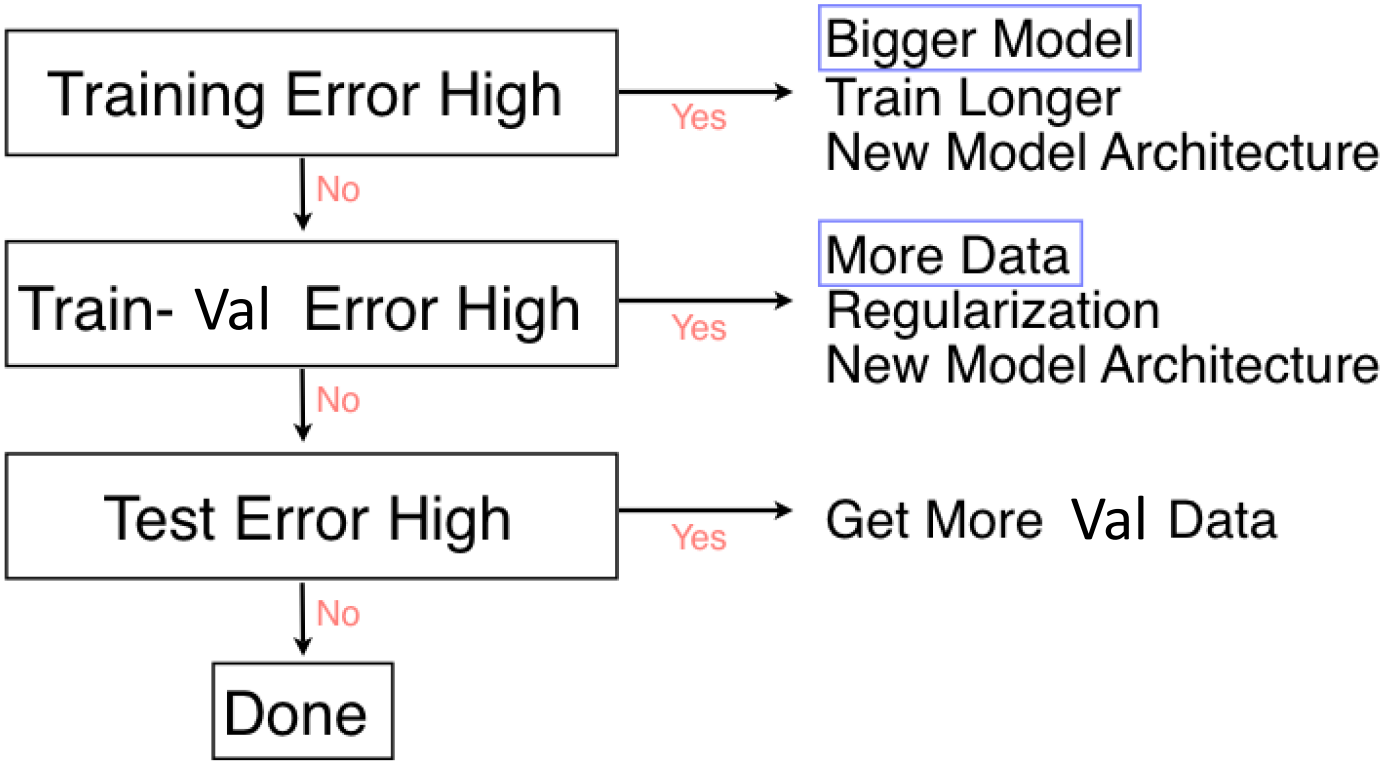
- Take all your data
  - 60% training
  - 40% testing
    - 20% testing
    - 20% validation (or ‘development’)

Properties

- Human level error = 1%
- Training set error = 10%
- Validation error = 10.2%
- Test error = 10.4%



The Nuts and Bolts of Building Applications Using Deep Learning



[Andrew Ng]

My Neural Network isn't working! What should I do?

Created on Aug. 19, 2017, 5:56 p.m.

So you're developing the next great breakthrough in deep learning but you've hit an unfortunate setback: your neural network isn't working and you have no idea what to do. You go to your boss/supervisor but they don't know either - they are just as new to all of this as you - so what now?

Well luckily for you I'm here with a list of all the things you've probably done wrong and compiled from my own experiences implementing neural networks and supervising other students with their projects:

1. You Forgot to Normalize Your Data
2. You Forgot to Check your Results
3. You Forgot to Preprocess Your Data
4. You Forgot to use any Regularization
5. You Used a too Large Batch Size
6. You Used an Incorrect Learning Rate
7. You Used the Wrong Activation Function on the Final Layer
8. Your Network contains Bad Gradients
9. You Initialized your Network Weights Incorrectly
10. You Used a Network that was too Deep
11. You Used the Wrong Number of Hidden Units

Daniel Holden

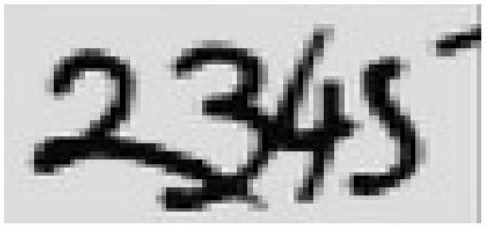
http://theorangeduck.com/page/neural-network-not-working

Outline

- Supervised Neural Networks
- Convolutional Neural Networks
- Examples
- Tips

CONV NETS: EXAMPLES

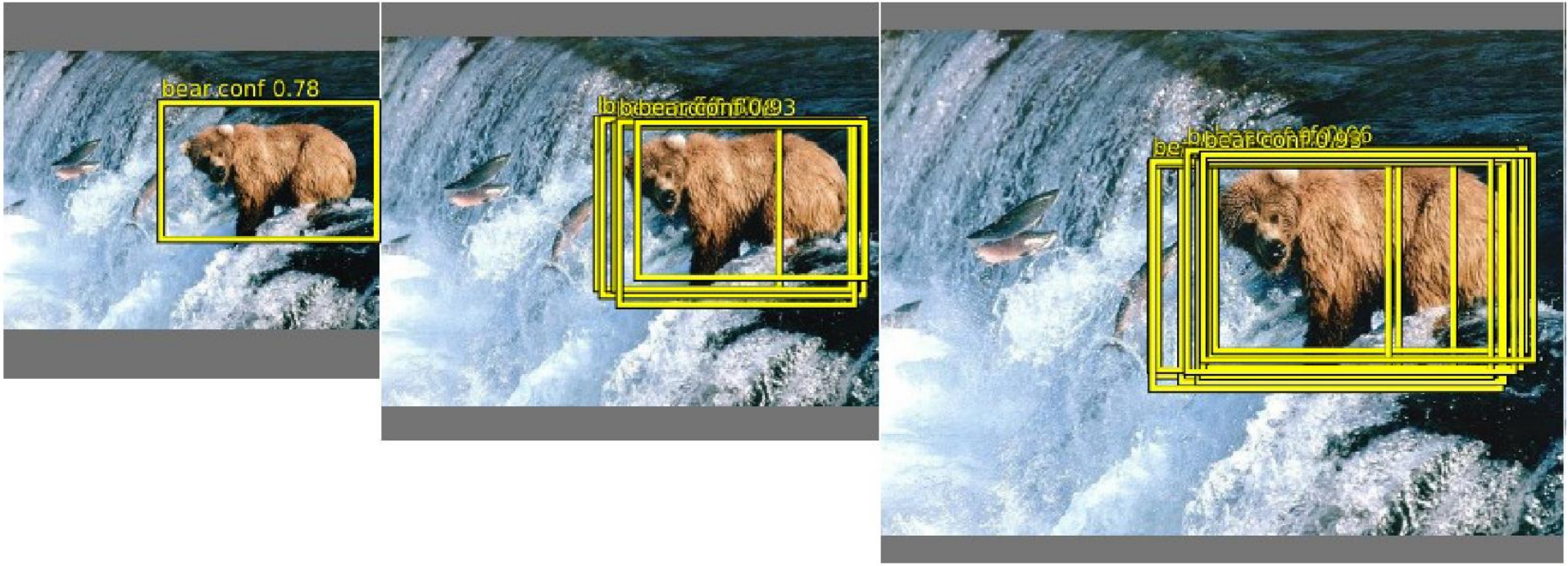
- **OCR / House number & Traffic sign classification**



Ciresan et al. “MCDNN for image classification” CVPR 2012
Wan et al. “Regularization of neural networks using dropconnect” ICML 2013
Jaderberg et al. “Synthetic data and ANN for natural scene text recognition” arXiv 2014

CONV NETS: EXAMPLES

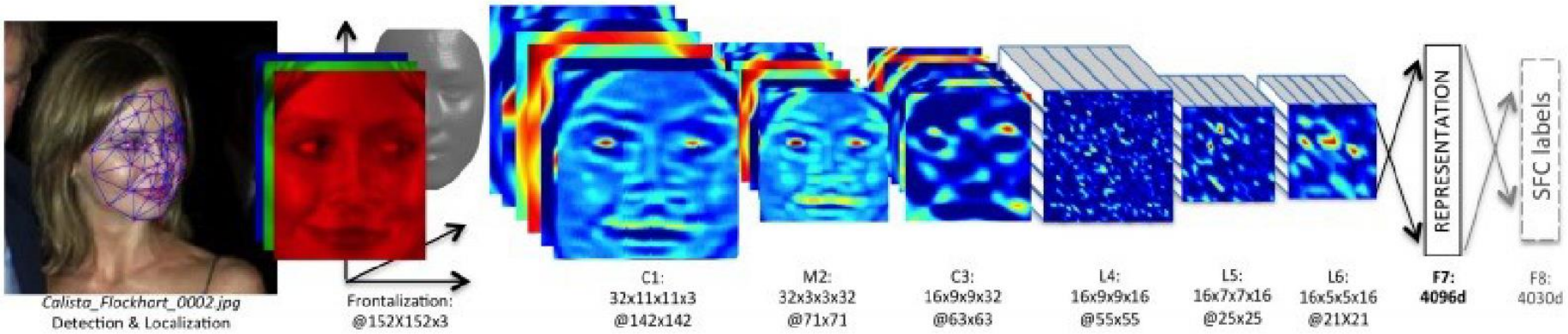
- **Object detection**



Sermanet et al. “OverFeat: Integrated recognition, localization, ...” arxiv 2013
Girshick et al. “Rich feature hierarchies for accurate object detection...” arxiv 2013
Szegedy et al. “DNN for object detection” NIPS 2013

CONV NETS: EXAMPLES

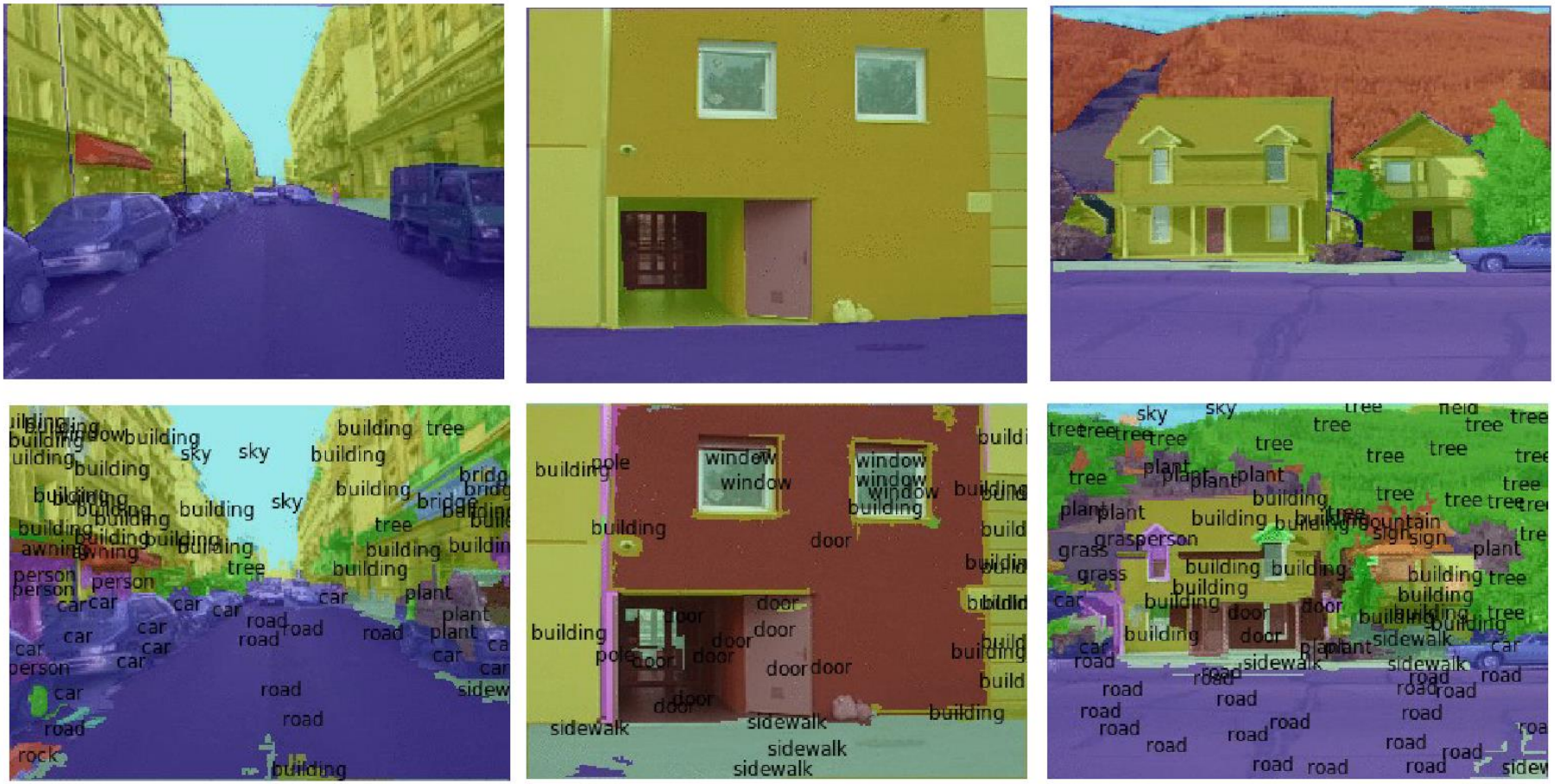
- **Face Verification & Identification**



Taigman et al. "DeepFace..." CVPR 2014

CONV NETS: EXAMPLES

- **Scene Parsing**

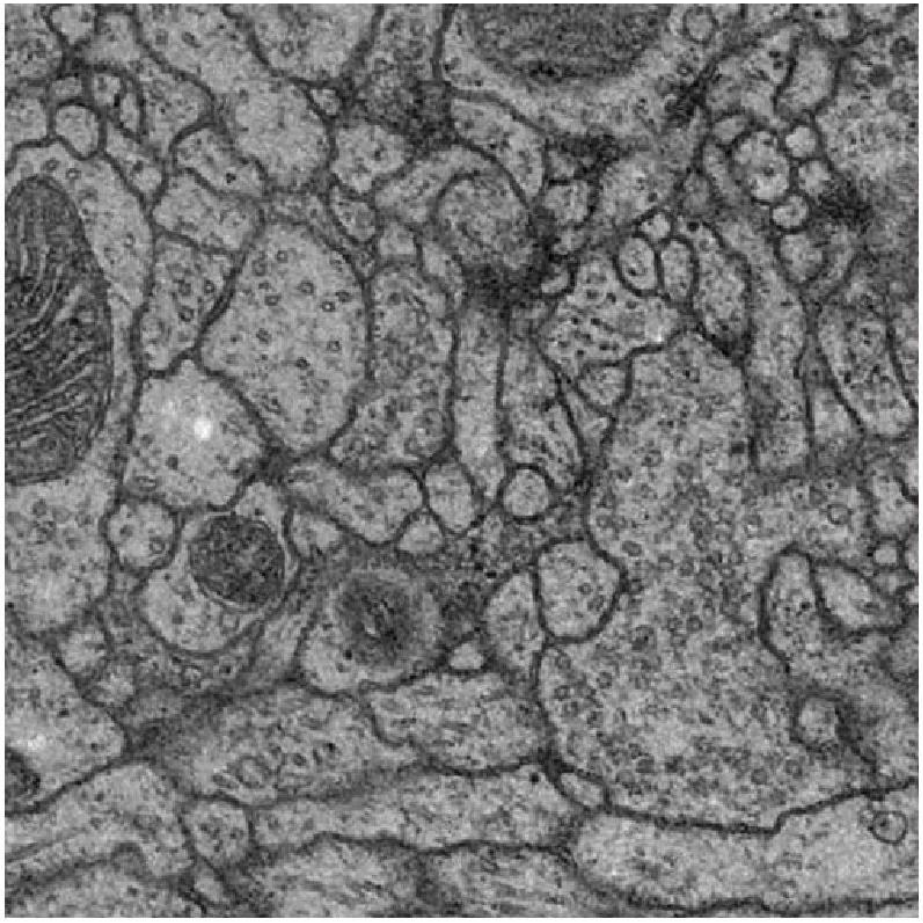


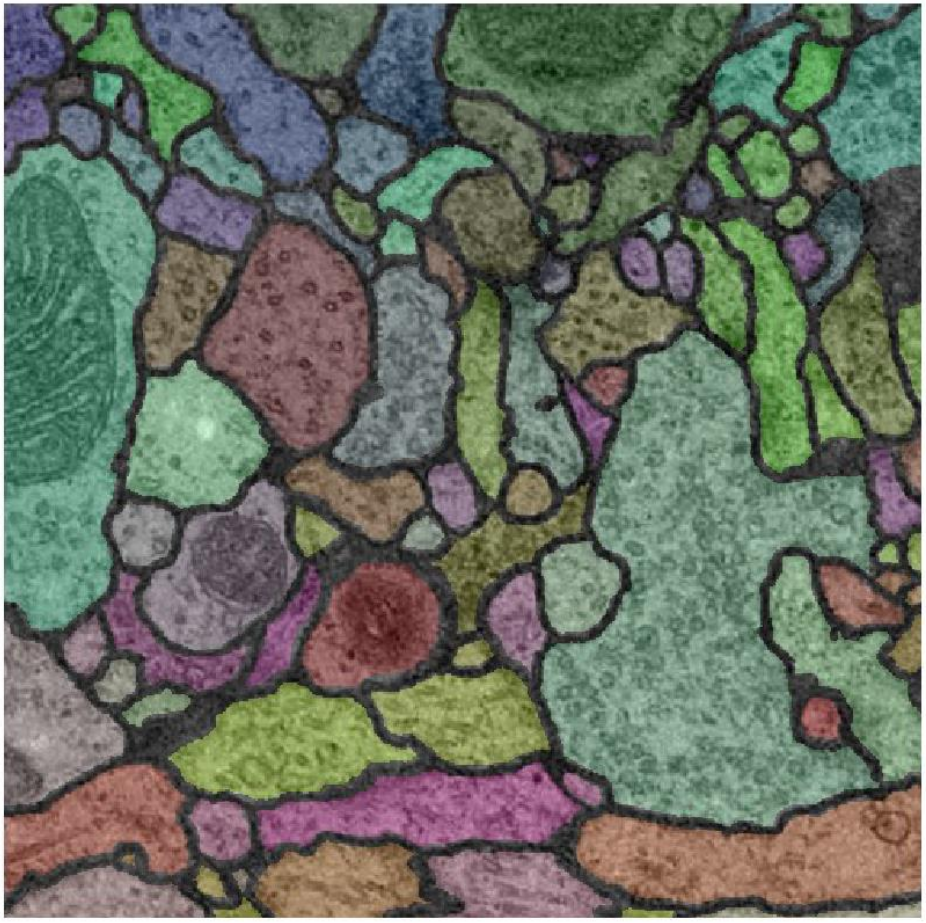
Farabet et al. “Learning hierarchical features for scene labeling” PAMI 2013

Pinheiro et al. “Recurrent CNN for scene parsing” arxiv 2013

CONV NETS: EXAMPLES

- **Segmentation 3D volumetric images**





Ciresan et al. “DNN segment neuronal membranes...” NIPS 2012
Turaga et al. “Maximin learning of image segmentation” NIPS 2009

CONV NETS: EXAMPLES

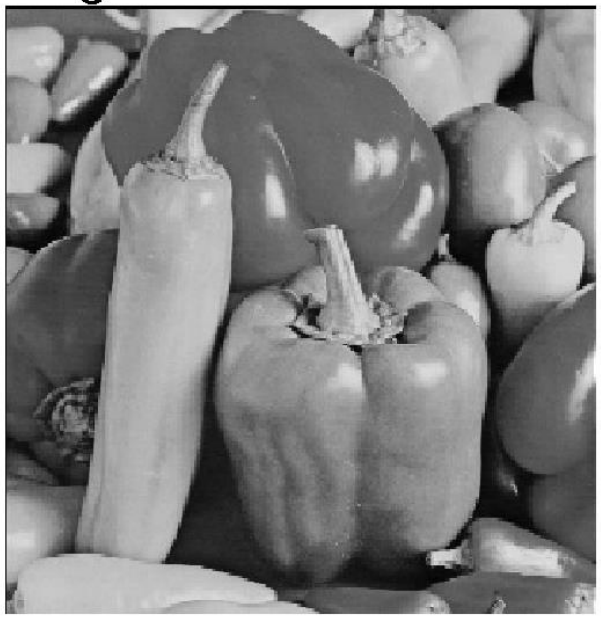
- **Robotics**

Sermanet et al. “Mapping and planning ...with long range perception” IROS 2008

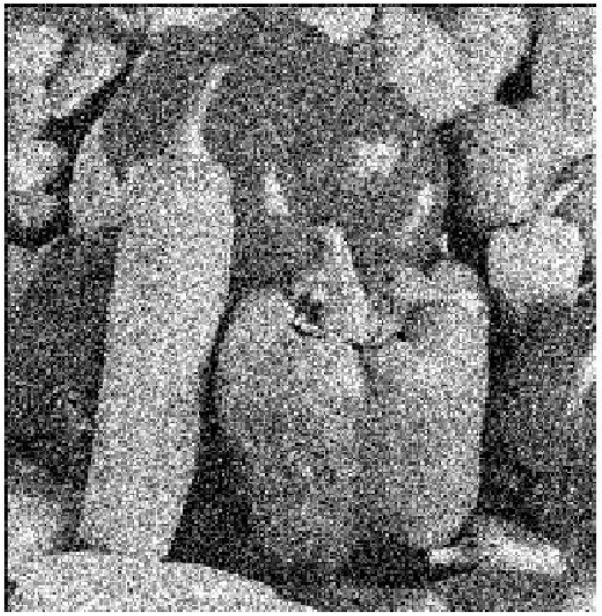
CONV NETS: EXAMPLES

- **Denoising**

original



noised

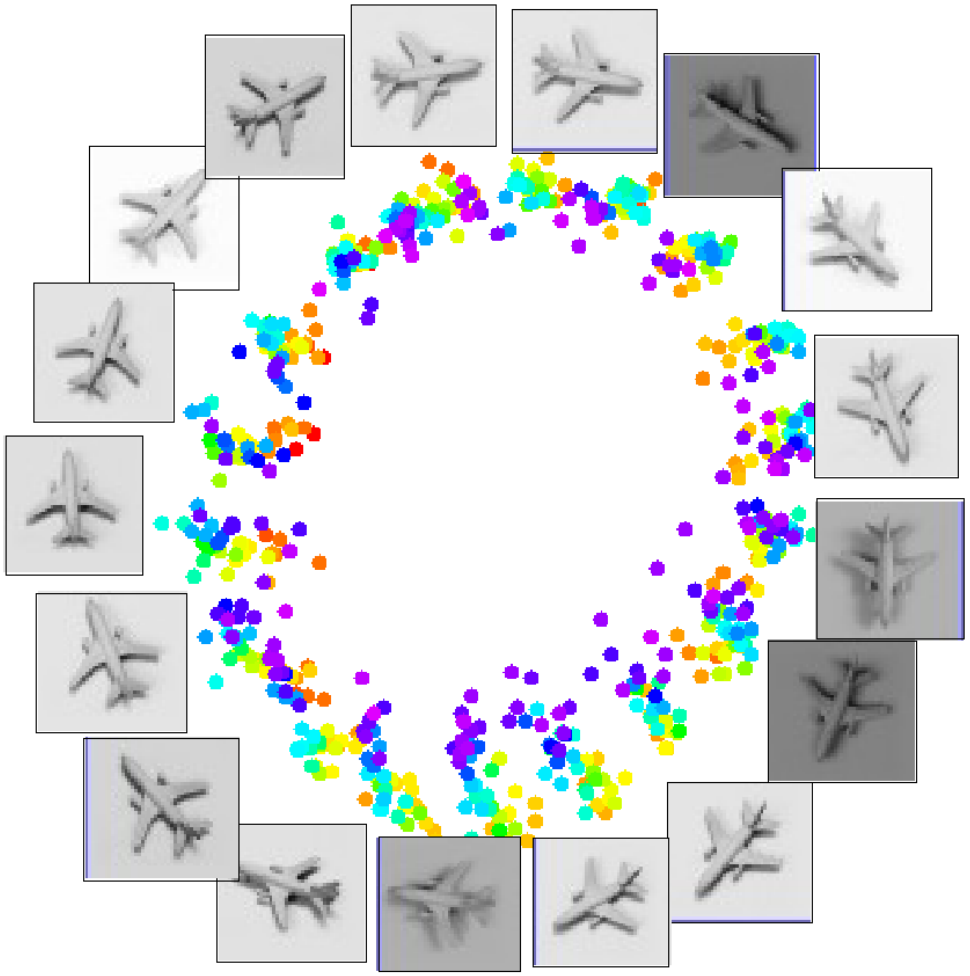


denoised

Burger et al. “Can plain NNs compete with BM3D?” CVPR 2012

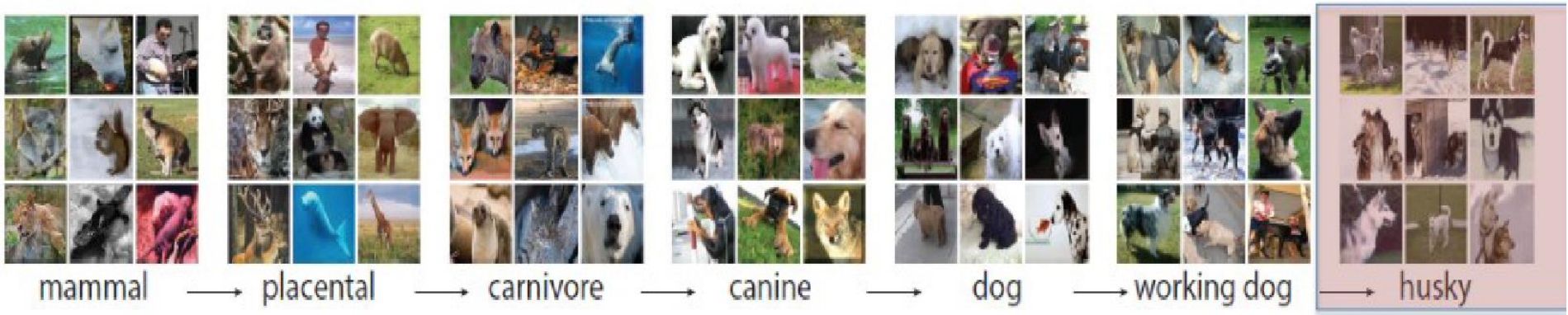
CONV NETS: EXAMPLES

- **Dimensionality reduction / learning embeddings**



Hadsell et al. “Dimensionality reduction by learning an invariant mapping” CVPR 2006

Dataset: ImageNet 2012



- S: (n) Eskimo dog, husky (breed of heavy-coated Arctic sled dog)
  - *direct hypernym / **inherited hypernym** / sister term*
    - S: (n) working dog (any of several breeds of usually large powerful dogs bred to work as draft animals and guard and guide dogs)
      - S: (n) dog, domestic dog, Canis familiaris (a member of the genus Canis (probably descended from the common wolf) that has been domesticated by man since prehistoric times; occurs in many breeds) *"the dog barked all night"*
        - S: (n) canine, canid (any of various fissiped mammals with nonretractile claws and typically long muzzles)
          - S: (n) carnivore (a terrestrial or aquatic flesh-eating mammal) *"terrestrial carnivores have four or five clawed digits on each limb"*
            - S: (n) placental, placental mammal, eutherian, eutherian mammal (mammals having a placenta; all mammals except monotremes and marsupials)
              - S: (n) mammal, mammalian (any warm-blooded vertebrate having the skin more or less covered with hair; young are born alive except for the small subclass of monotremes and nourished with milk)
                - S: (n) vertebrate, craniate (animals having a bony or cartilaginous skeleton with a segmented spinal column and a large brain enclosed in a skull or cranium)
                  - S: (n) chordate (any animal of the phylum Chordata having a notochord or spinal column)
                    - S: (n) animal, animate being, beast, brute, creature, fauna (a living organism characterized by voluntary movement)
                      - S: (n) organism, being (a living thing that has (or can develop) the ability to act or function independently)
                        - S: (n) living thing, animate thing (a living (or once living) entity)
                          - S: (n) whole, unit (an assemblage of parts that is regarded as a single entity) *"how big is that part compared to the whole?"; "the team is a unit"*
                            - S: (n) object, physical object (a tangible and visible entity; an entity that can cast a shadow) *"it was full of rackets, balls and other objects"*
                              - S: (n) physical entity (an entity that has physical existence)
                                - S: (n) entity (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))

Deng et al. “Imagenet: a large scale hierarchical image database” CVPR 2009

mite

mite	
black widow	
cockroach	
tick	
starfish	

container ship

container ship	
lifeboat	
amphibian	
fireboat	
drilling platform	

motor scooter

motor scooter	
go-kart	
moped	
bumper car	
golfcart	

leopard

leopard	
jaguar	
cheetah	
snow leopard	
Egyptian cat	

grille

convertible	
grille	
pickup	
beach wagon	
fire engine	

mushroom

agaric	
mushroom	
jelly fungus	
gill fungus	
dead-man's-fingers	

cherry

dalmatian	
grape	
elderberry	
ffordshire bullterrier	
currant	

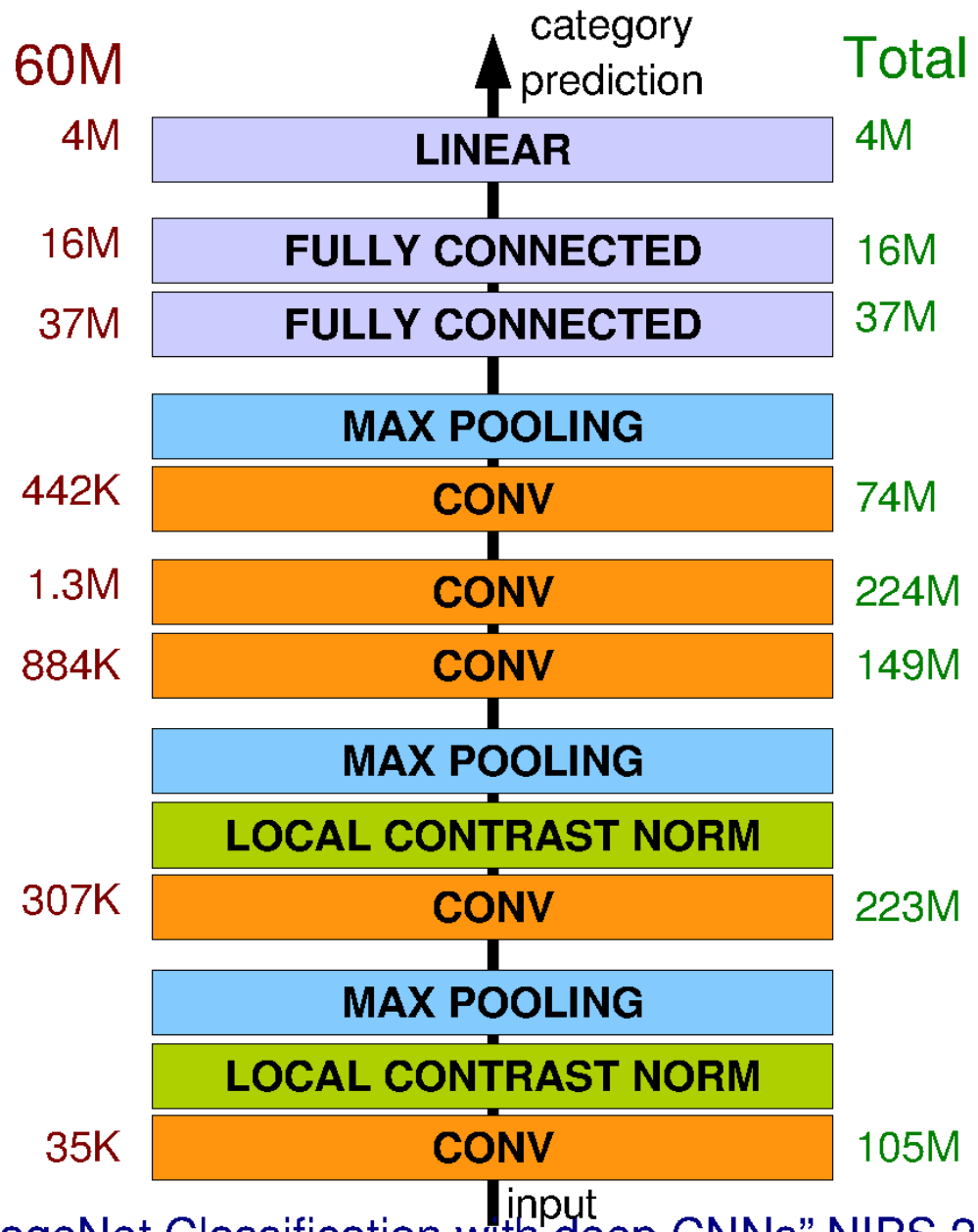
Madagascar cat

squirrel monkey	
spider monkey	
titi	
indri	
howler monkey	

Architecture for Classification

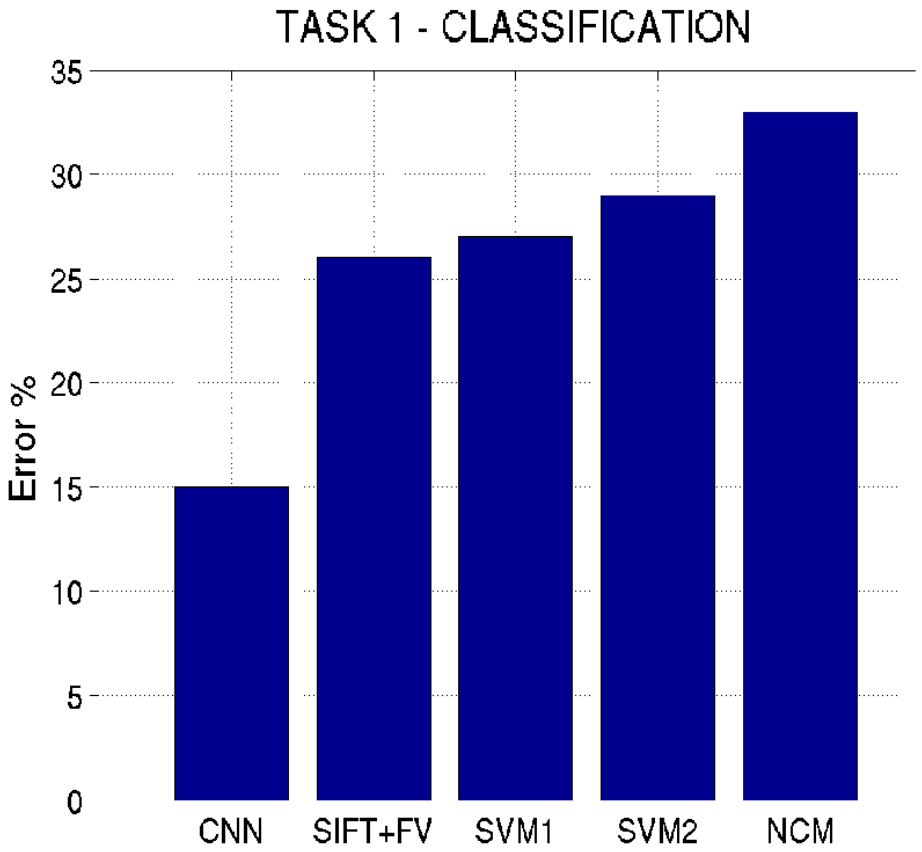
Total nr. params: 60M

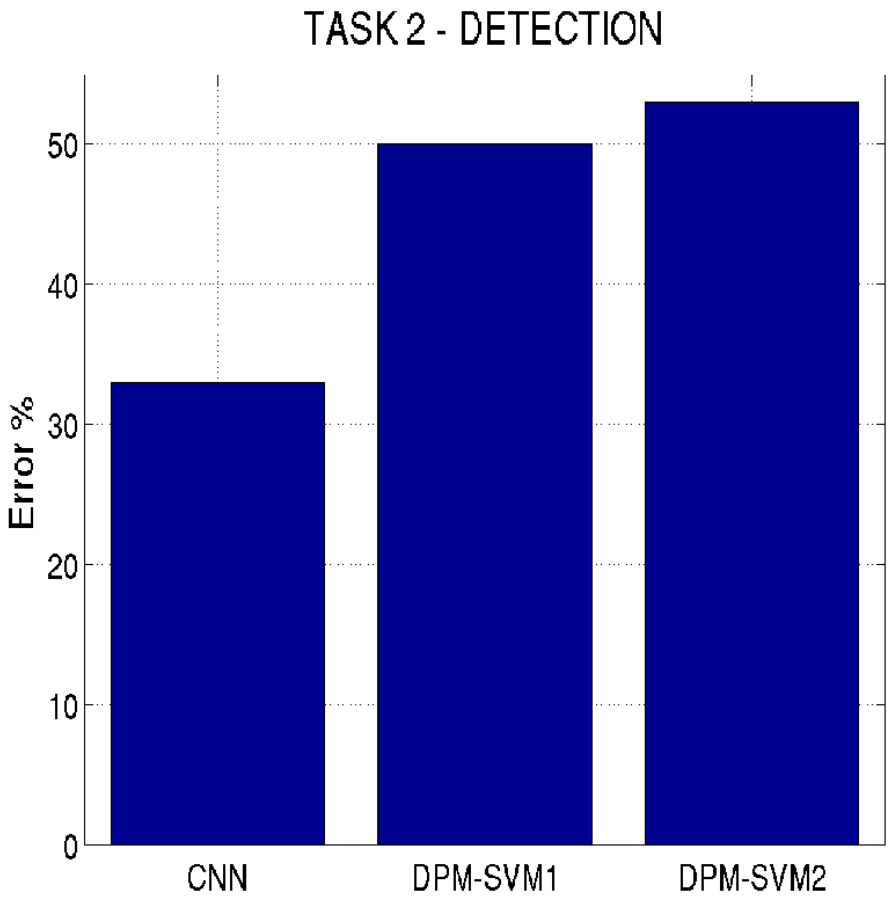
Total nr. flops: 832M



Krizhevsky et al. "ImageNet Classification with deep CNNs" NIPS 2012

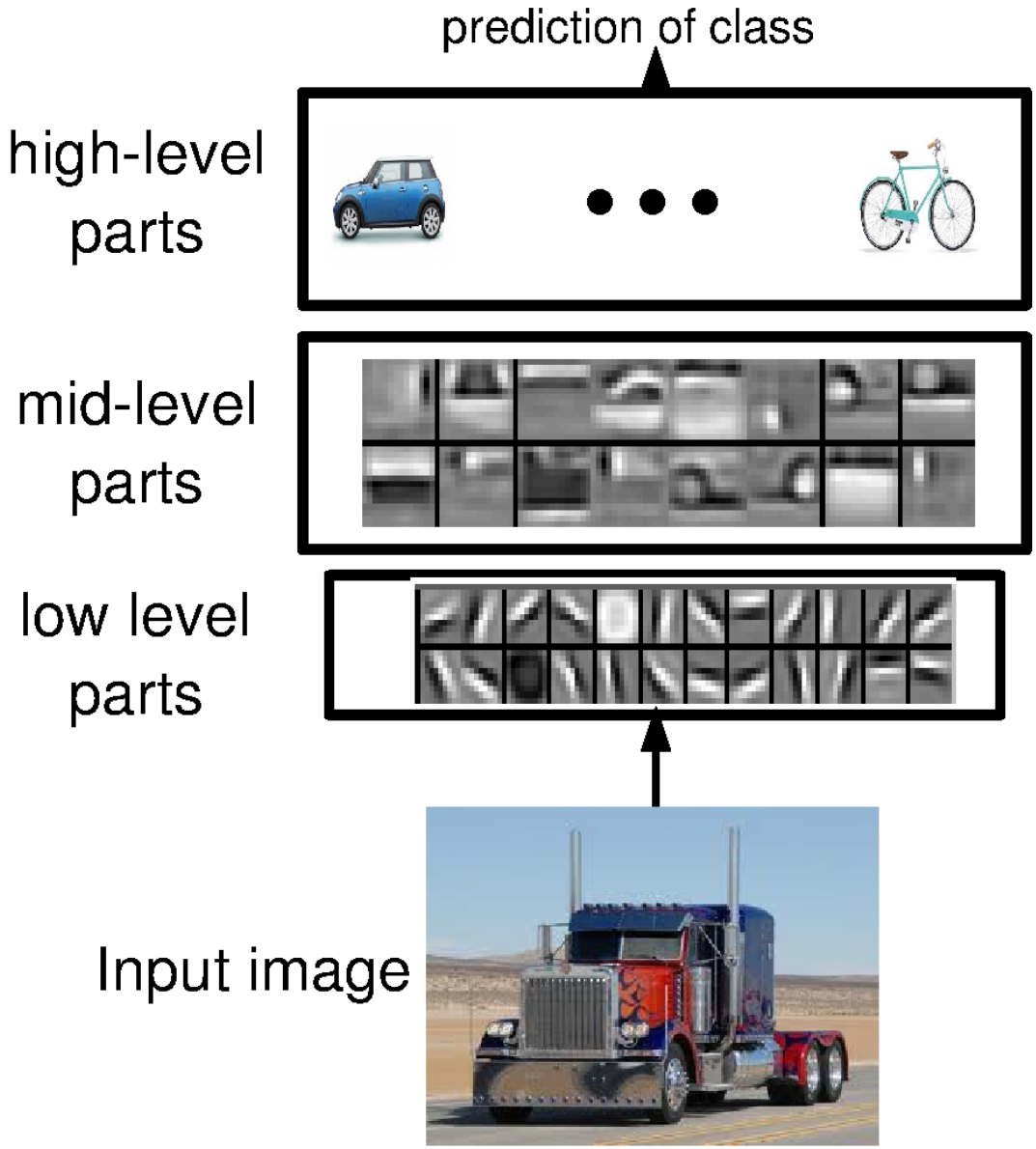
Results: ILSVRC 2012





Krizhevsky et al. "ImageNet Classification with deep CNNs" NIPS 2012

Interpretation



- distributed representations
- feature sharing
- compositionality

Lee et al. “Convolutional DBN's ...” ICML 2009

Object Detectors Emerge in Deep Scene CNNs

Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, AntonioTorralba

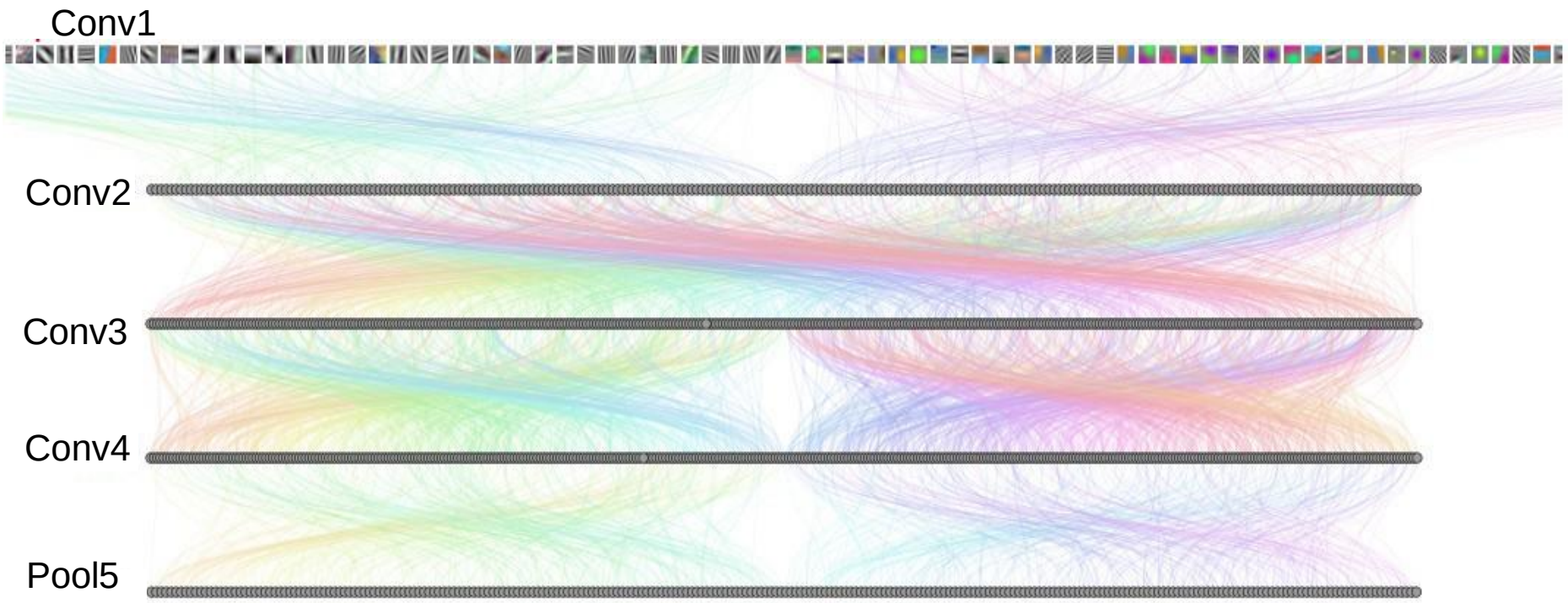



Massachusetts Institute of Technology

ICLR 2015

How Objects are Represented in CNN?

CNN uses **distributed code** to represent objects.

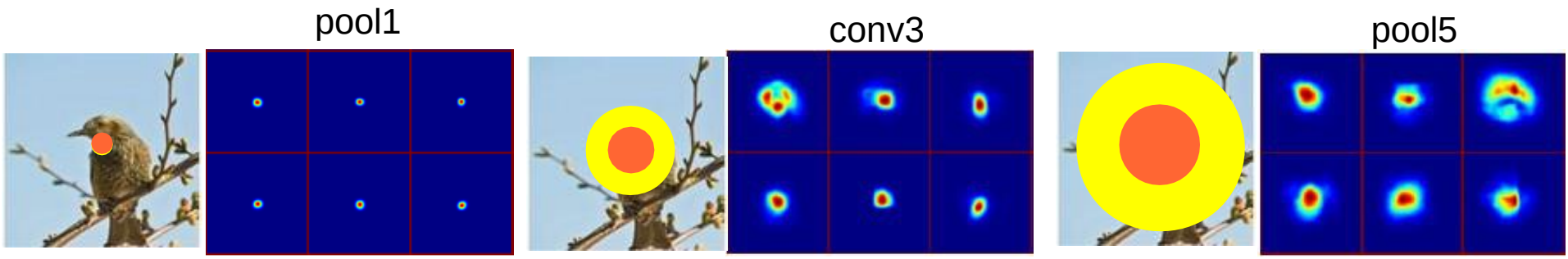


Agrawal, et al. Analyzing the performance of multilayer neural networks for object recognition. ECCV, 2014
Szegedy, et al. Intriguing properties of neural networks.arXiv preprint arXiv:1312.6199, 2013.
Zeiler, M. et al. Visualizing and Understanding Convolutional Networks, ECCV 2014.

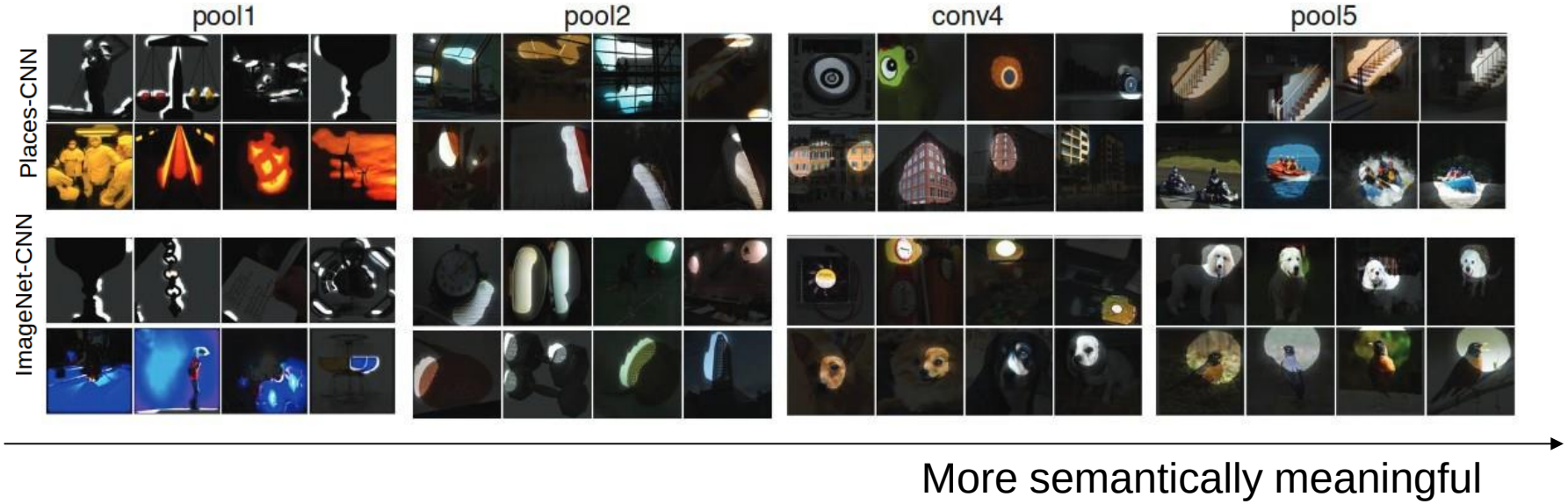
Estimating the Receptive Fields

Estimated receptive fields

Actual size of RF is much smaller than the theoretic size

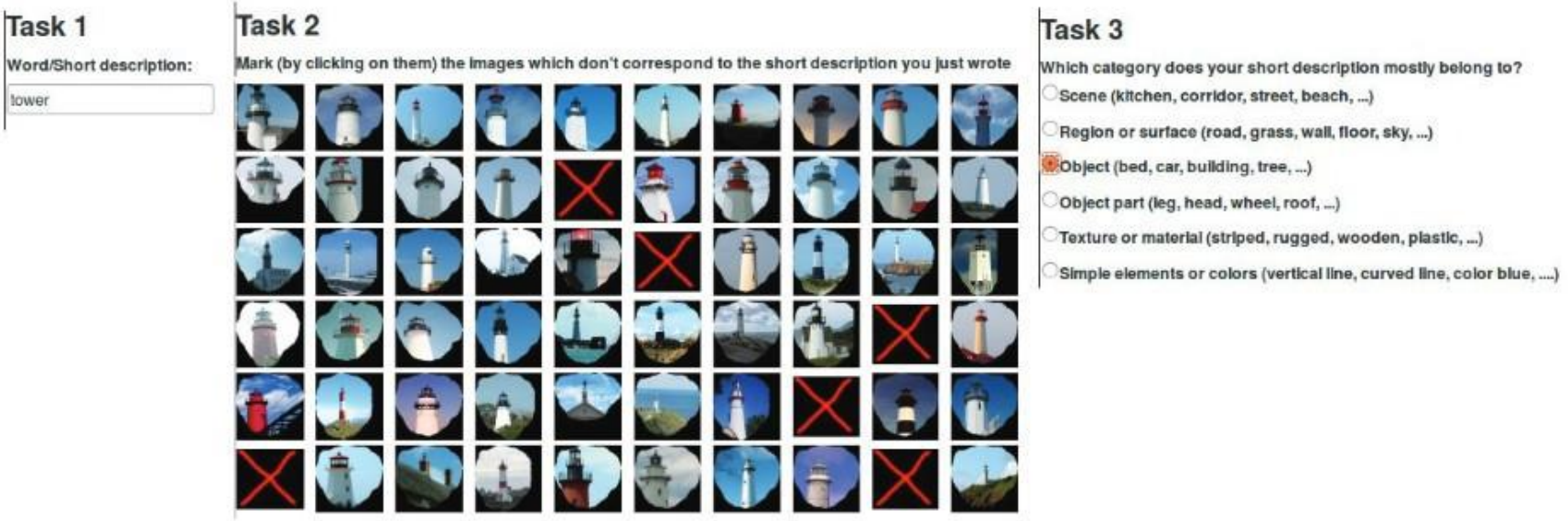


Segmentation using the RF of Units



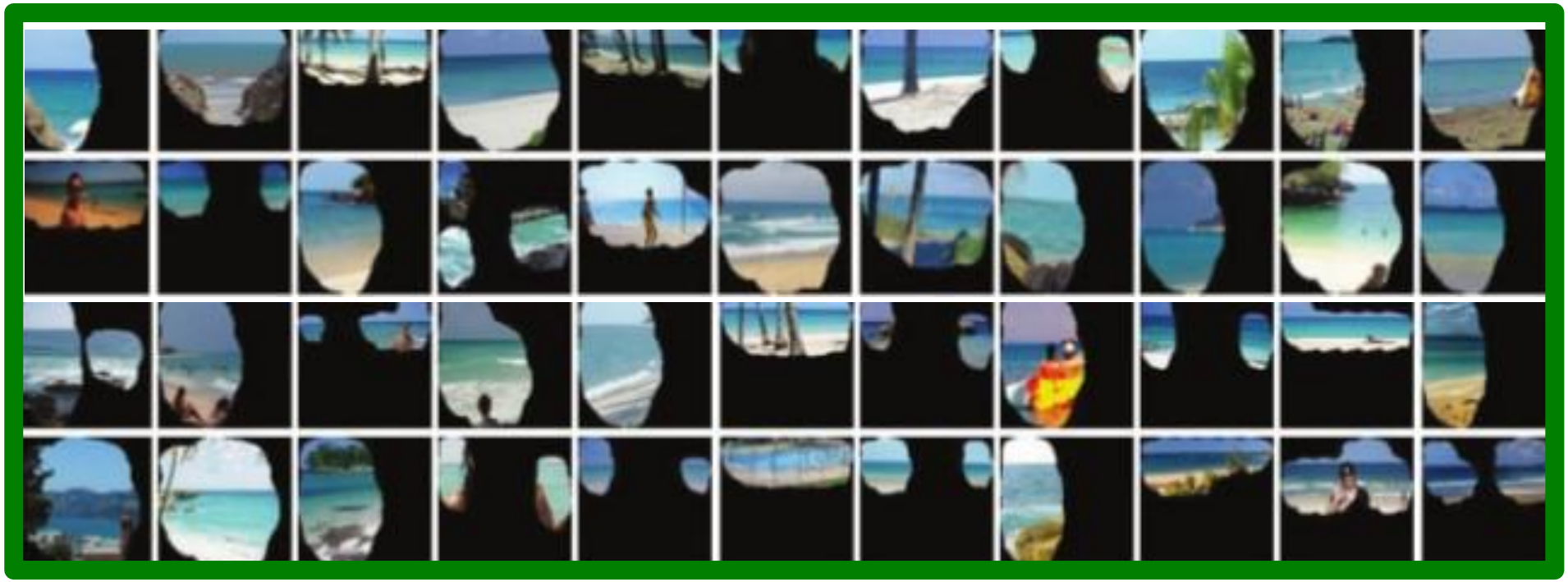
Annotating the Semantics of Units

Top ranked segmented images are cropped and sent to Amazon Turk for annotation.



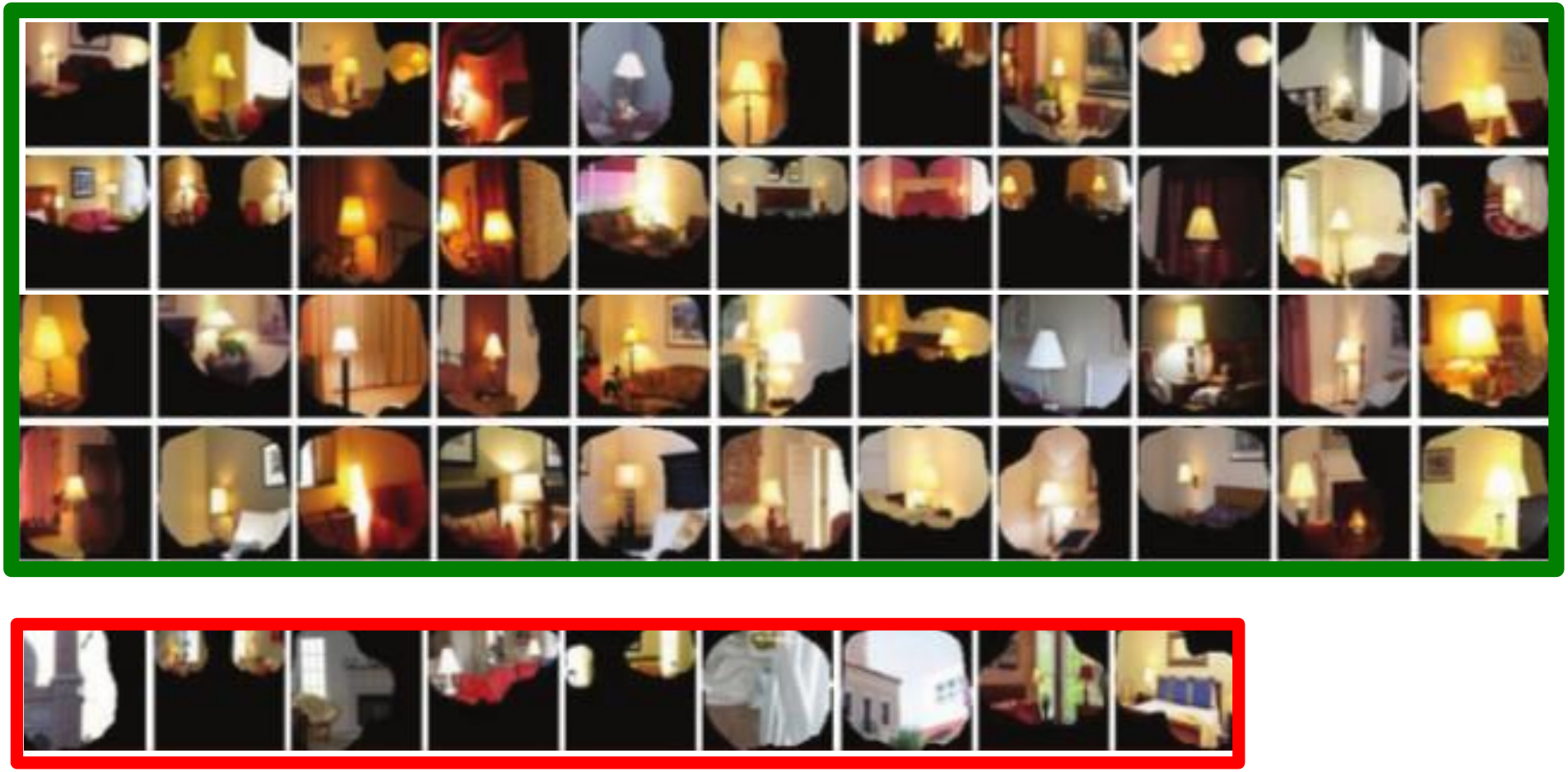
Annotating the Semantics of Units

Pool5, unit 76; Label: ocean; Type: scene; Precision: 93%



Annotating the Semantics of Units

Pool5, unit 13; Label: Lamps; Type: object; Precision: 84%

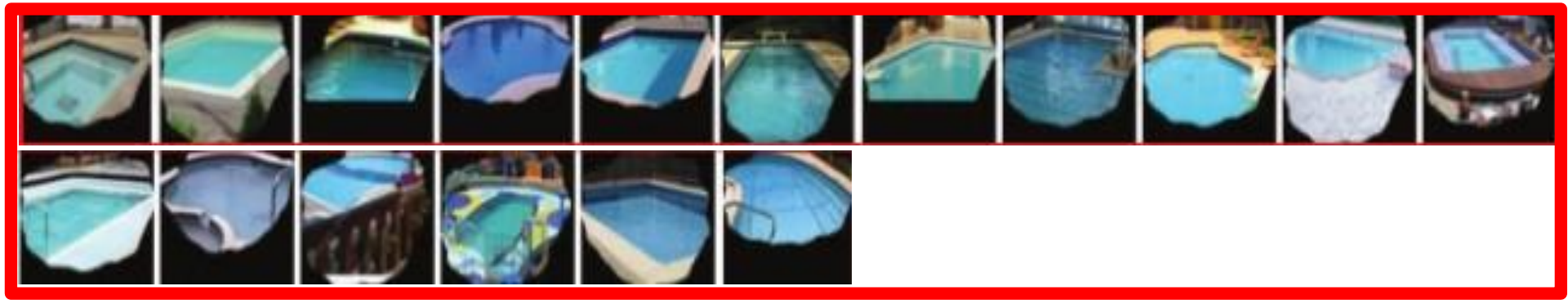


Annotating the Semantics of Units

Pool5, unit 77; Label:legs; Type: object part; Precision: 96%

Annotating the Semantics of Units

Pool5, unit 112; Label: pool table; Type: object; Precision: 70%



Annotating the Semantics of Units

Pool5, unit 22; Label: dinner table; Type: scene; Precision: 60%

ImageNet vs. PlacesNet

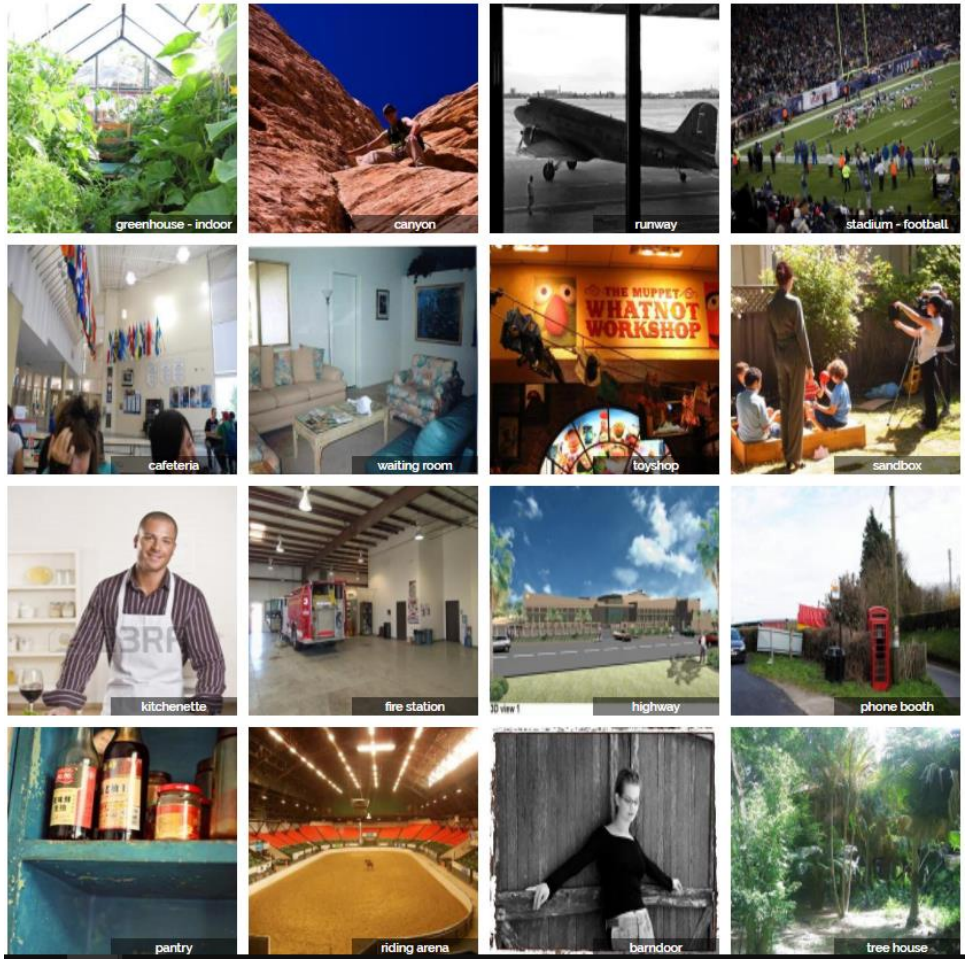
http://places2.csail.mit.edu/demo.html

ImageNet

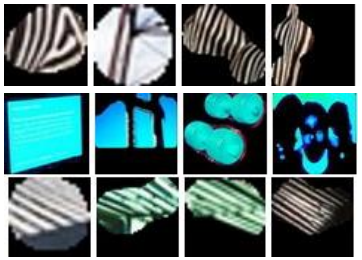
- ~1 mil object-level images over 1000 classes

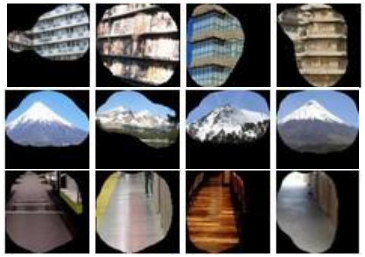
PlacesNet

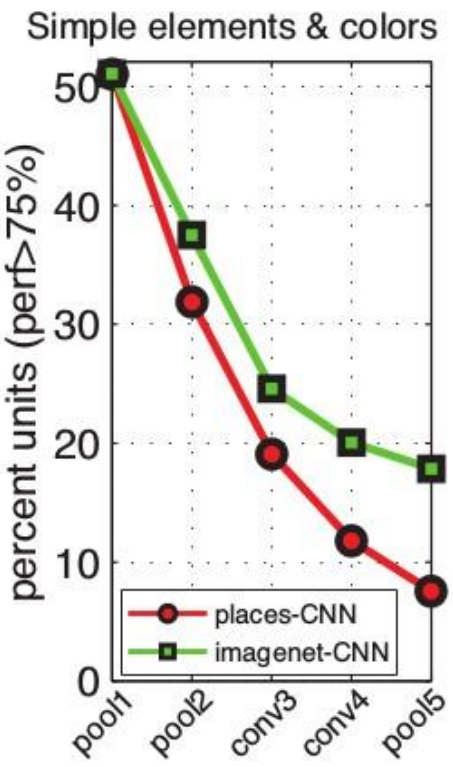
- ~1.8 million images from 365 scene categories (at most 5000 images per category).

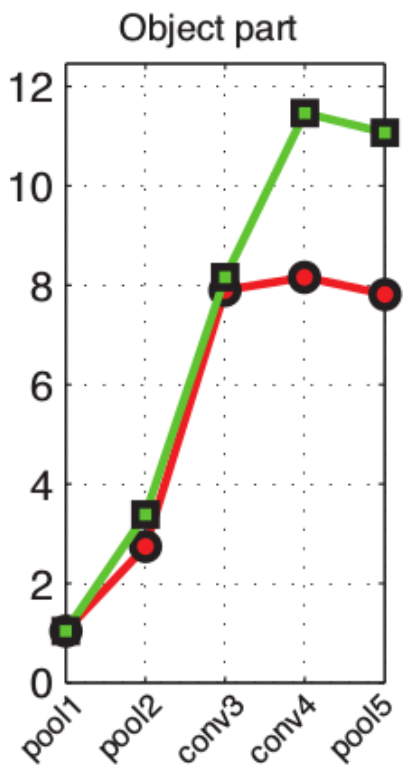


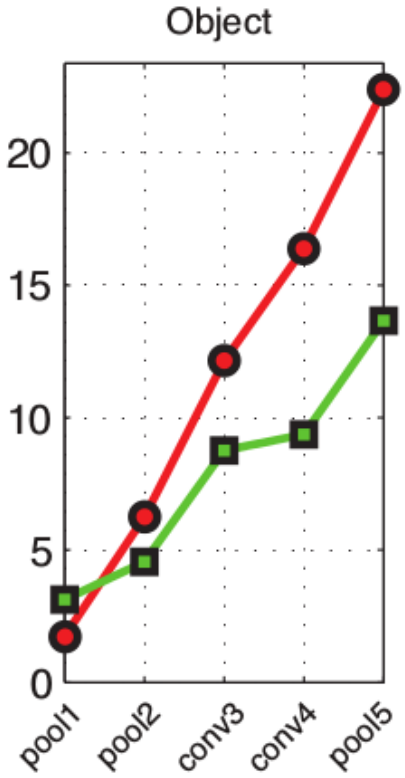
Distribution of Semantic Types at Each Layer

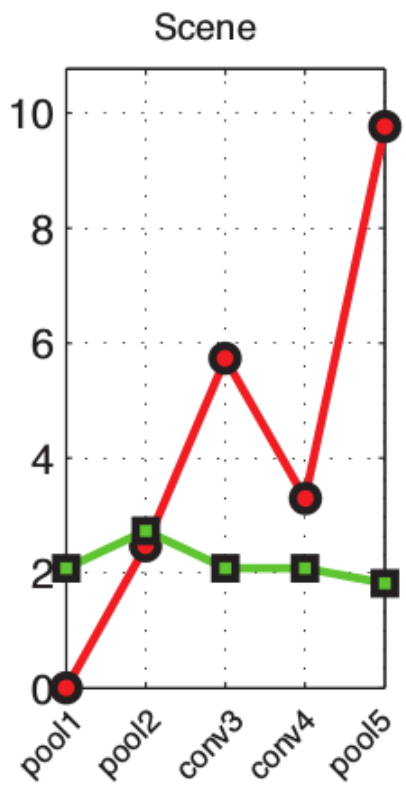




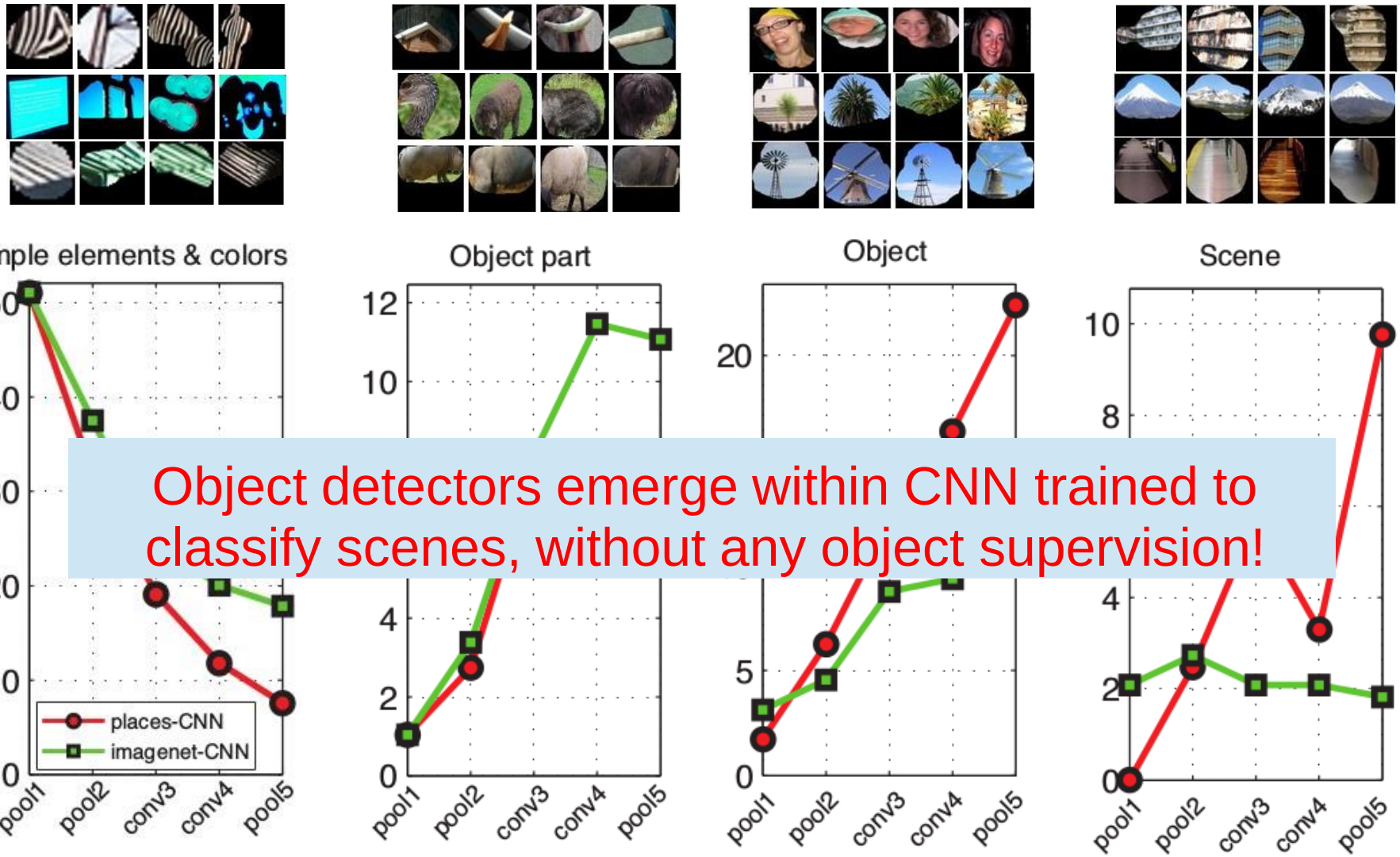








Distribution of Semantic Types at Each Layer



Object detectors emerge within CNN trained to classify scenes, without any object supervision!

How can free will coexist with divine preordination?

Ah yes.

Related works:

- The Ontological Argument
- The Problem of Evil
- Ship of Theseus / Sorites Paradox
- What is Art
- $0.99\dot{9} = 1$
- Chinese Room AI

Short cuts to AI

With billions of images on the web, it's often possible to find a close nearest neighbor.

We can shortcut hard problems by "looking up" the answer, stealing the labels from our nearest neighbor.

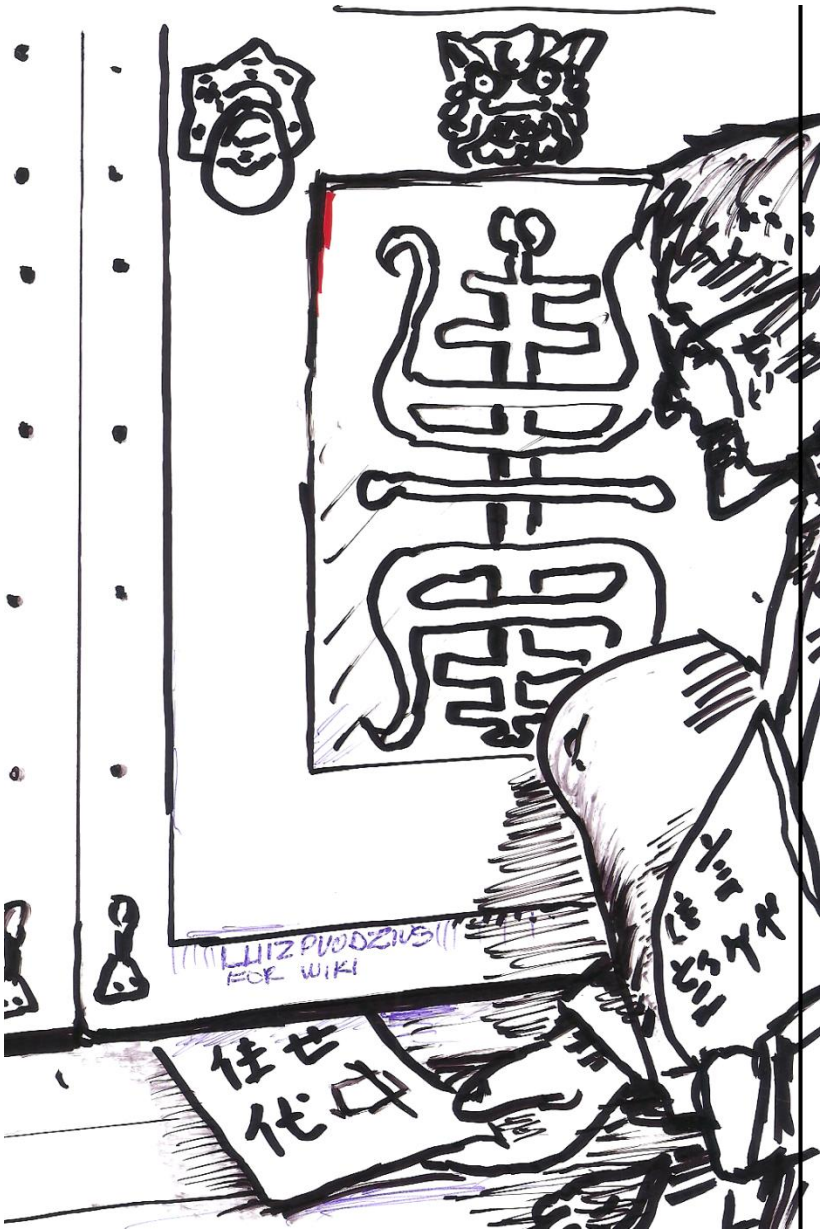
So what is intelligence?

Weak AI:
The simulation of a ‘mind’ is a model for the ‘mind’.

Strong AI:
The simulation of a ‘mind’ is a ‘mind’.

Chinese Room experiment, John Searle (1980)

If a machine can convincingly simulate an intelligent conversation, does it understand?



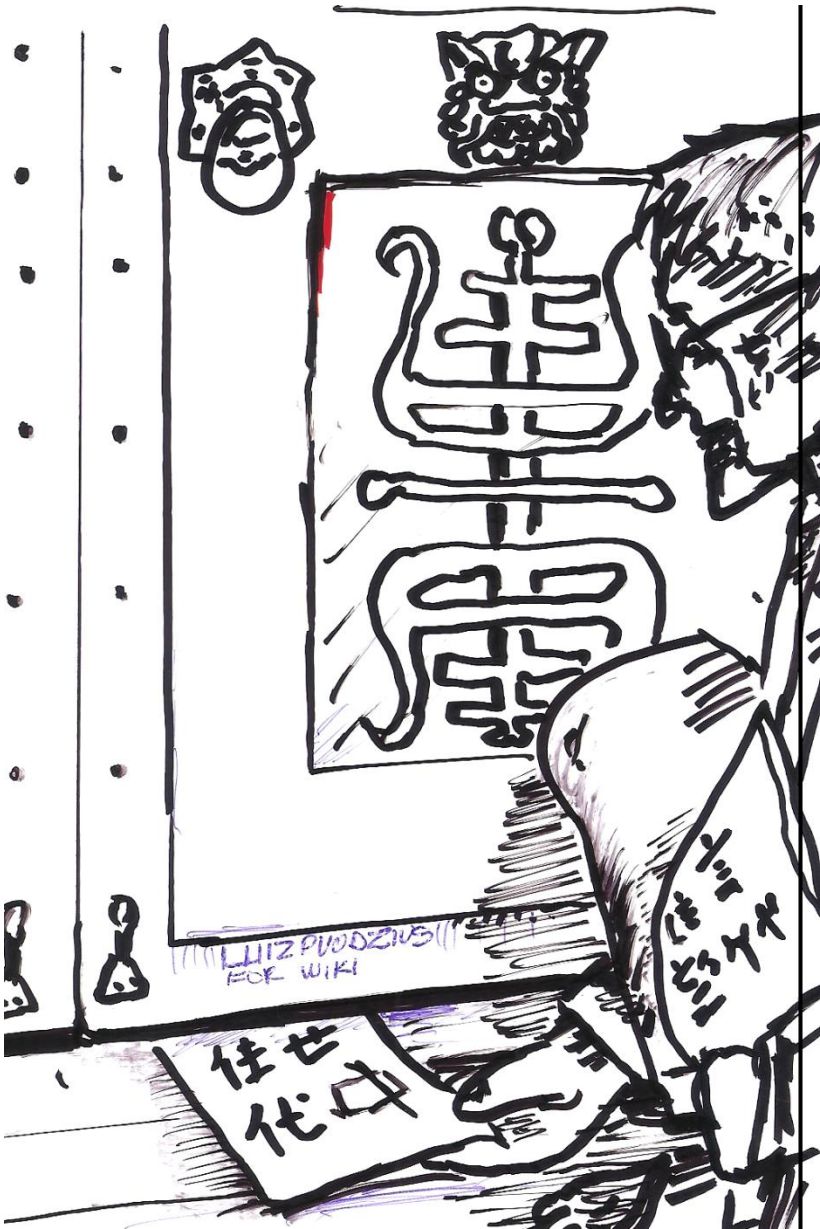
Chinese Room experiment, John Searle (1980)

If a machine can convincingly simulate an intelligent conversation, does it understand?

Searle imagines himself in a room, acting as a computer by manually executing a program that convincingly simulates the behavior of a native Chinese speaker.

Most of the discussion consists of attempts to refute it.
"The overwhelming majority," notes *BBS* editor Stevan Harnad,“ still think that the Chinese Room Argument is dead wrong.“

The sheer volume of the literature that has grown up around it inspired Pat Hayes to quip that the field of cognitive science ought to be redefined as "the ongoing research program of showing Searle's Chinese Room Argument to be false.”



Yann LeCun
October 23 at 9:58pm ·

Questions from the piece:

Q1. Does the Chinese Room argument prove the impossibility of machine consciousness?
A1: Hell no. ... See More

Can Machines Become Moral?

The question is heard more and more often, both from those who think that machines cannot become moral, and who think that to believe otherwise is a dangerous illusion, and from those who think that machines must become moral,…

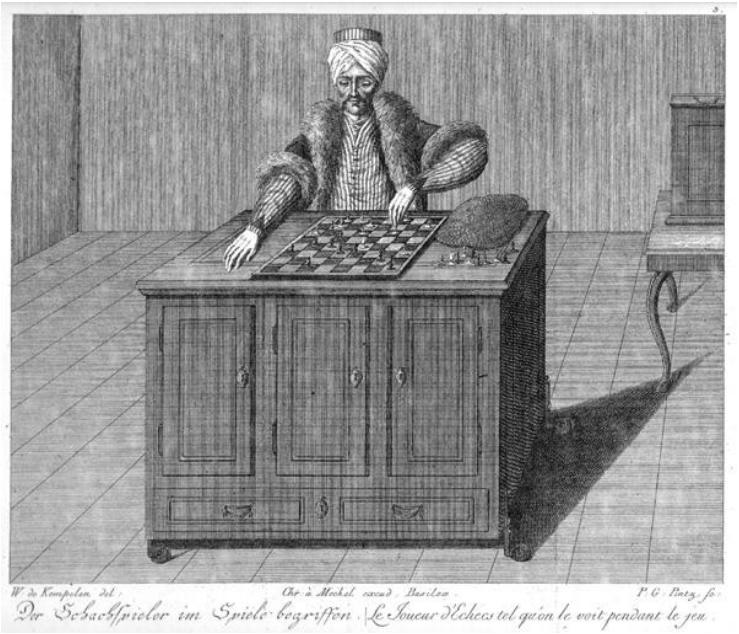
BIGQUESTIONSONLINE.COM | BY DON HOWARD

You and 156 others 30 Comments 20 Shares

Like Comment Share

Mechanical Turk

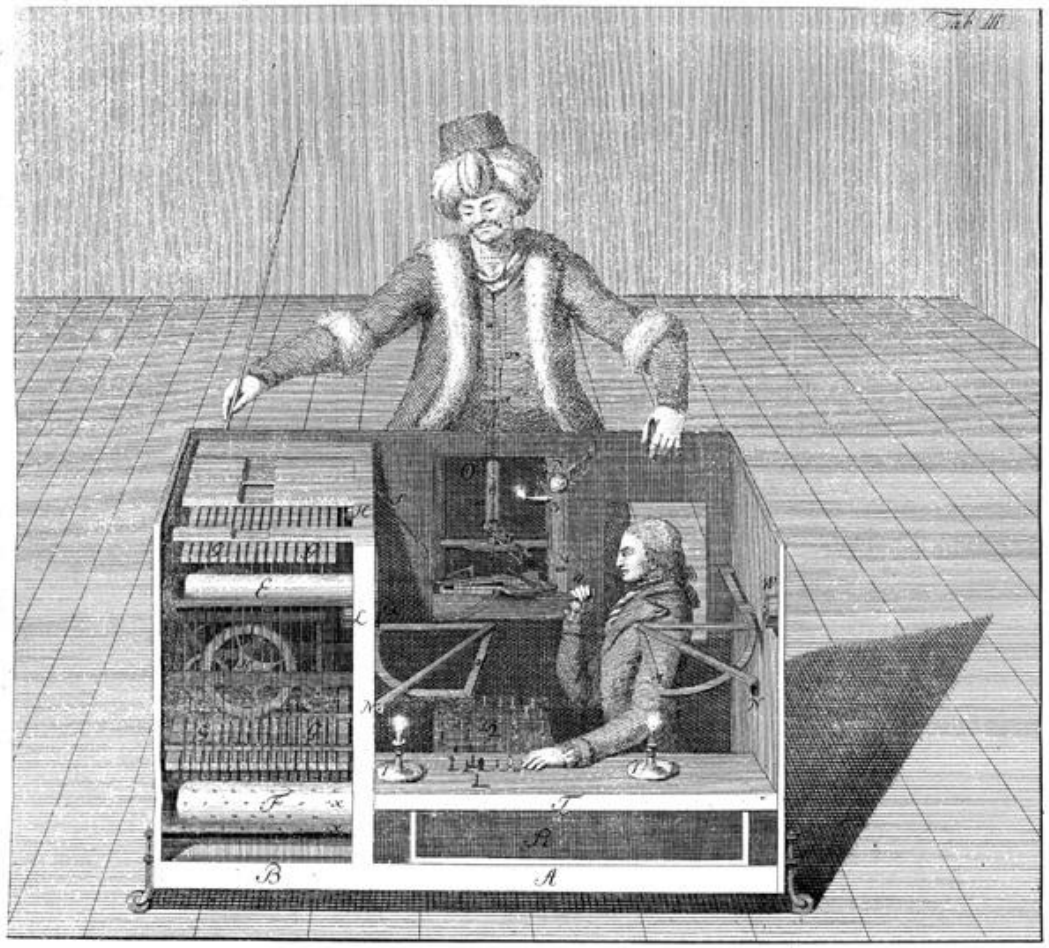
- von Kempelen, 1770.
- Robotic chess player.
- Clockwork routines.
- Magnetic induction (not vision)



- Toured the world; played Napoleon Bonaparte and Benjamin Franklin.

Mechanical Turk

- It was all a ruse!
- Ho ho ho.



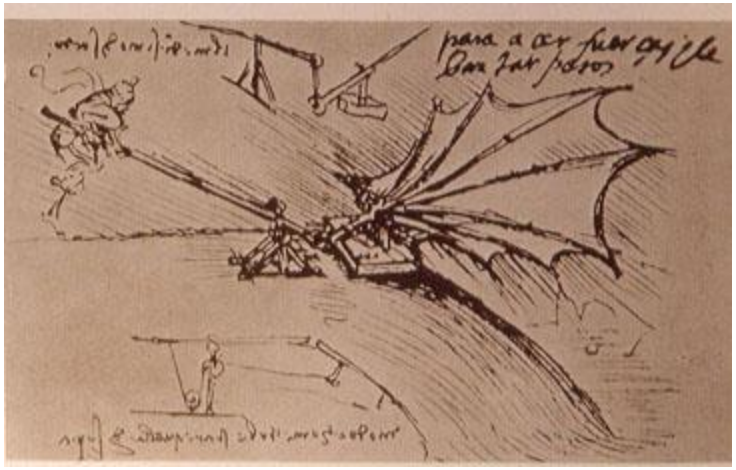
"Can machines fly?"
Yes; aeroplanes exist.

"Can machines fly like a bird?"
No, because aeroplanes don’t flap.

"Can machines perceive?”
“Can machines understand?"
Are these question like the first, or like the second?

[Adapted from Norvig]

Ornithopters



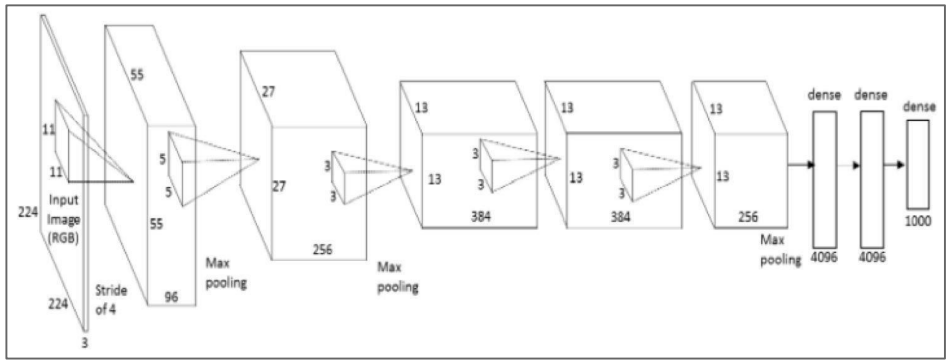
Festo SmartBird [2011]

Interesting CNN properties

…or other ways to measure reception

http://yosinski.com/deepvis

What input to a neuron maximizes a class score?

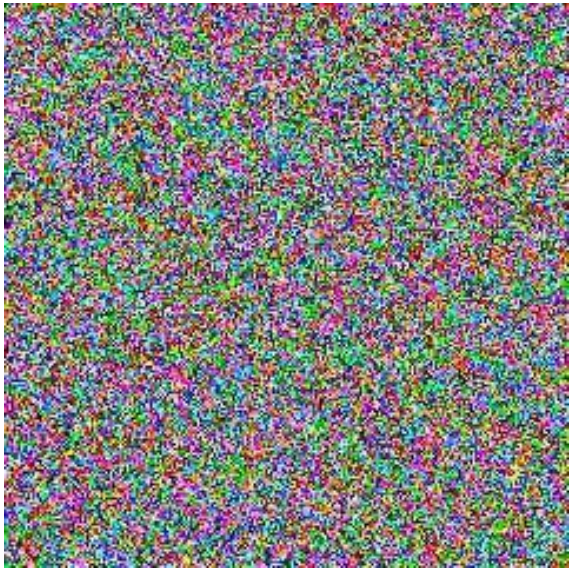


To visualize the function of a specific unit in a neural network, we synthesize an input to that unit which causes high activation.

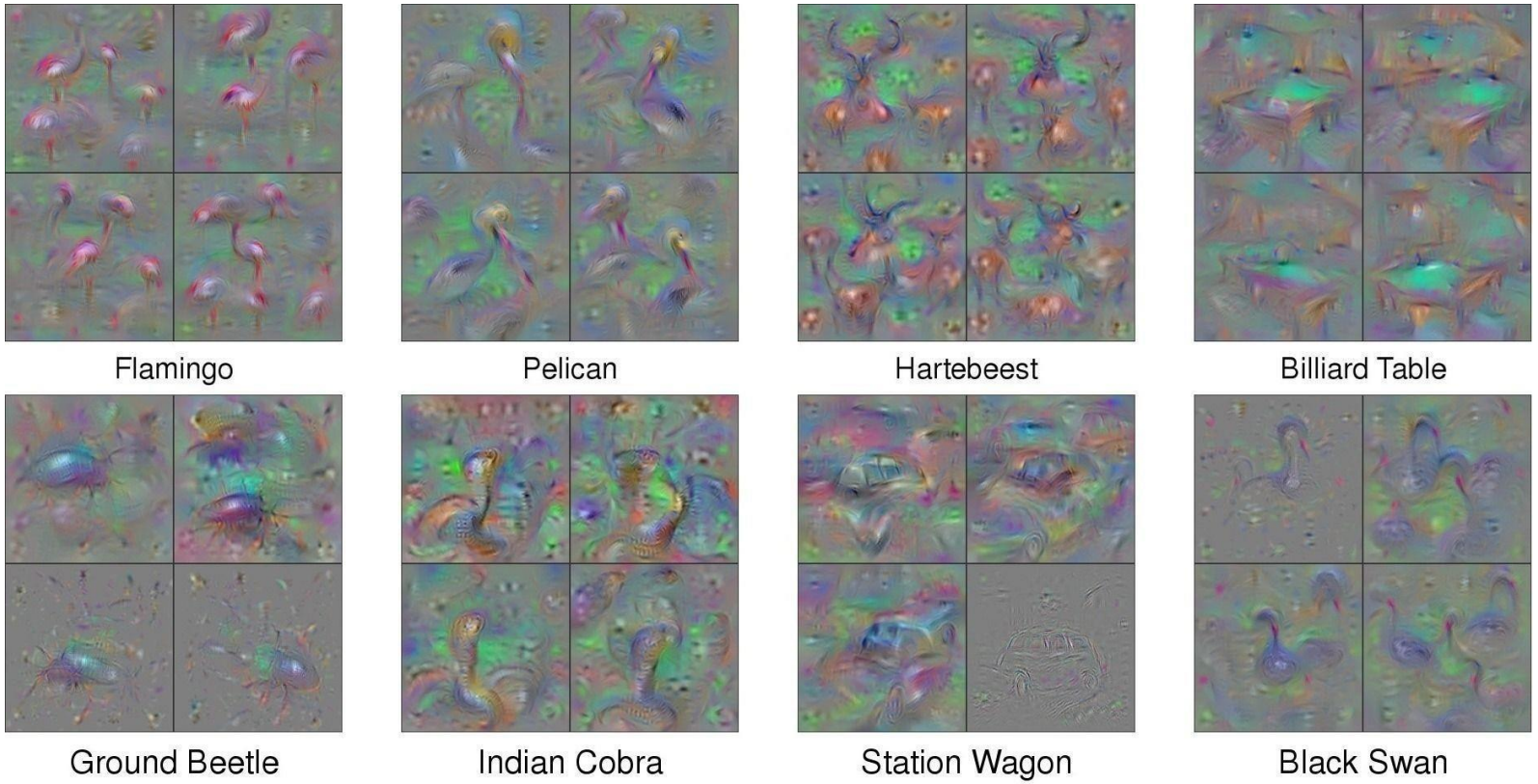
Neuron of choice *i*
An image of random noise *x*.

Repeat:

1. Forward propagate: compute activation $a_i(x)$
2. Back propagate: compute gradient at neuron $\partial a_i(x) / \partial x$
3. Add small amount of gradient back to noisy image.



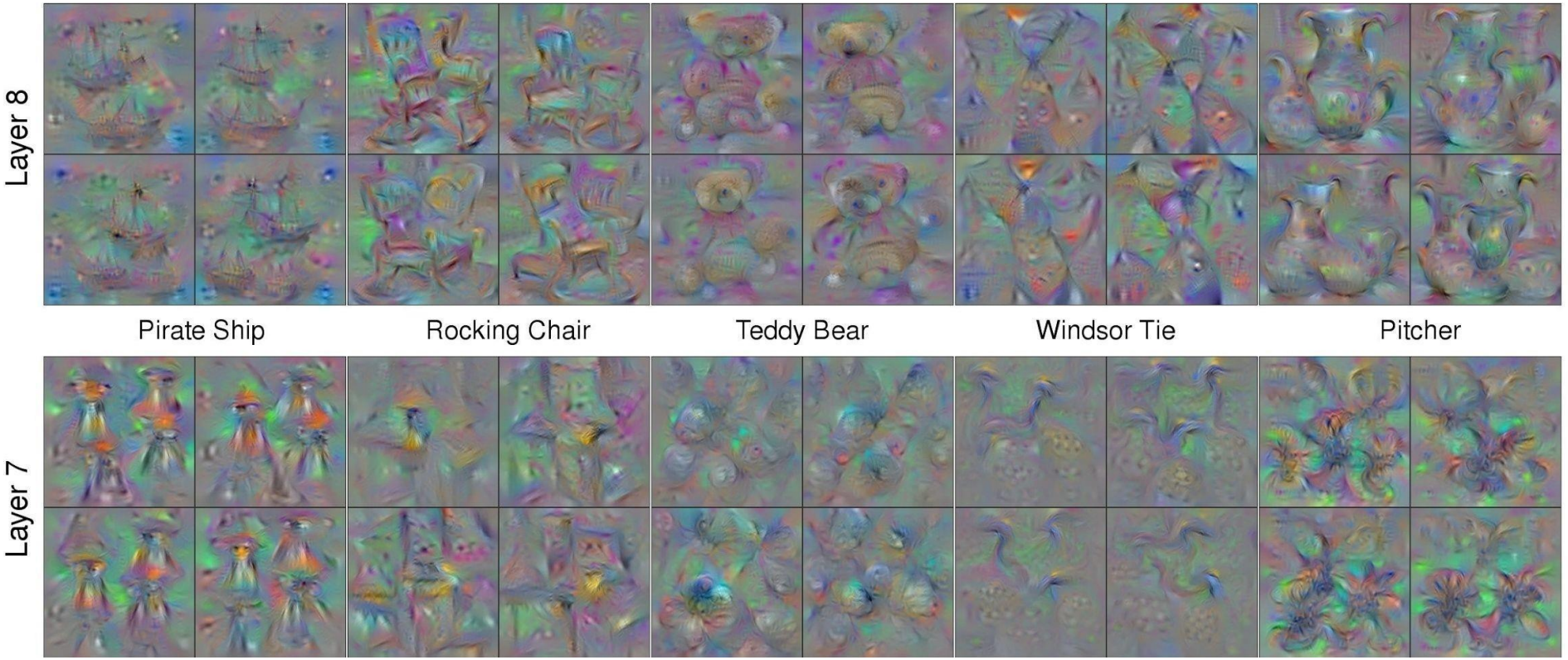
What image maximizes a class score?



[Understanding Neural Networks Through Deep Visualization, Yosinski et al. , 2015]

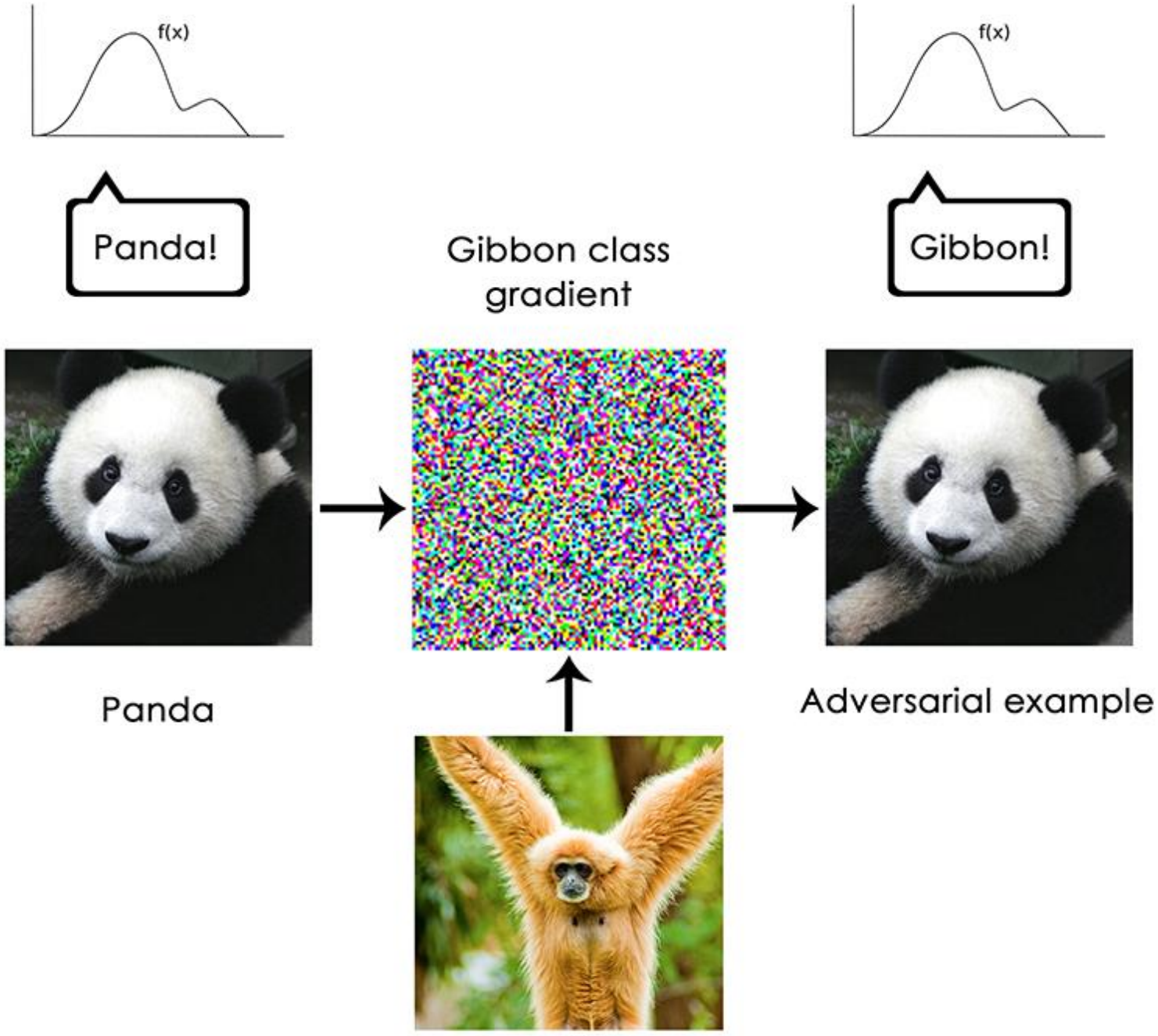
http://yosinski.com/deepvis

What image maximizes a class score?



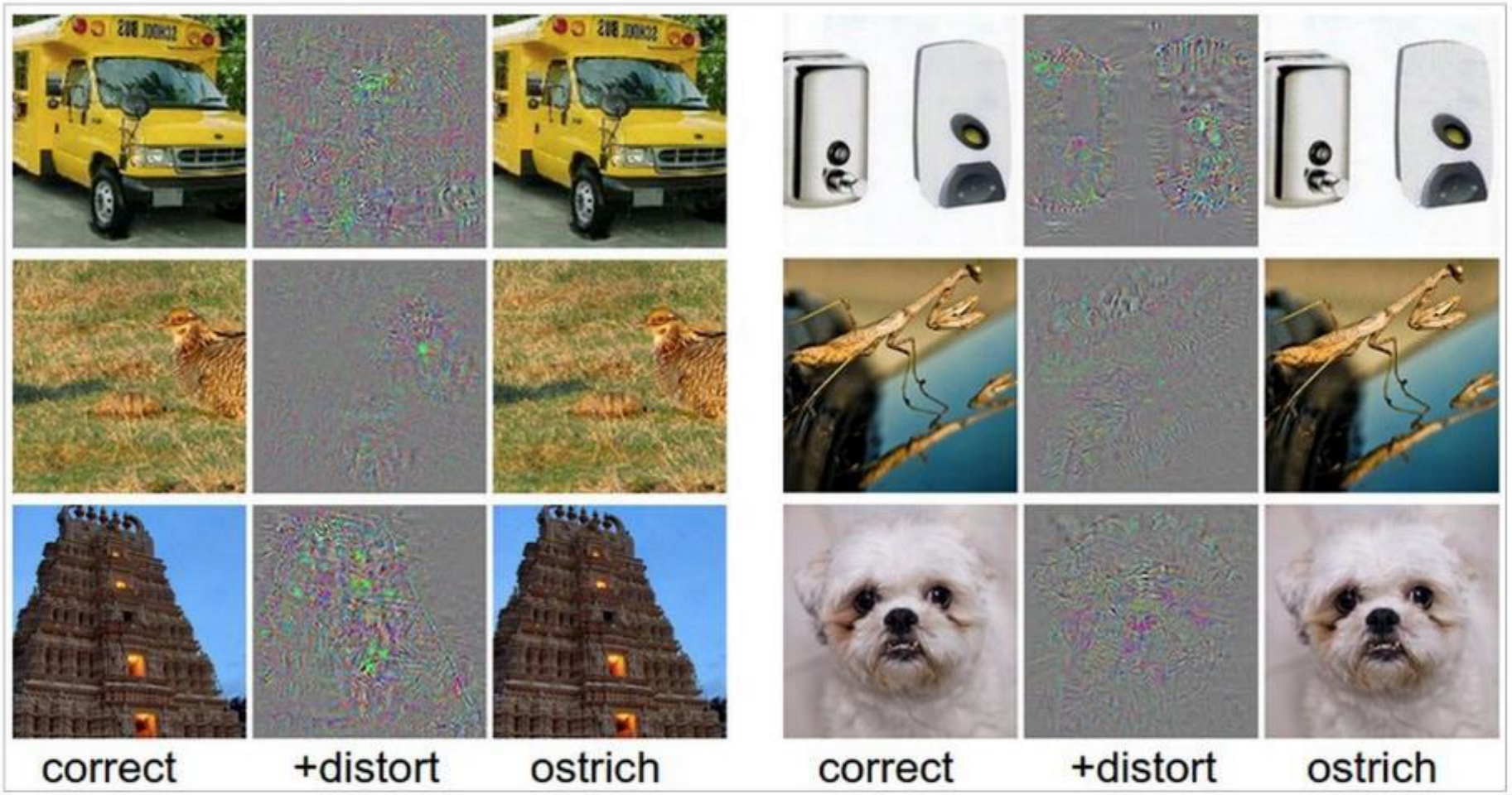
Wow!

They just ‘fall out’!



Francois Chollet - https://blog.keras.io/the-limitations-of-deep-learning.html

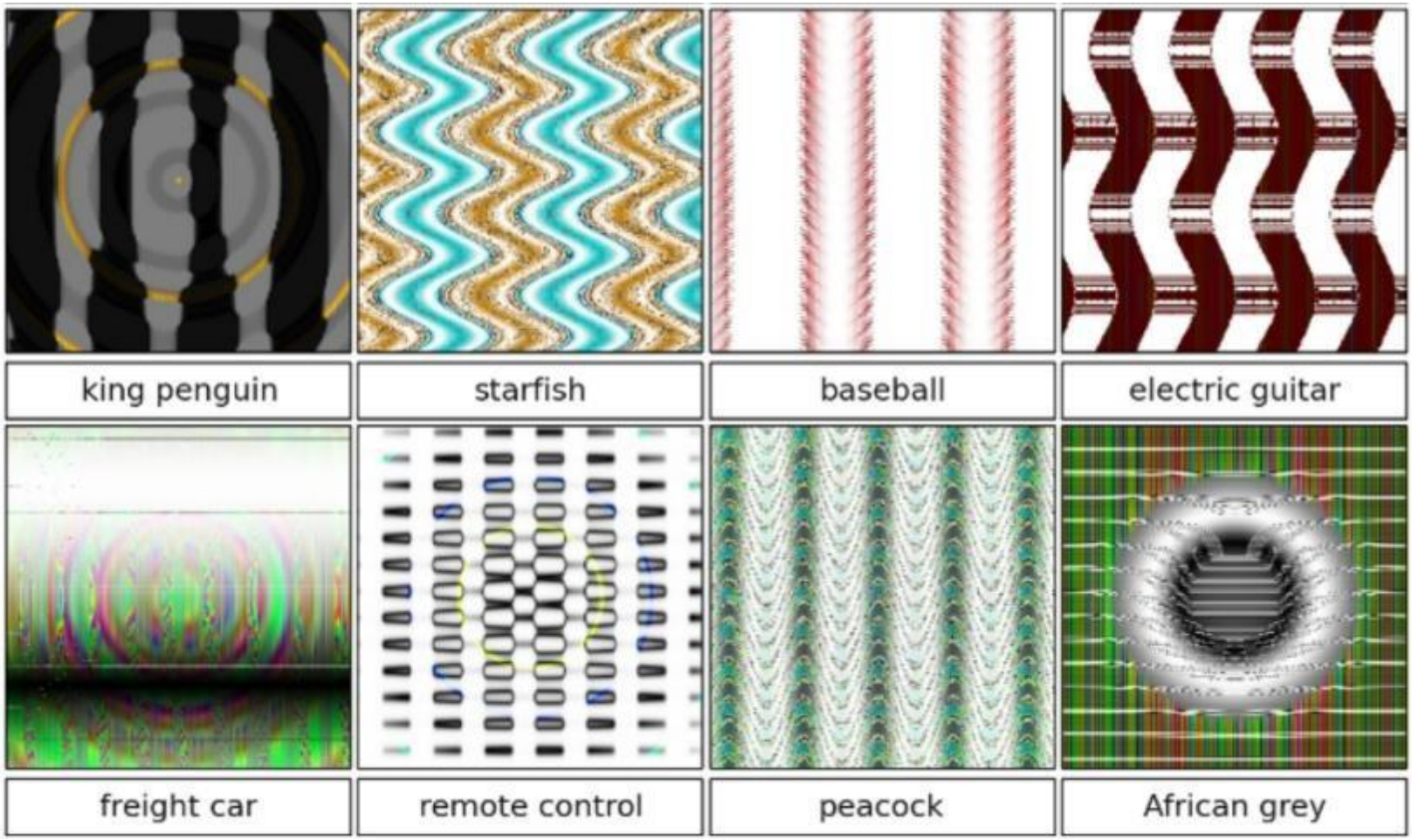
Breaking CNNs



Take a correctly classified image (left image in both columns), and add a tiny distortion (middle) to fool the ConvNet with the resulting image (right).

Intriguing properties of neural networks [Szegedy ICLR 2014]

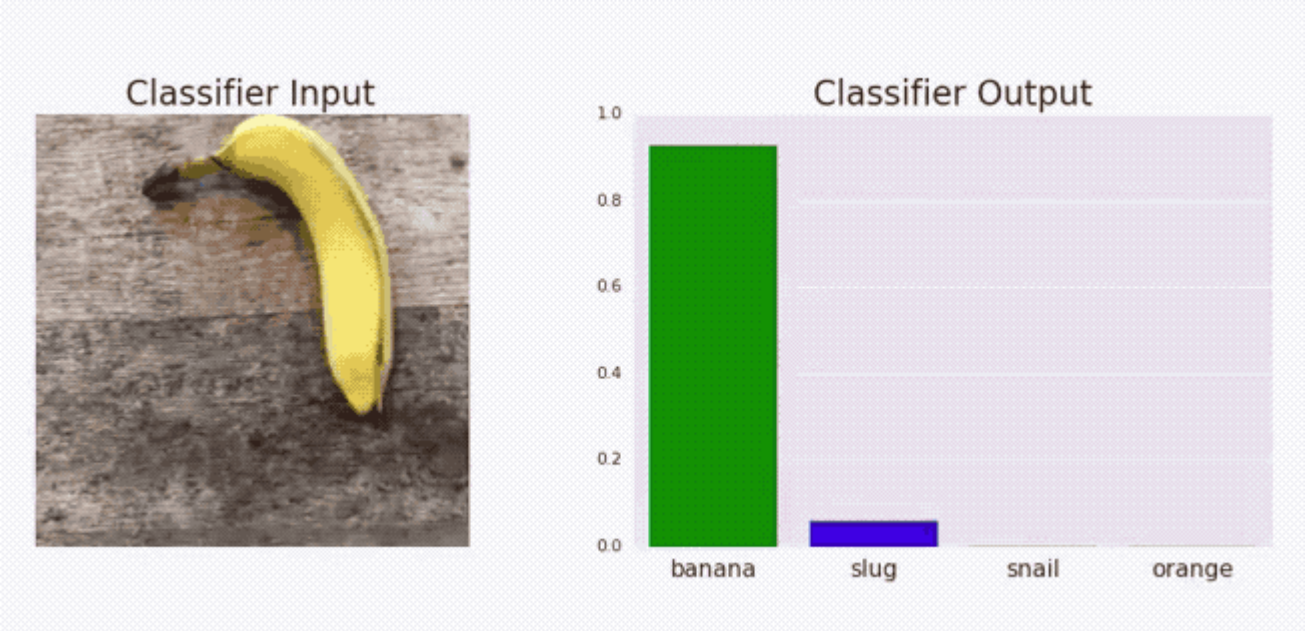
Breaking CNNs



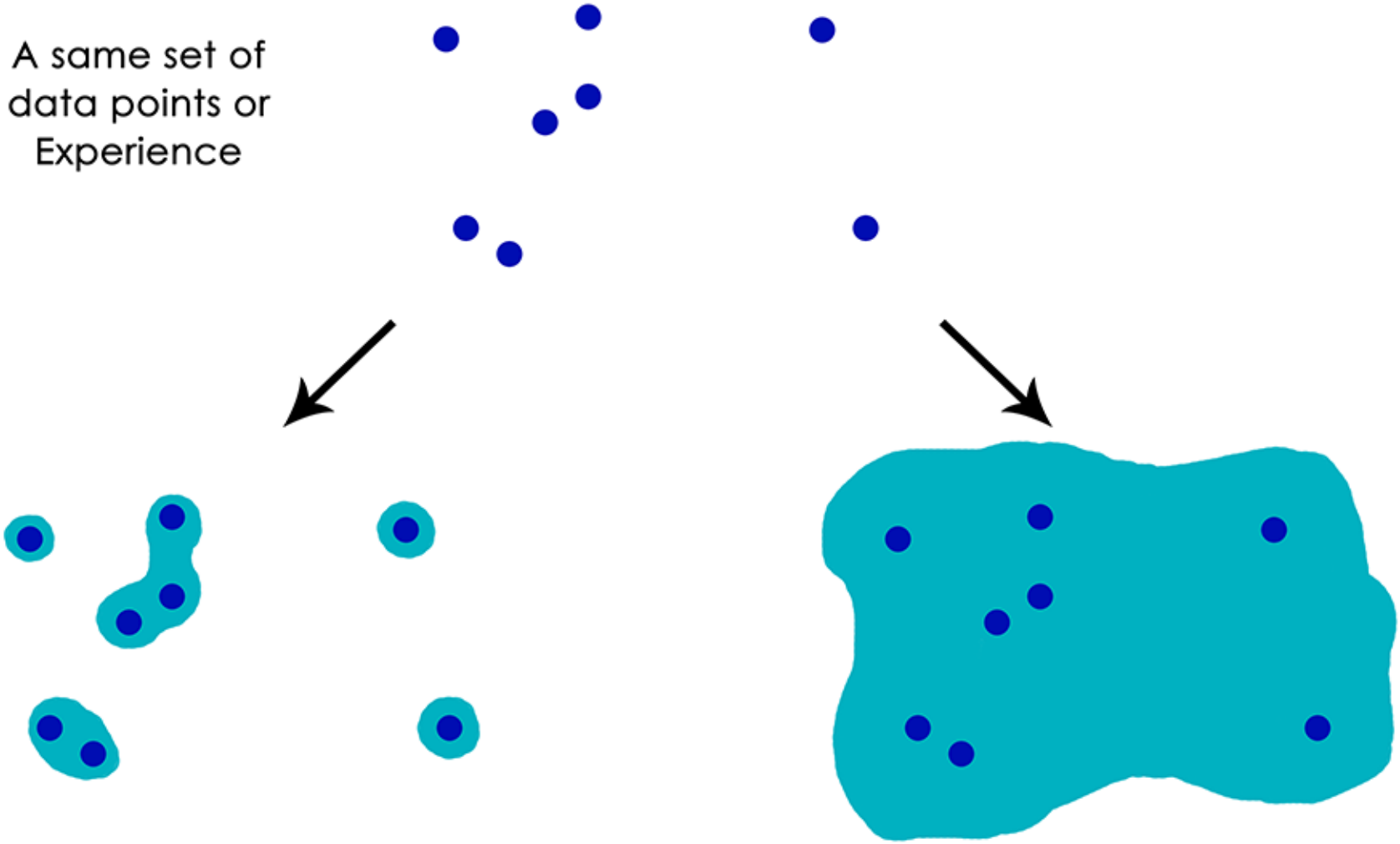
Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images [Nguyen et al. CVPR 2015]

Adversarial Patches

- https://www.theverge.com/2018/1/3/16844842/ai-computer-vision-trick-adversarial-patches-google
- https://arxiv.org/pdf/1712.09665.pdf



[Brown et al., Google, 2018]



Francois Chollet - https://blog.keras.io/the-limitations-of-deep-learning.html

The boy is holding a baseball bat.

Francois Chollet - https://blog.keras.io/the-limitations-of-deep-learning.html

Curiosity: The success of obfuscating gradients

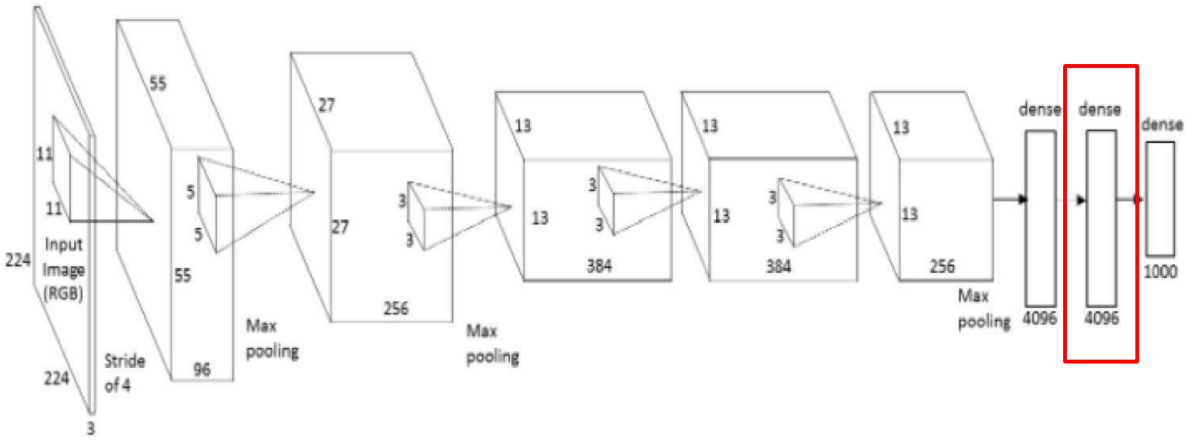
- https://github.com/anishathalye/obfuscated-gradients

In our recent paper, we evaluate the robustness of eight papers accepted to ICLR 2018 as non-certified white-box-secure defenses to adversarial examples. We find that seven of the eight defenses provide a limited increase in robustness and can be broken by improved attack techniques we develop.

The only defense we observe that significantly increases robustness to adversarial examples within the threat model proposed is "Towards Deep Learning Models Resistant to Adversarial Attacks" (Madry et al. 2018), and we were unable to defeat this defense without stepping outside the threat model. Even then, this technique has been shown to be difficult to scale to ImageNet-scale (Kurakin et al. 2016). The remainder of the papers rely either inadvertently or intentionally on what we call *obfuscated gradients*. Standard attacks apply gradient descent to maximize the loss of the network on a given image to generate an adversarial example on a neural network. Such optimization methods require a useful gradient signal to succeed. When a defense obfuscates gradients, it breaks this gradient signal and causes optimization based methods to fail.

Reconstructing images

Question: Given a CNN code, is it possible to reconstruct the original image?



Reconstructing images

Find an image such that:

- Its code is like a given code
- It “looks natural”
  - Neighboring pixels should look similar

Image $\mathbf{x}^* = \underset{\mathbf{x} \in \mathbb{R}^{H \times W \times C}}{\operatorname{argmin}} \ell(\Phi(\mathbf{x}), \Phi_0) + \lambda \mathcal{R}(\mathbf{x})$

$$\ell(\Phi(\mathbf{x}), \Phi_0) = \|\Phi(\mathbf{x}) - \Phi_0\|^2$$

Reconstructing images

original image

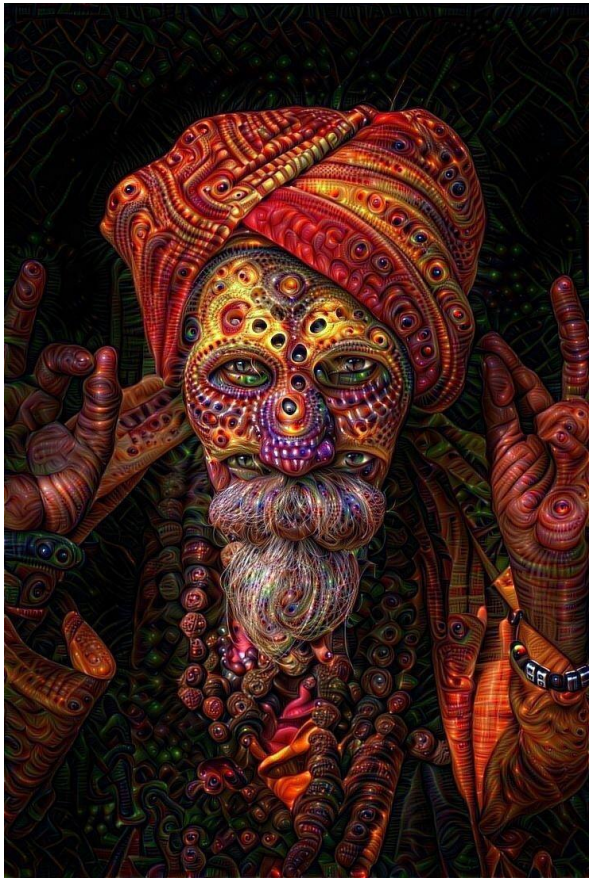
Reconstructions from the 1000 log probabilities for ImageNet (ILSVRC) classes

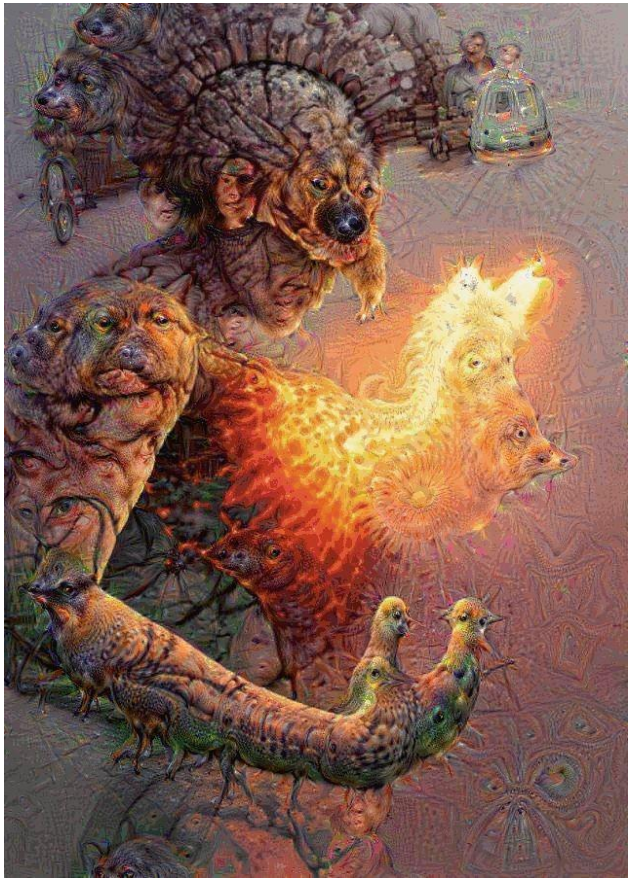
Understanding Deep Image Representations by Inverting Them
[Mahendran and Vedaldi, 2014]

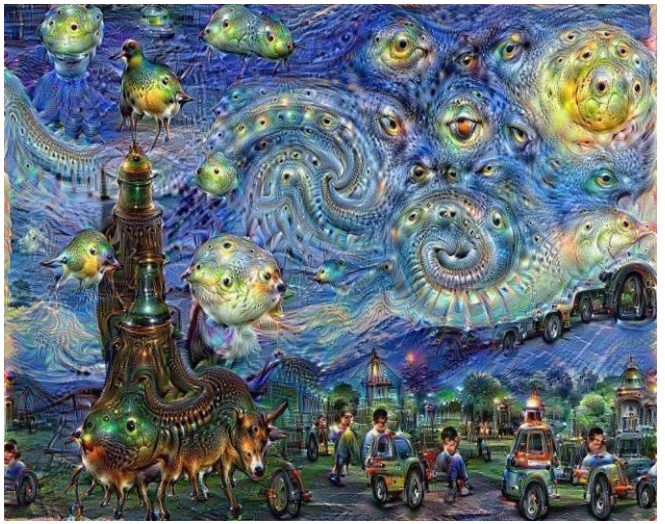
Reconstructing images

Reconstructions from the representation after last last pooling layer (immediately before the first Fully Connected layer)

DeepDream

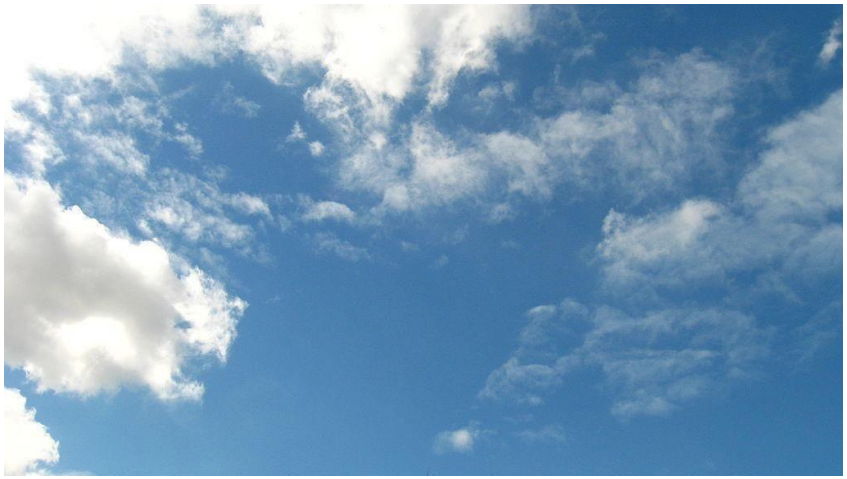






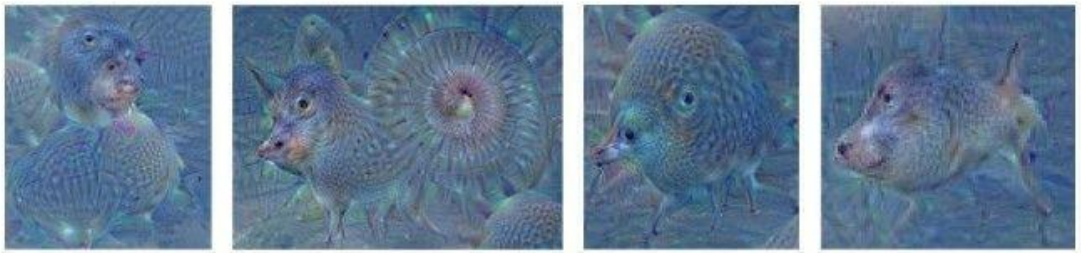
DeepDream https://github.com/google/deepdream

DeepDream



DeepDream modifies the image in a way that “boosts” all activations, at any layer

This creates a feedback loop: e.g., any slightly detected dog face will be made more and more dog-like over time.



DeepDream

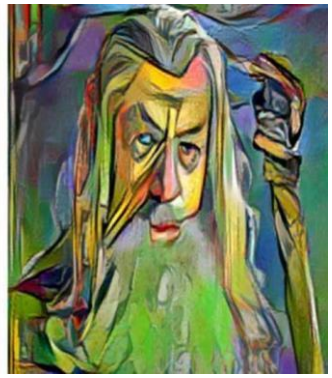
Deep Dream Grocery Trip
https://www.youtube.com/watch?v=DgPaCWJL7XI

Deep Dreaming Fear & Loathing in Las Vegas: the Great San Francisco Acid Wave
https://www.youtube.com/watch?v=oyxSerkkP4o

Style transfer

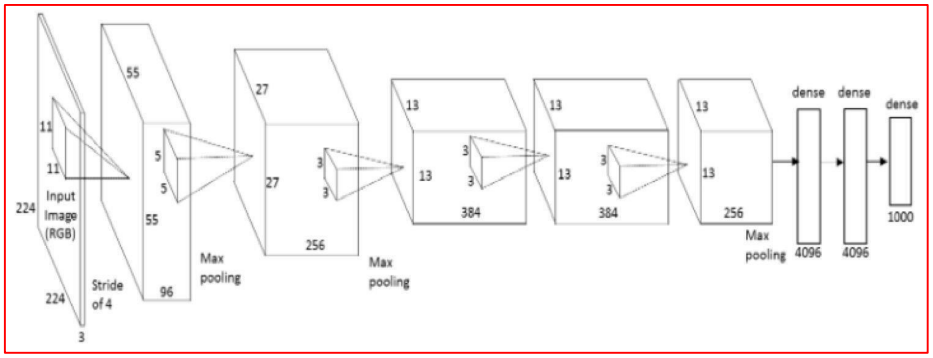
Neural Style

[A Neural Algorithm of Artistic Style by Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge, 2015]
good implementation by Justin Johnson in Torch:
https://github.com/jcjohnson/neural-style



Neural Style

Step 1: Extract **content targets** (ConvNet activations of all layers for the given content image)

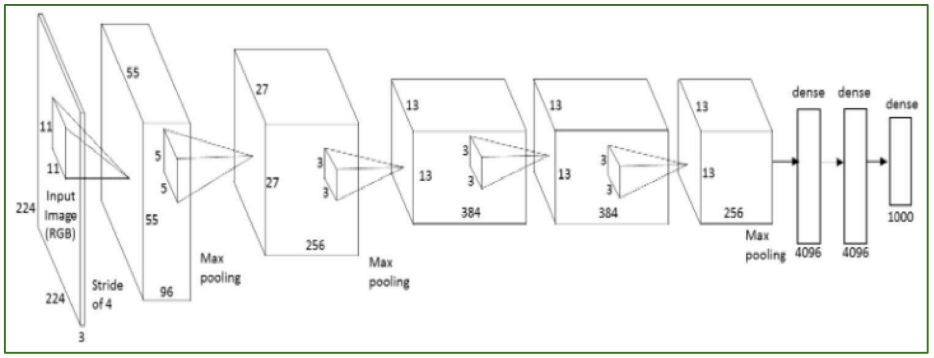


content activations

e.g.
at CONV5_1 layer we would have a [14x14x512] array of target activations

Neural Style

Step 2: Extract **style targets** (Gram matrices of ConvNet activations of all layers for the given style image)



style gram matrices

$$G = V^{\mathrm{T}} V$$

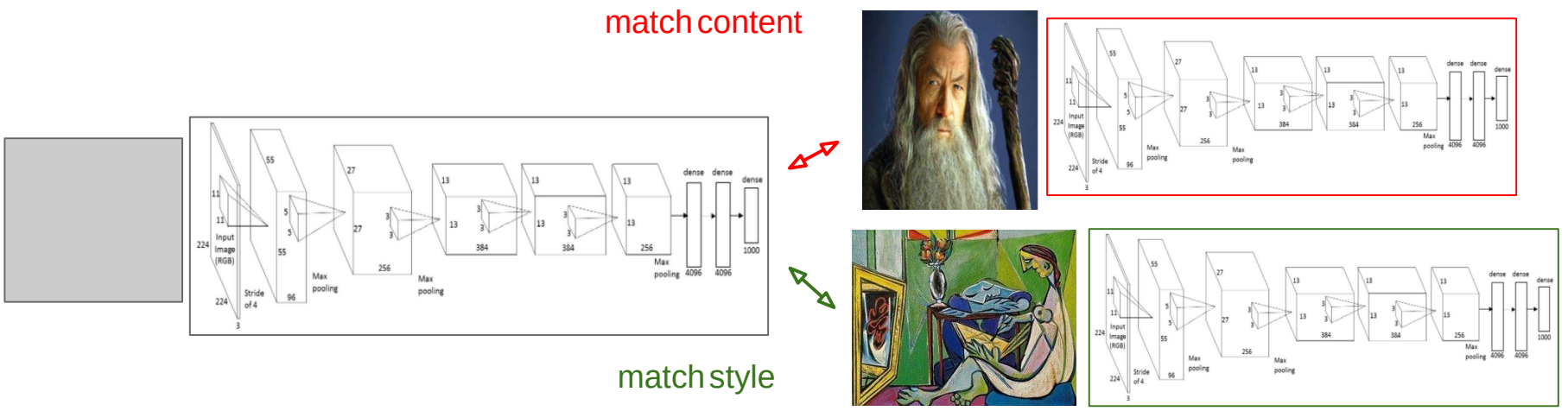
e.g.
at CONV1 layer (with [224x224x64] activations) would give a [64x64] Gram matrix of all pairwise activation covariances (summed across spatial locations)

Neural Style

Step 3: Optimize over image to have:

- The **content** of the content image (activations match content)
- The **style** of the style image (Gram matrices of activations match style)

$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$



Adapted from Andrej Karpathy

Neural Style

make your own easily on deepart.io

Dataset Distillation

- https://arxiv.org/pdf/1811.10959.pdf

DATASET DISTILLATION

Tongzhou Wang
Facebook AI Research, MIT CSAIL

Jun-Yan Zhu
MIT CSAIL

Antonio Torralba
MIT CSAIL

Alexei A. Efros
UC Berkeley

ABSTRACT

Model distillation aims to distill the knowledge of a complex model into a simpler one. In this paper, we consider an alternative formulation called *dataset distillation*: we keep the model fixed and instead attempt to distill the knowledge from a large training dataset into a small one. The idea is to *synthesize* a small number of data points that do not need to come from the correct data distribution, but will, when given to the learning algorithm as training data, approximate the model trained on the original data. For example, we show that it is possible to compress $60,000$ MNIST training images into just 10 synthetic *distilled images* (one per class) and achieve close to original performance with only a few gradient descent steps, given a fixed network initialization. We evaluate our method in various initialization settings and with different learning objectives. Experiments on multiple datasets show the advantage of our approach compared to alternative methods.