Lecture 14:

Understanding and Visualizing Convolutional Networks

Previously: Computer Vision Tasks

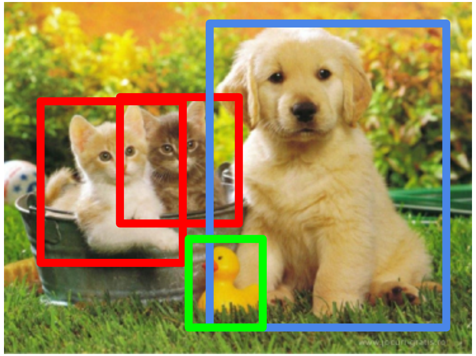
Classification

CAT

Classification + Localization

CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation

CAT, DOG, DUCK

Single object

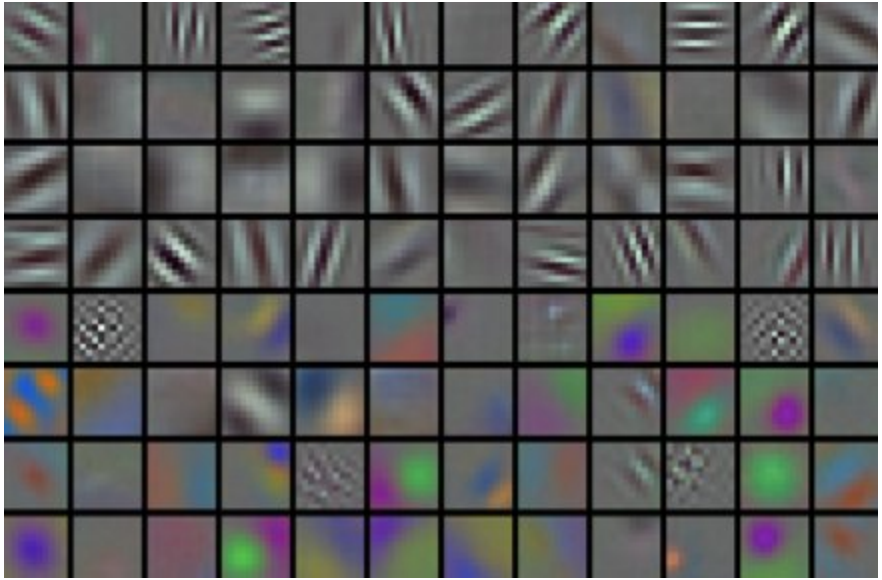
Multiple objects

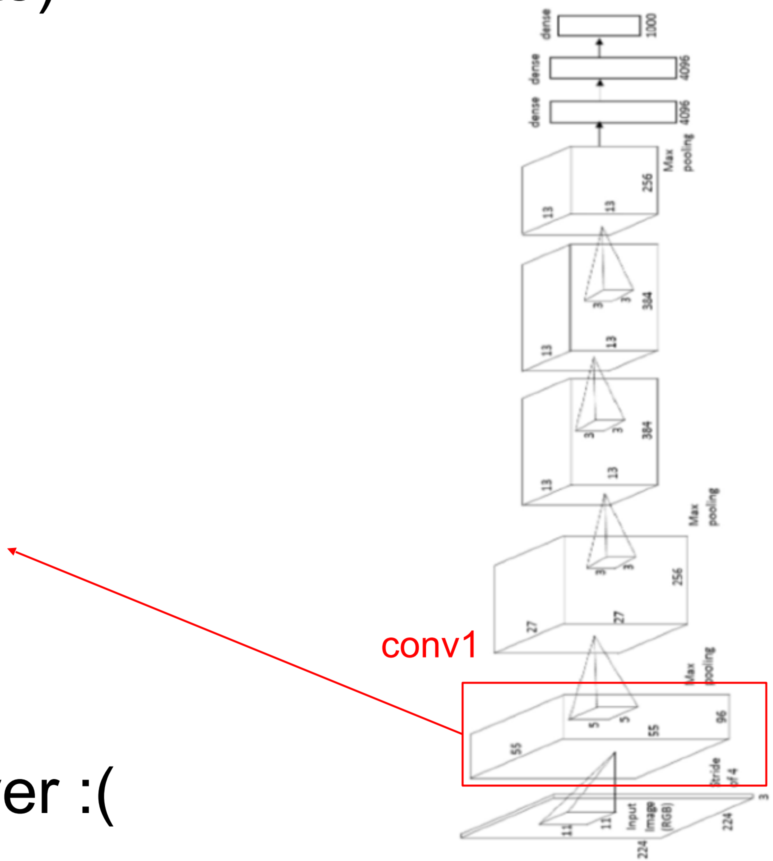
Today: Understanding ConvNets

- Visualize the weights
- Visualize patches that maximally activate neurons
- Visualize the representation space (e.g. with t-SNE)
- Occlusion experiments
- Human experiment comparisons
- Deconv approaches (single backward pass)
- Optimization over image approaches (optimization)

Visualize the filters/kernels (raw weights)

one-stream AlexNet

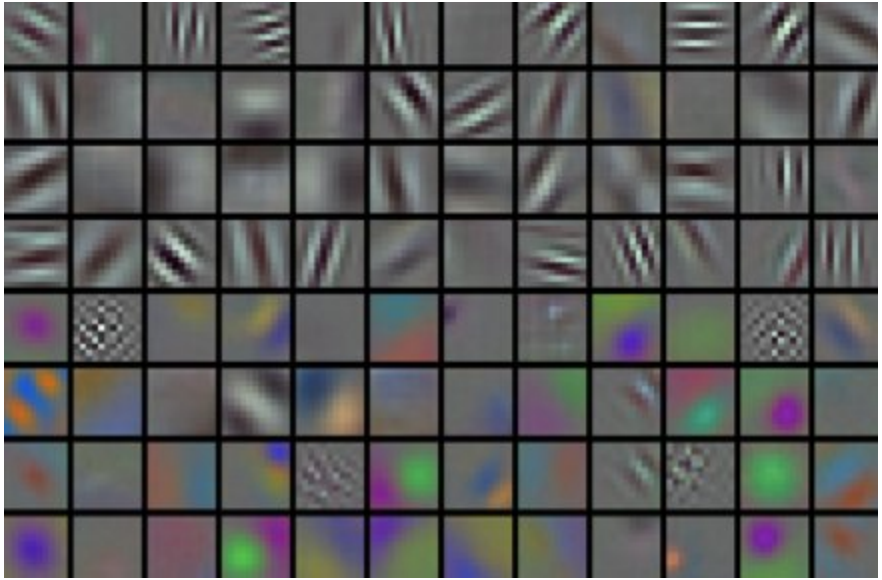


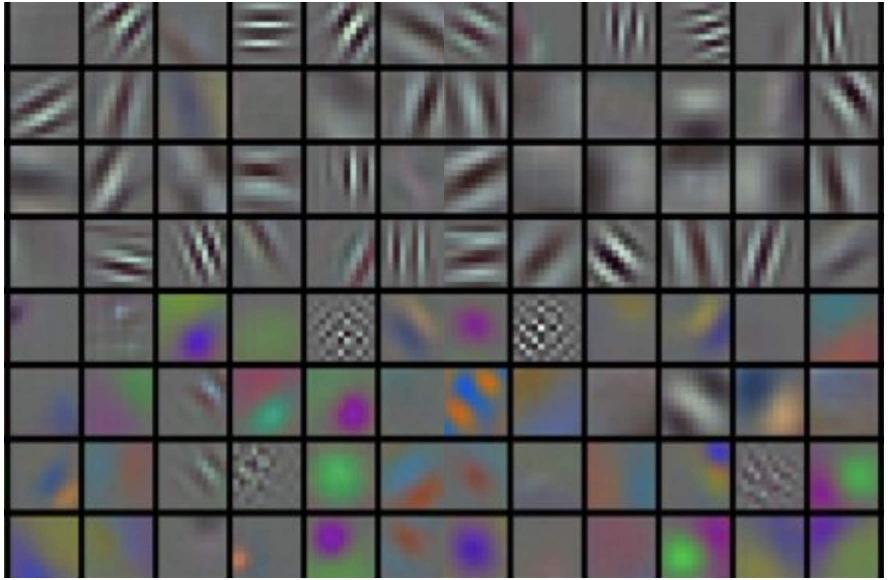


only interpretable on the first layer :(

Visualize the filters/kernels (raw weights)

one-stream AlexNet





Visualize the filters/kernels (raw weights)

you can still do it for higher layers, it's just not that interesting

(these are taken from ConvNetJS CIFAR-10 demo)

layer 1 weights

layer 2 weights

layer 3 weights

Visualize patches that maximally activate neurons

one-stream AlexNet

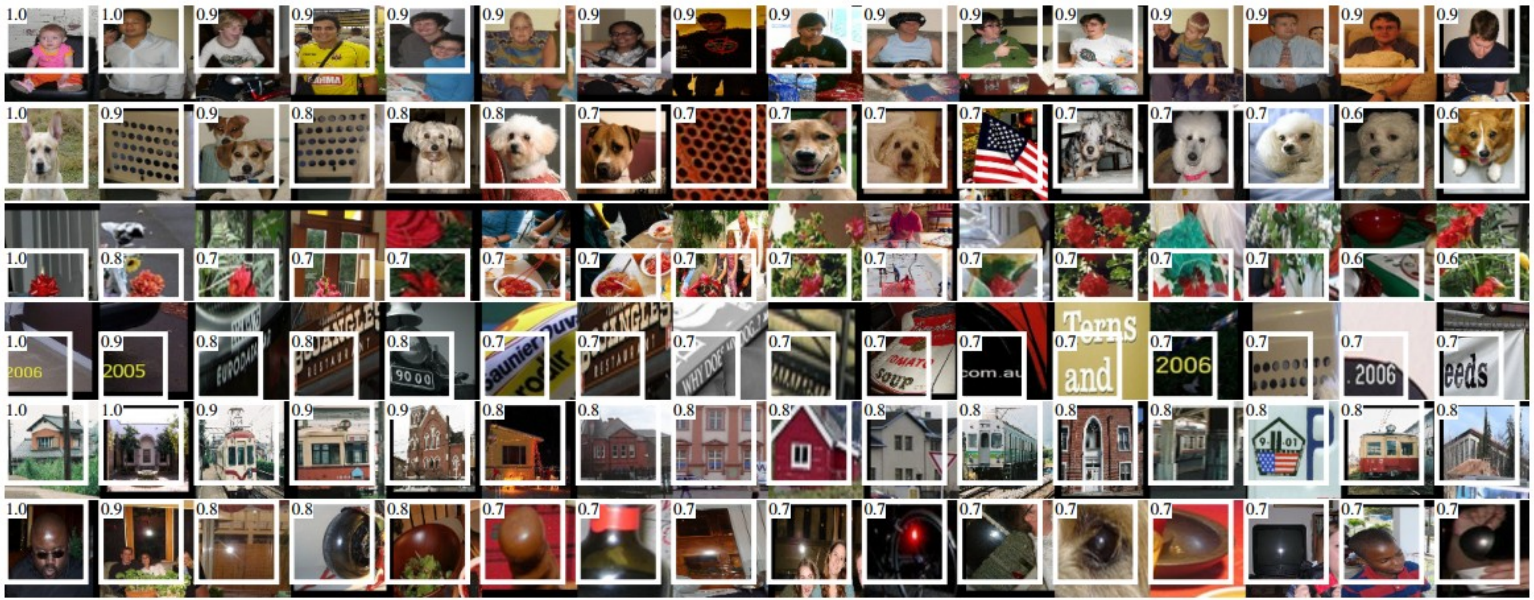
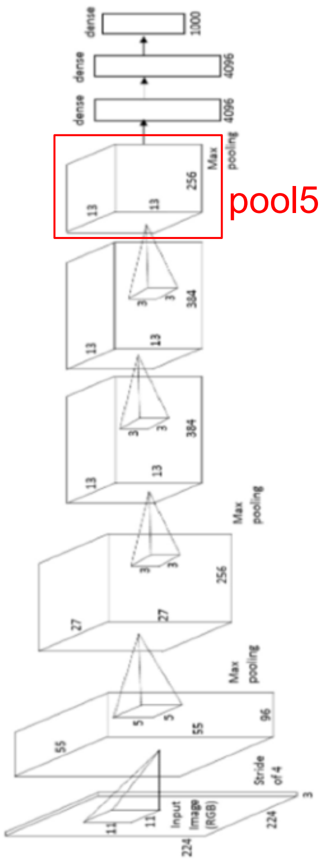


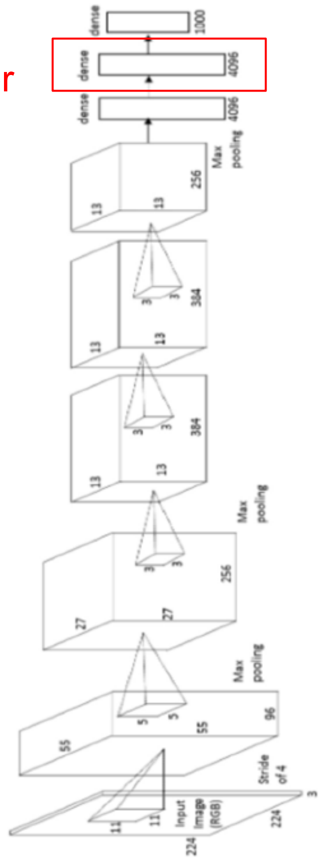
Figure 4: Top regions for six pool$_5$ units. Receptive fields and activation values are drawn in white. Some units are aligned to concepts, such as people (row 1) or text (4). Other units capture texture and material properties, such as dot arrays (2) and specular reflections (6).



Rich feature hierarchies for accurate object detection and semantic segmentation [Girshick, Donahue, Darrell, Malik]

Visualizing the representation

fc7 layer



4096-dimensional “code” for an image
(layer immediately before the classifier)

can collect the code for many images

Visualizing the representation

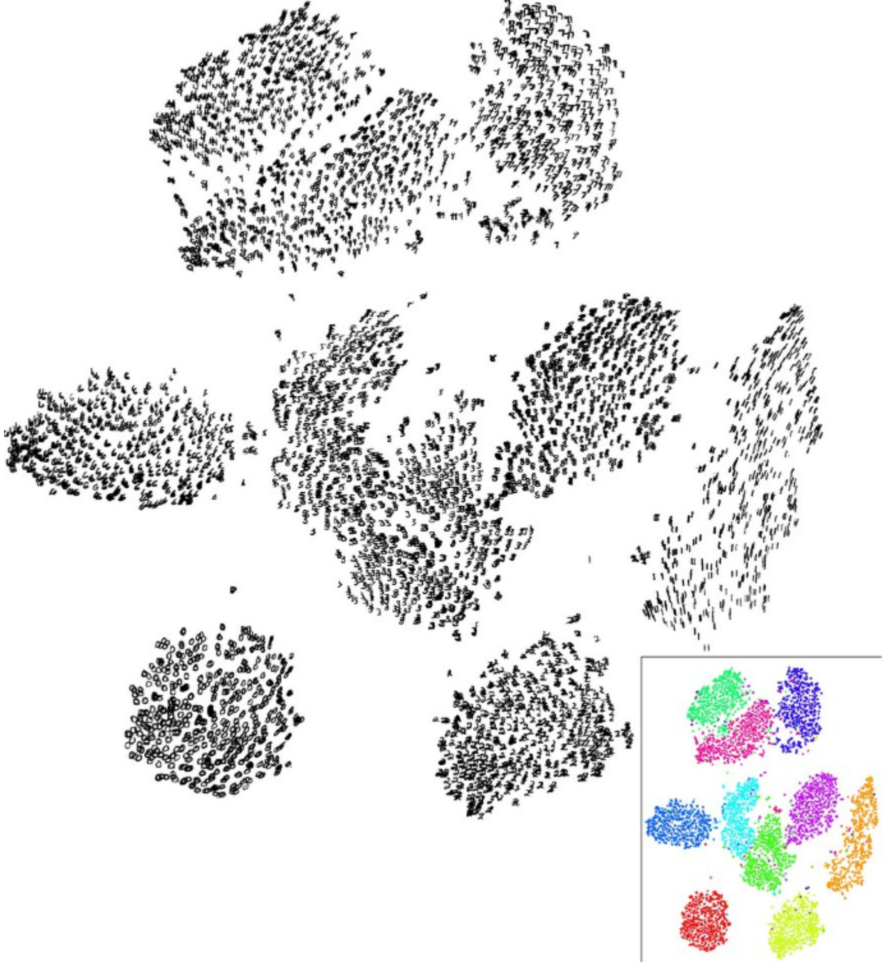
t-SNE visualization

[van der Maaten & Hinton]
(t-distributed stochastic neighbor embed.)

Embed high-dimensional points so that locally, pairwise distances are conserved

i.e. similar things end up in similar places. dissimilar things end up wherever

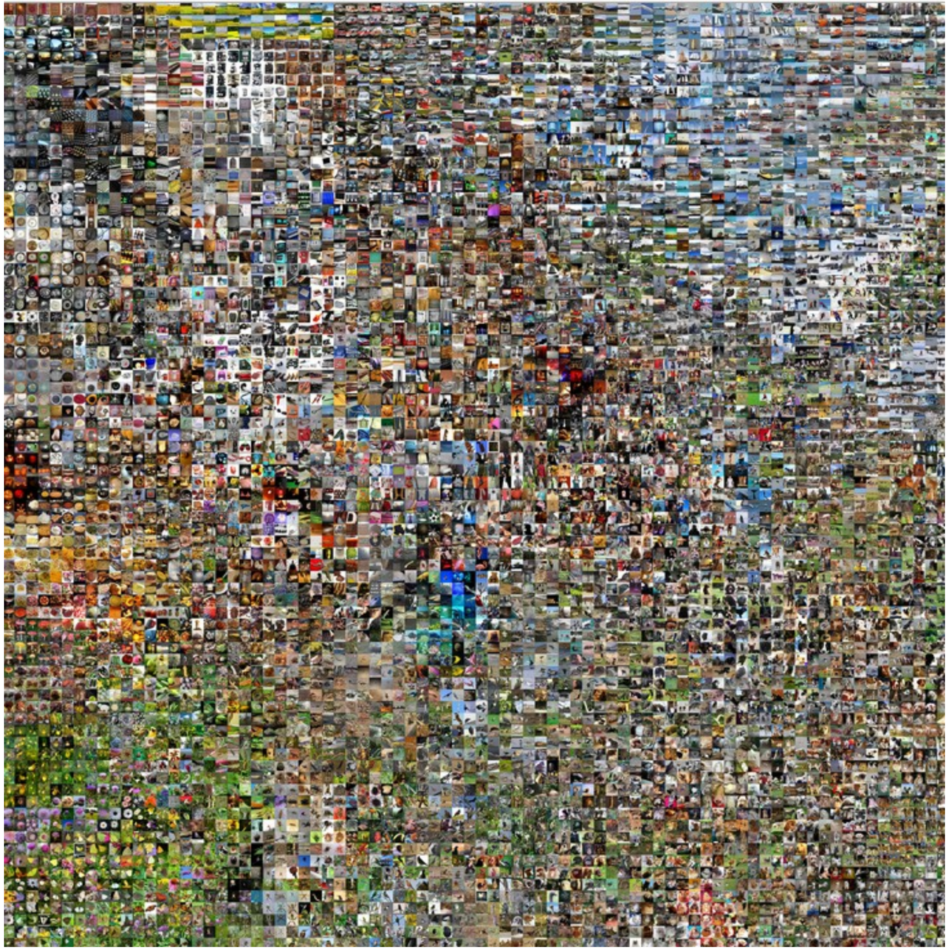
Right: Example embedding of MNIST digits (0-9) in 2D



t-SNE visualization:

two images are placed nearby if their CNN codes are close. See more:

http://cs.stanford.edu/people/karpathy/cnnembed/



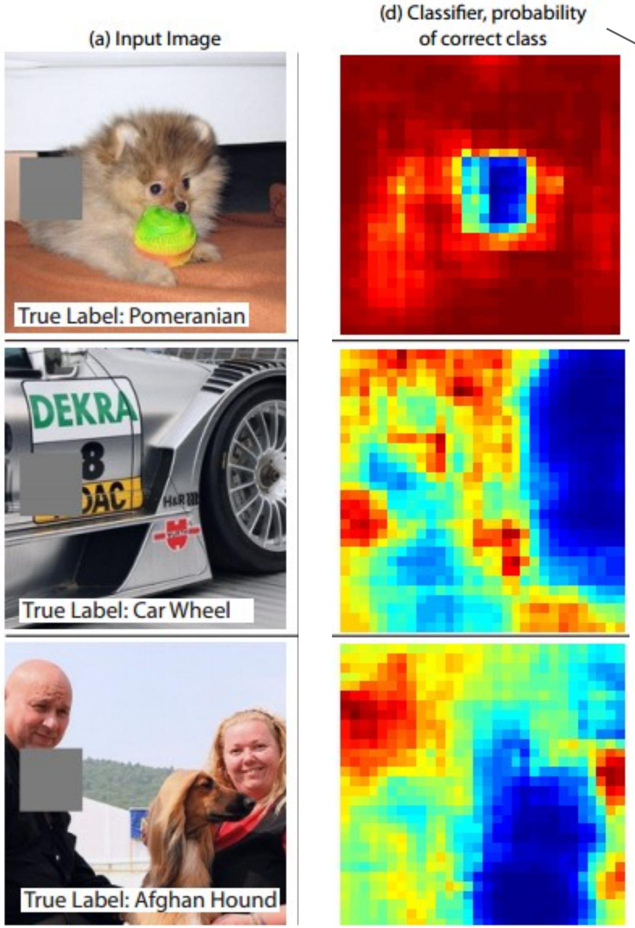
Occlusion experiments
[Zeiler & Fergus 2013]

(a) Input Image

(d) Classifier, probability of correct class

(as a function of the position of the square of zeros in the original image)

Occlusion experiments
[Zeiler & Fergus 2013]

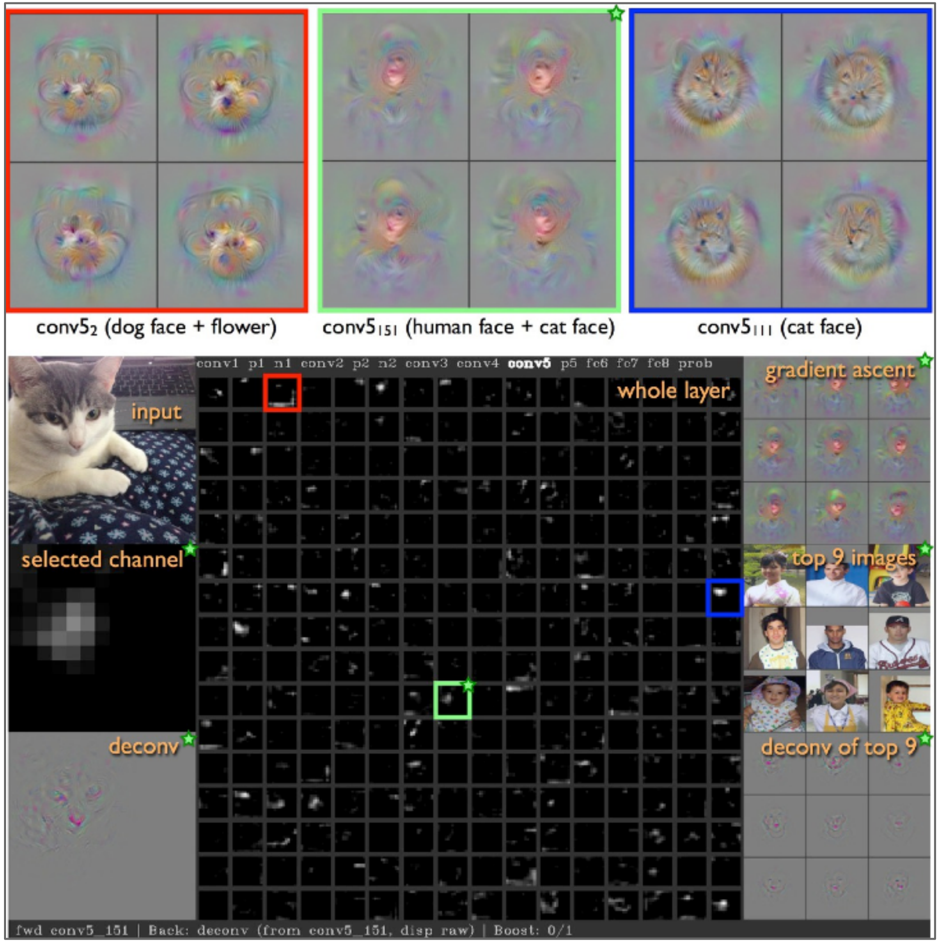


(as a function of the position of the square of zeros in the original image)

Visualizing Activations

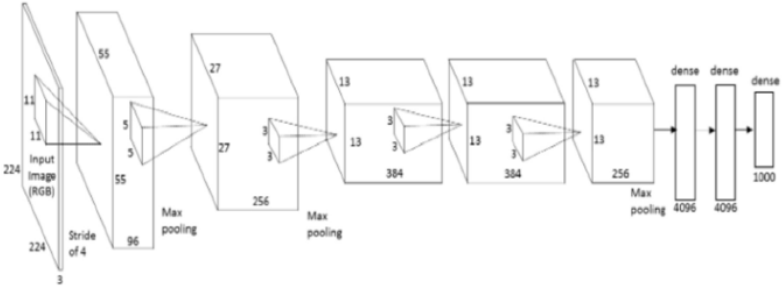
http://yosinski.com/deepvis

YouTube video
https://www.youtube.com/watch?v=AgkfIQ4IGaM
(4min)



Deconv approaches

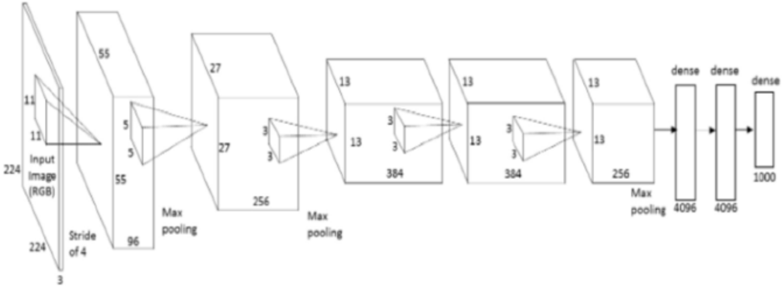
1. Feed image into net

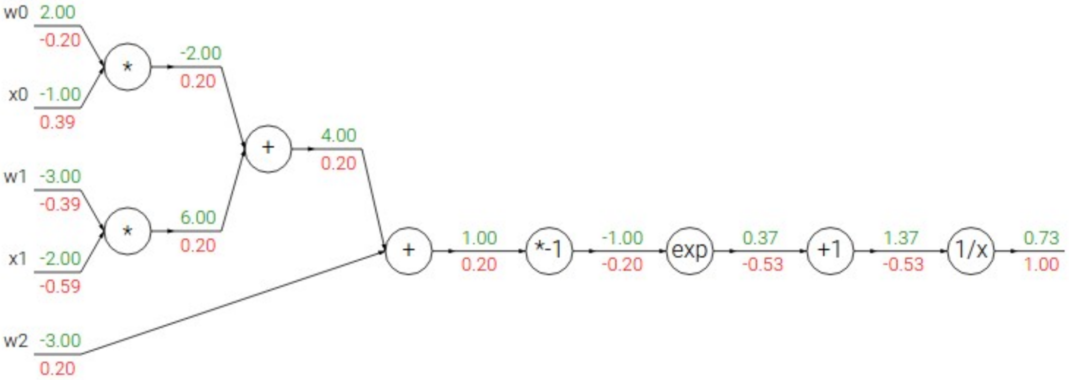


Q: how can we compute the gradient of any arbitrary neuron in the network w.r.t. the image?

Deconv approaches

1. Feed image into net





Deconv approaches

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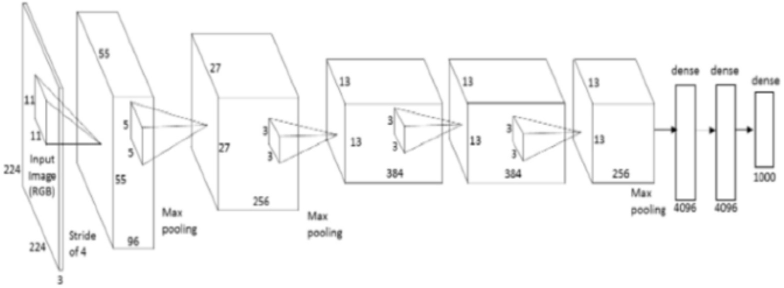
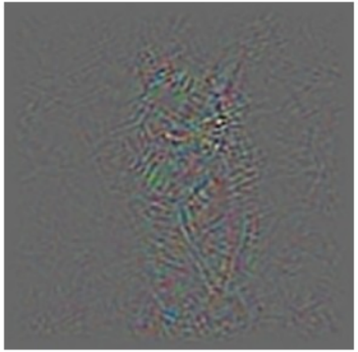


2. Pick a layer, set the gradient there to be all zero except for one 1 for some neuron of interest
3. Backprop to image:



Deconv approaches

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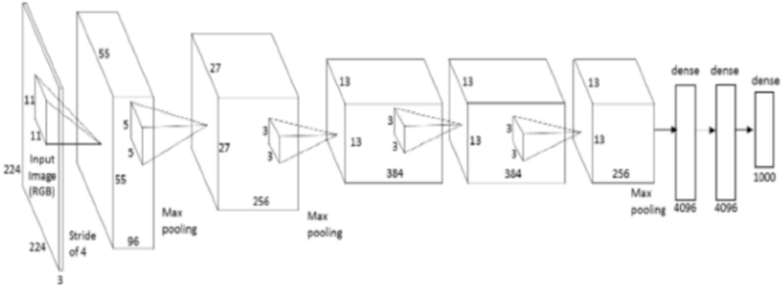

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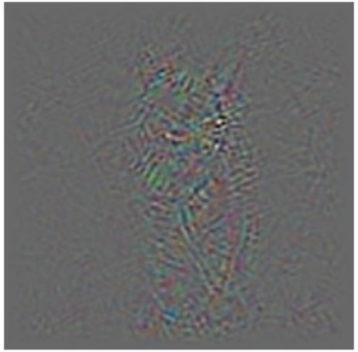
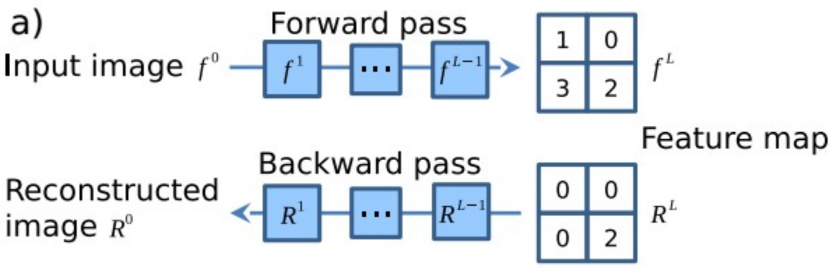


“Guided backpropagation:” instead

Deconv approaches

[Visualizing and Understanding Convolutional Networks, Zeiler and Fergus 2013]
[Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps, Simonyan et al., 2014]
[Striving for Simplicity: The all convolutional net, Springenberg, Dosovitskiy, et al., 2015]



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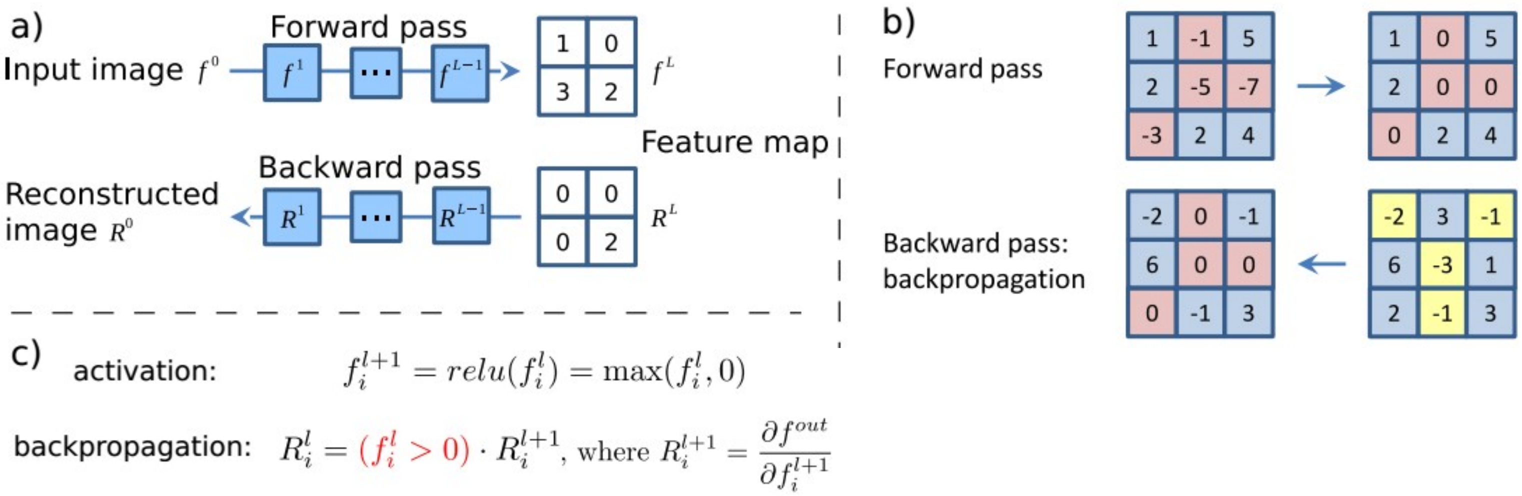

Backward pass for a ReLU (will be changed in Guided Backprop)

Deconv approaches

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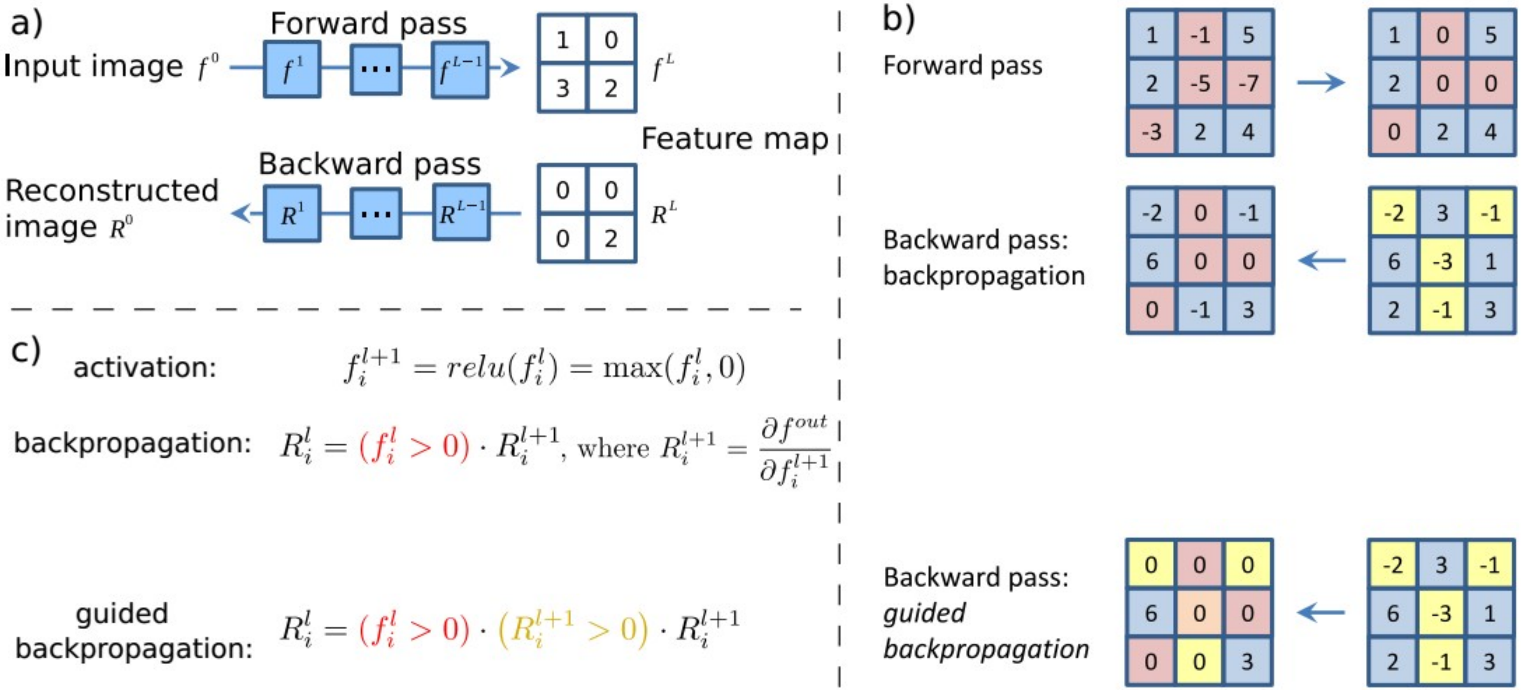
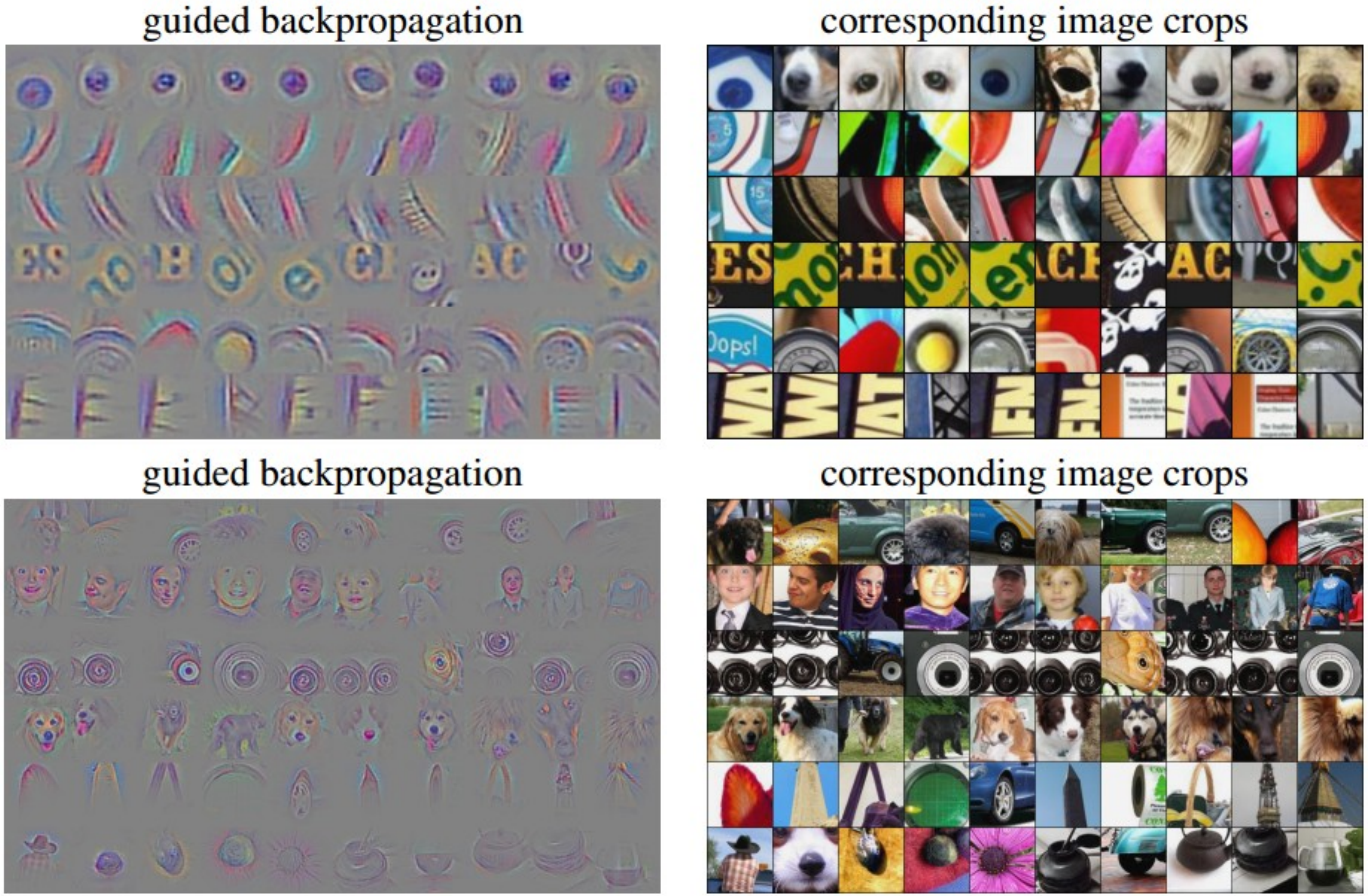


Visualization of patterns learned by the layer **conv6** (top) and layer **conv9** (bottom) of the network trained on ImageNet.

Each row corresponds to one filter.

The visualization using “guided backpropagation” is based on the top 10 image patches activating this filter taken from the ImageNet dataset.



[Striving for Simplicity: The all convolutional net, Springenberg, Dosovitskiy, et al., 2015]

Deconv approaches

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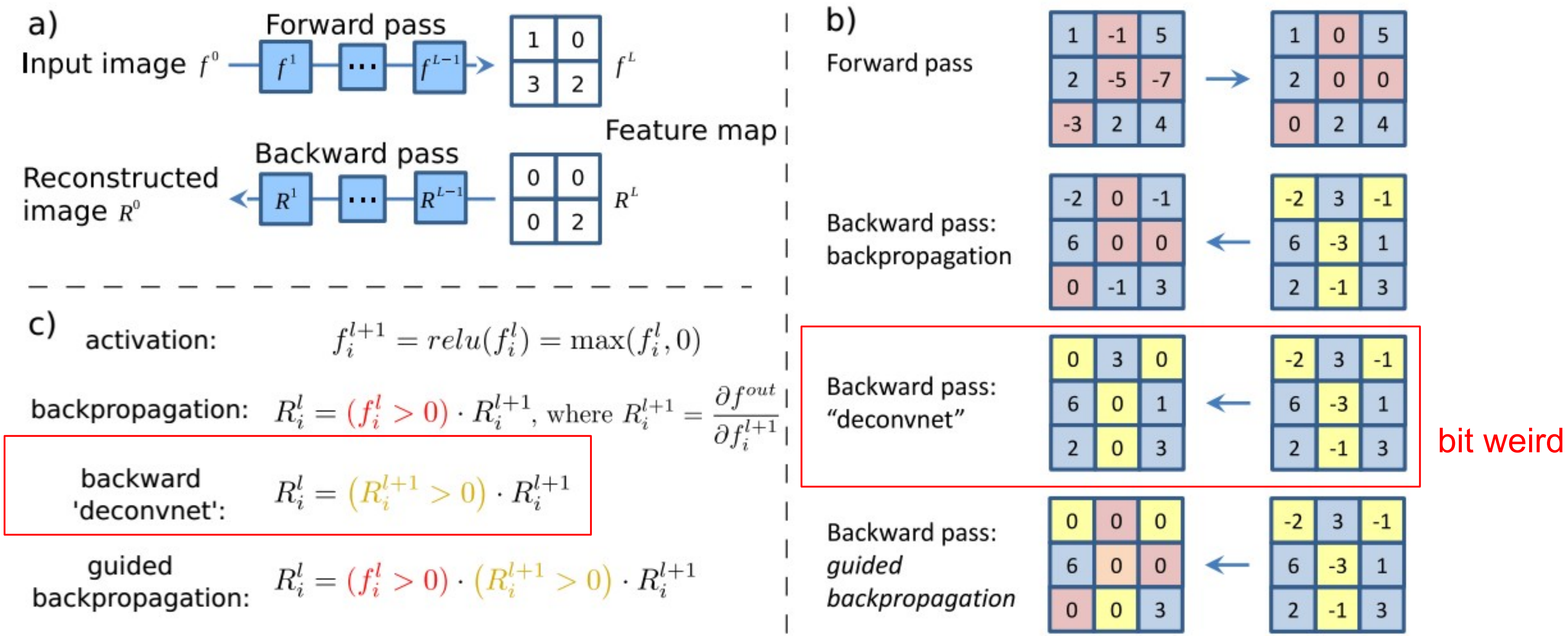
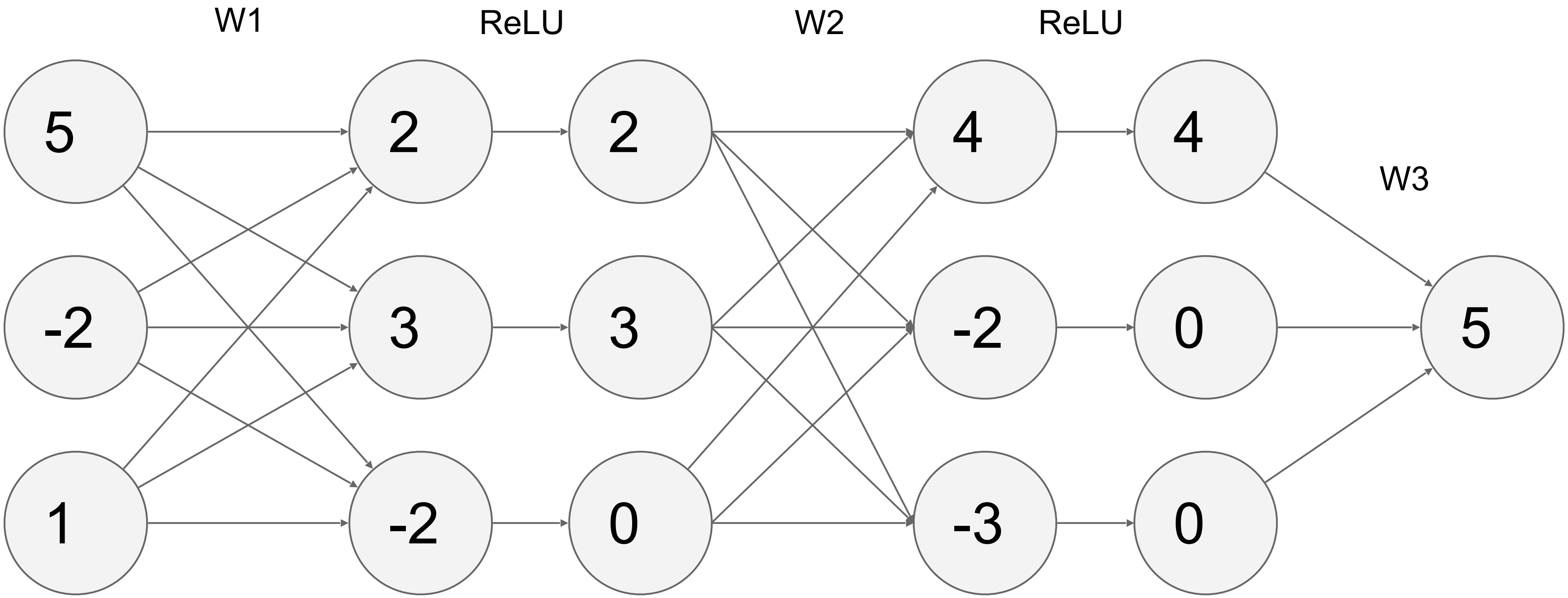
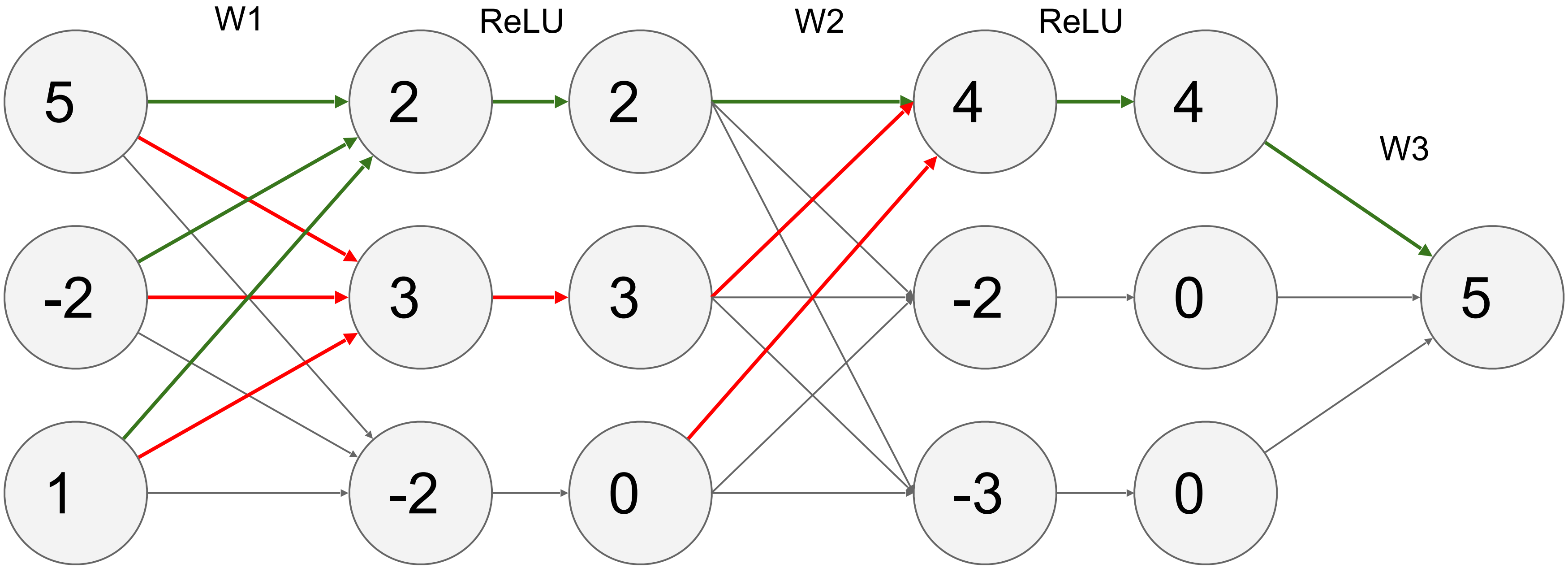


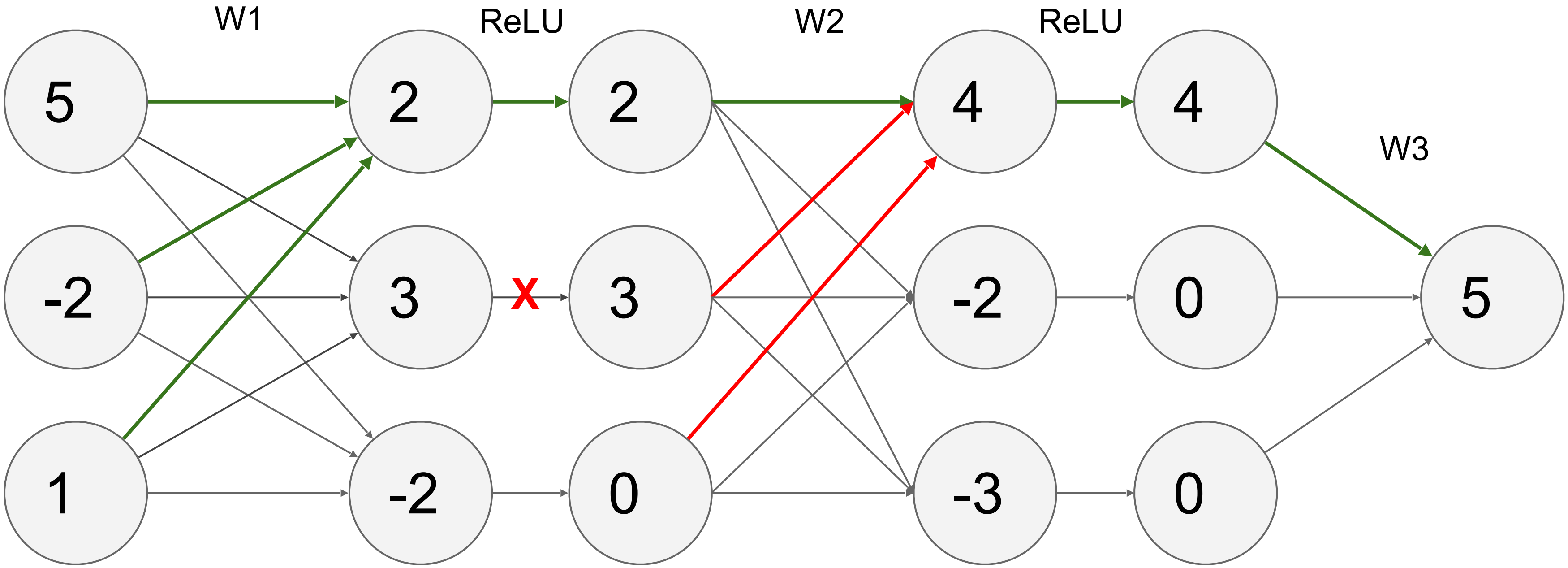

W1
ReLU
W2
ReLU
W3
5
-2
1
2
3
-2
2
3
0
4
-2
-3
4
0
0
5

In backprop: all +ve and -ve paths of influence through the graph interfere



positive gradient, negative gradient, zero gradient

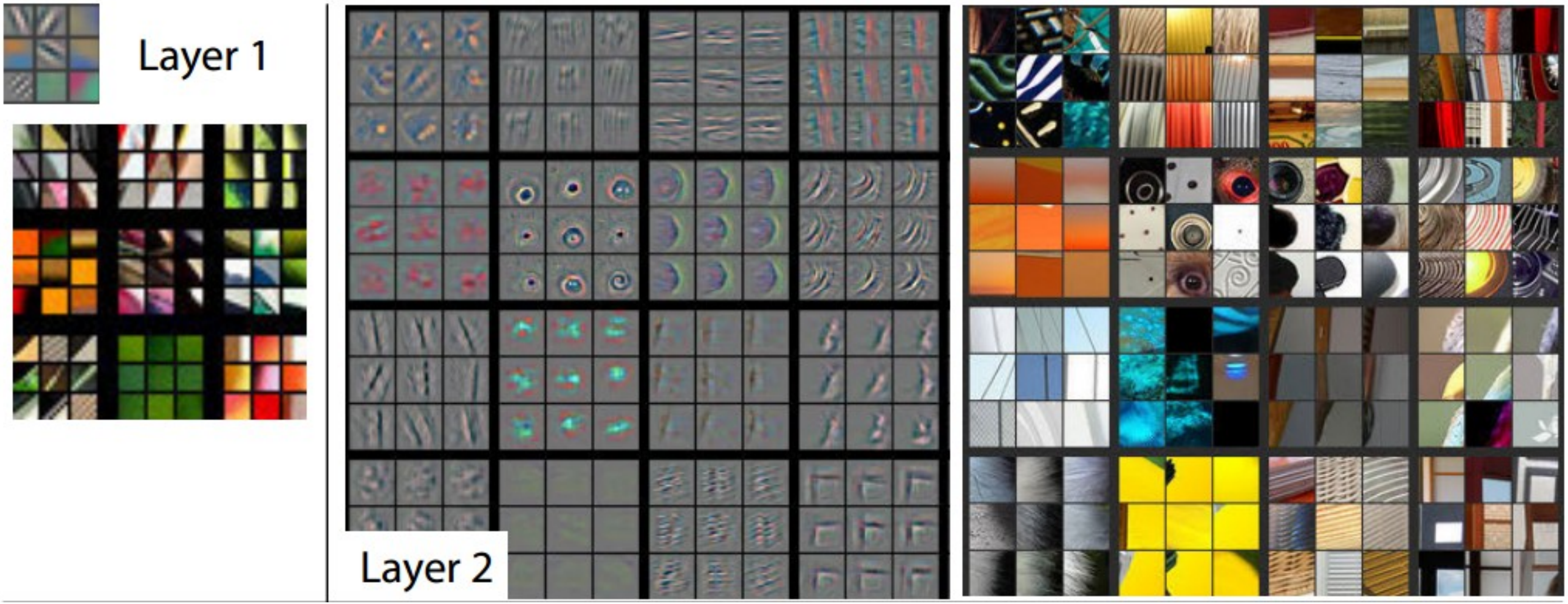
In guided backprop: cancel out -ve paths of influence at each step
(i.e. we only keep positive paths of influence)



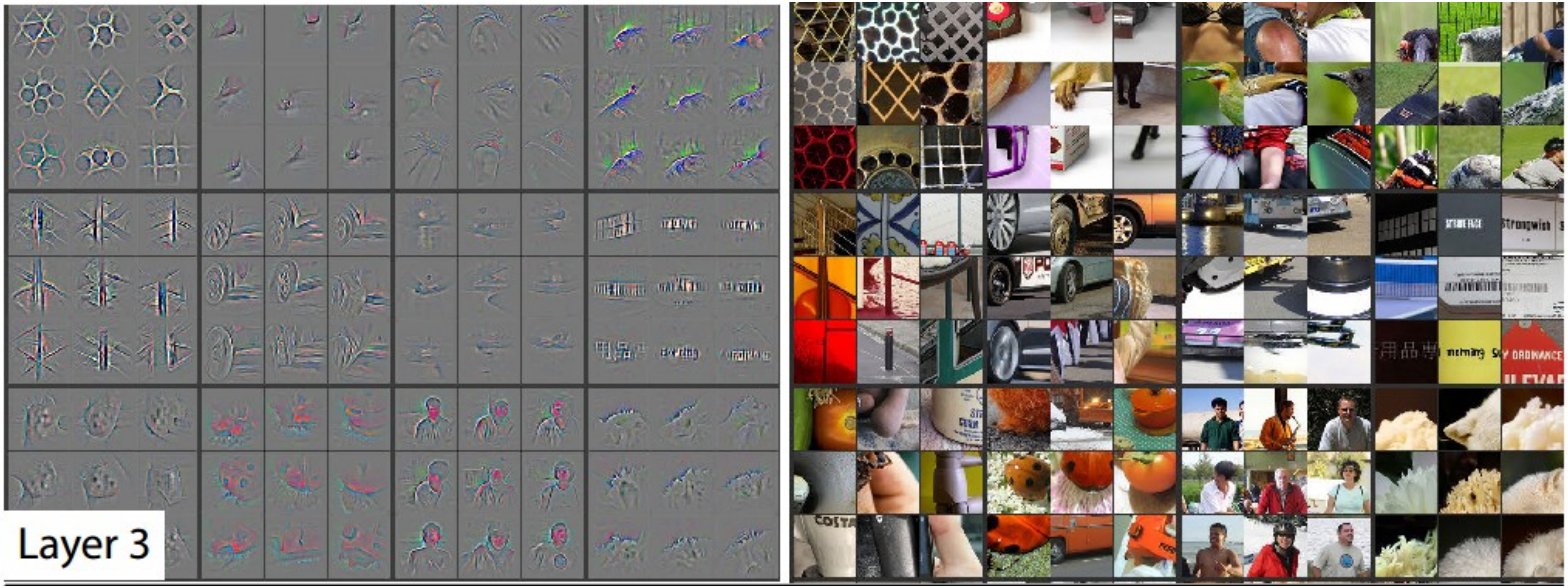
positive gradient, negative gradient, zero gradient

Visualizing and Understanding Convolutional Networks
Zeiler & Fergus, 2013

Visualizing arbitrary neurons along the way to the top...



Visualizing arbitrary neurons along the way to the top...



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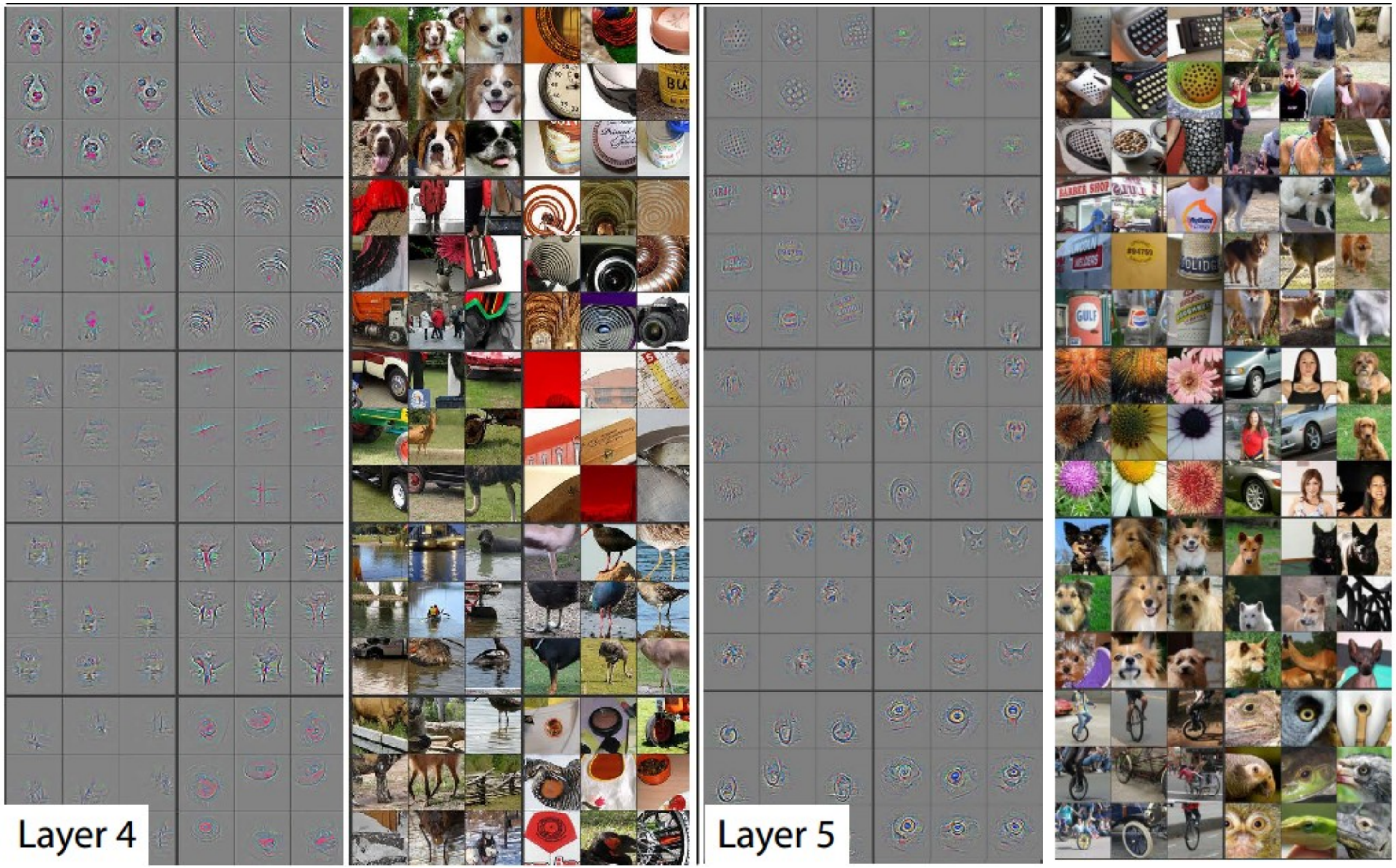
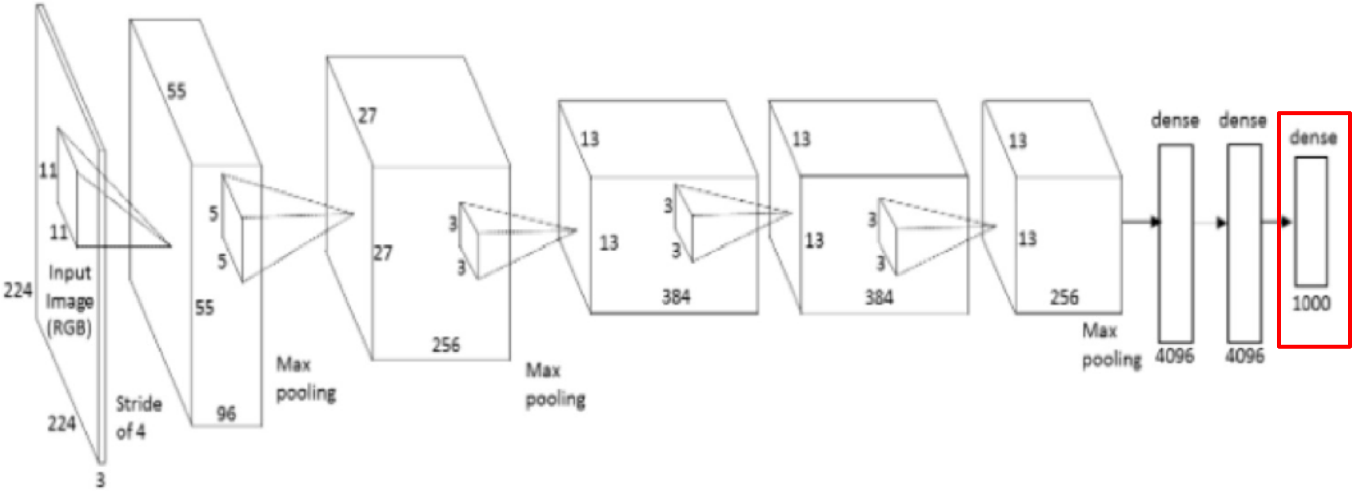


Optimization to Image

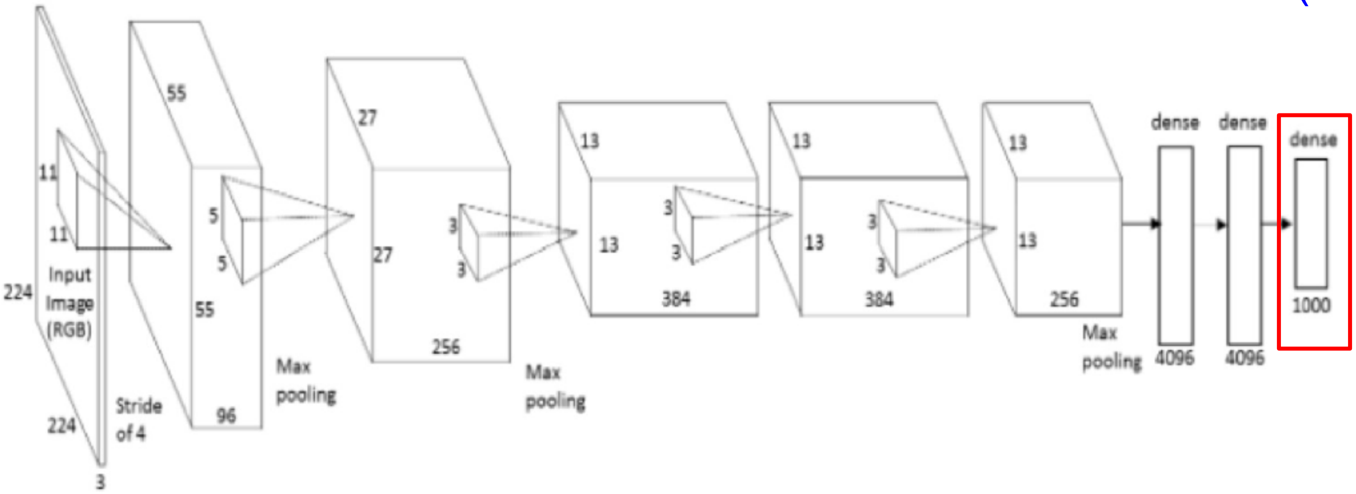


Q: can we find an image that maximizes some class score?

Optimization to Image

$$\boxed{\arg\max_{I} \boxed{S_c(I)} - \lambda \|I\|_2^2}$$

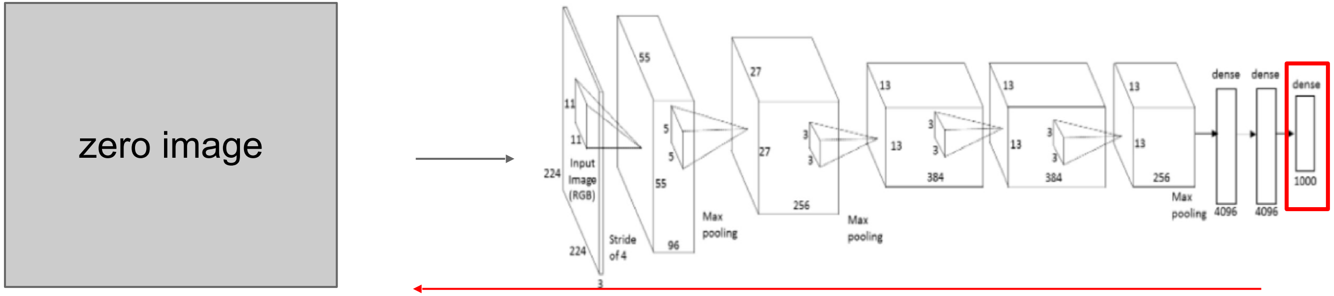
score for class c (before Softmax)



Q: can we find an image that maximizes some class score?

Optimization to Image

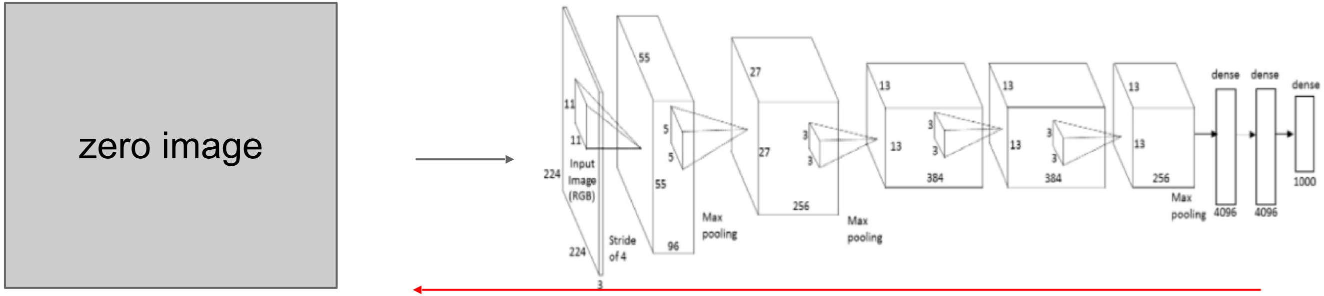
1. feed in zeros.



2. set the gradient of the scores vector to be [0,0,....1,....,0], then backprop to image

Optimization to Image

1. feed in zeros.



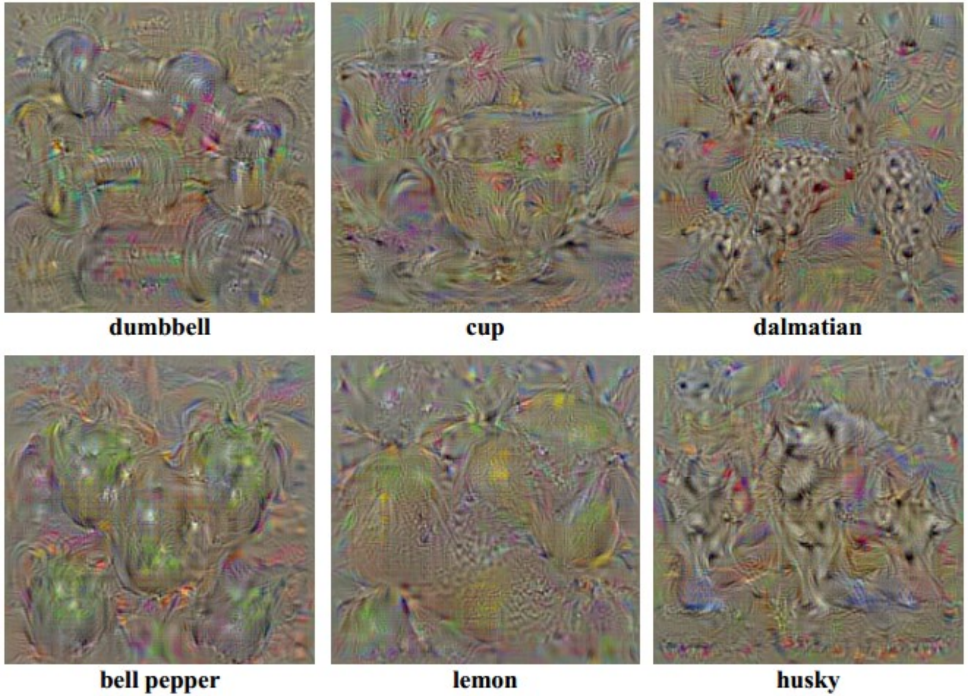
2. set the gradient of the scores vector to be [0,0,....1,....,0], then backprop to image
3. do a small “image update”
4. forward the image through the network.
5. go back to 2.

$$\arg\max_{I} \boxed{S_c(I)} - \lambda \|I\|_2^2$$

score for class c (before Softmax)

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps
Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, 2014

1. Find images that maximize some class score:



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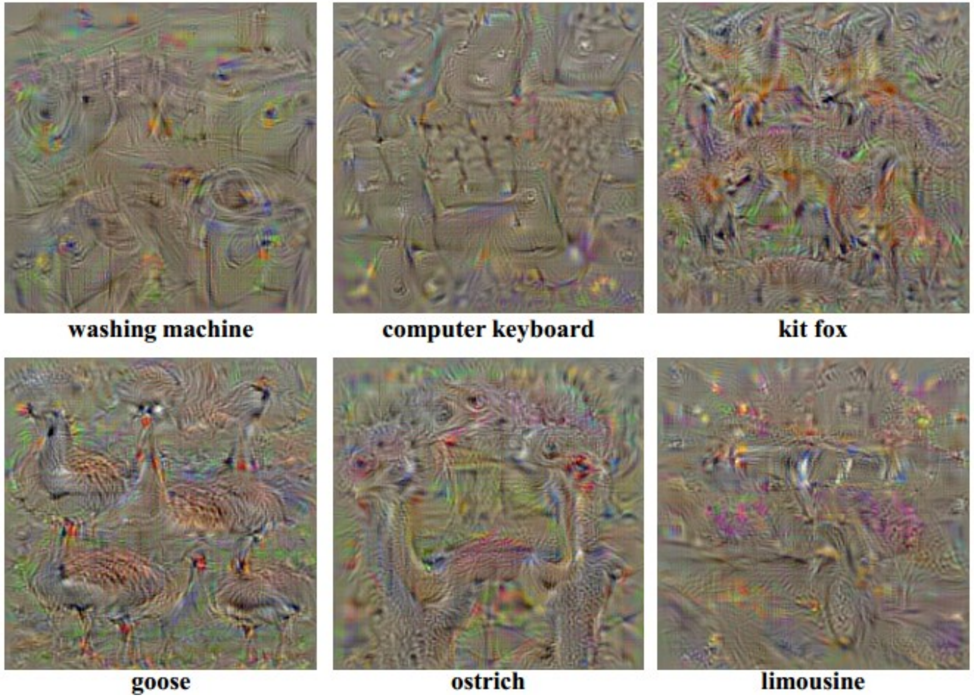

2. Visualize the Data gradient:

M = ?

(note that the gradient on data has three channels. Here they visualize M, s.t.:

$$M_{ij} = \max_c |w_{h(i,j,c)}|$$

(at each pixel take abs val, and max over channels)

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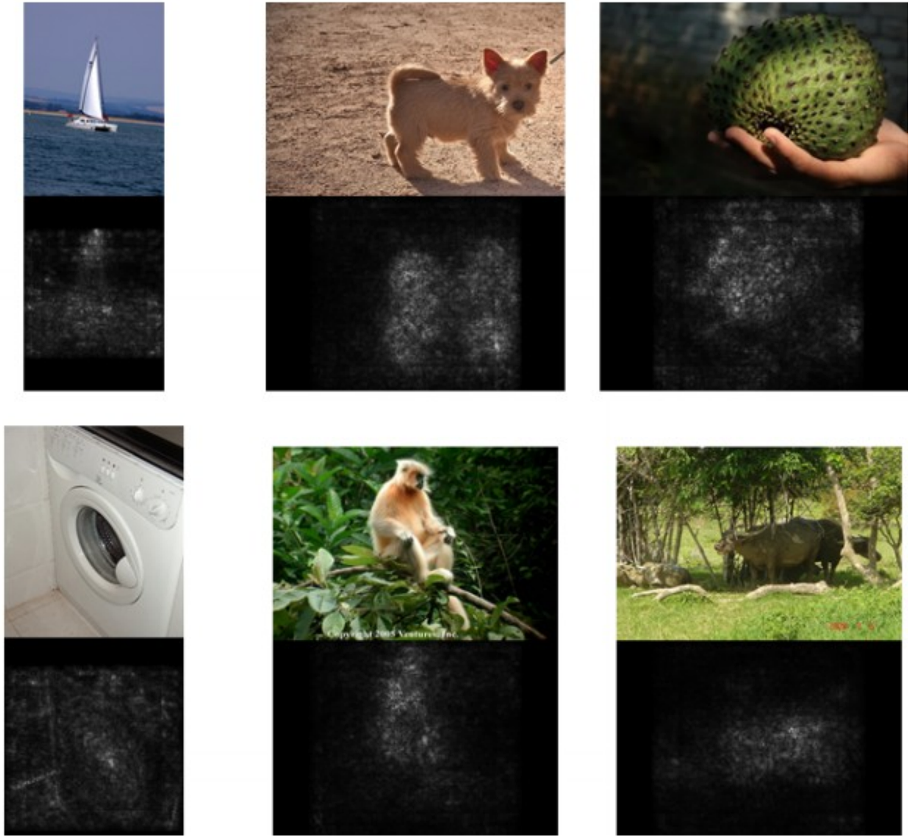
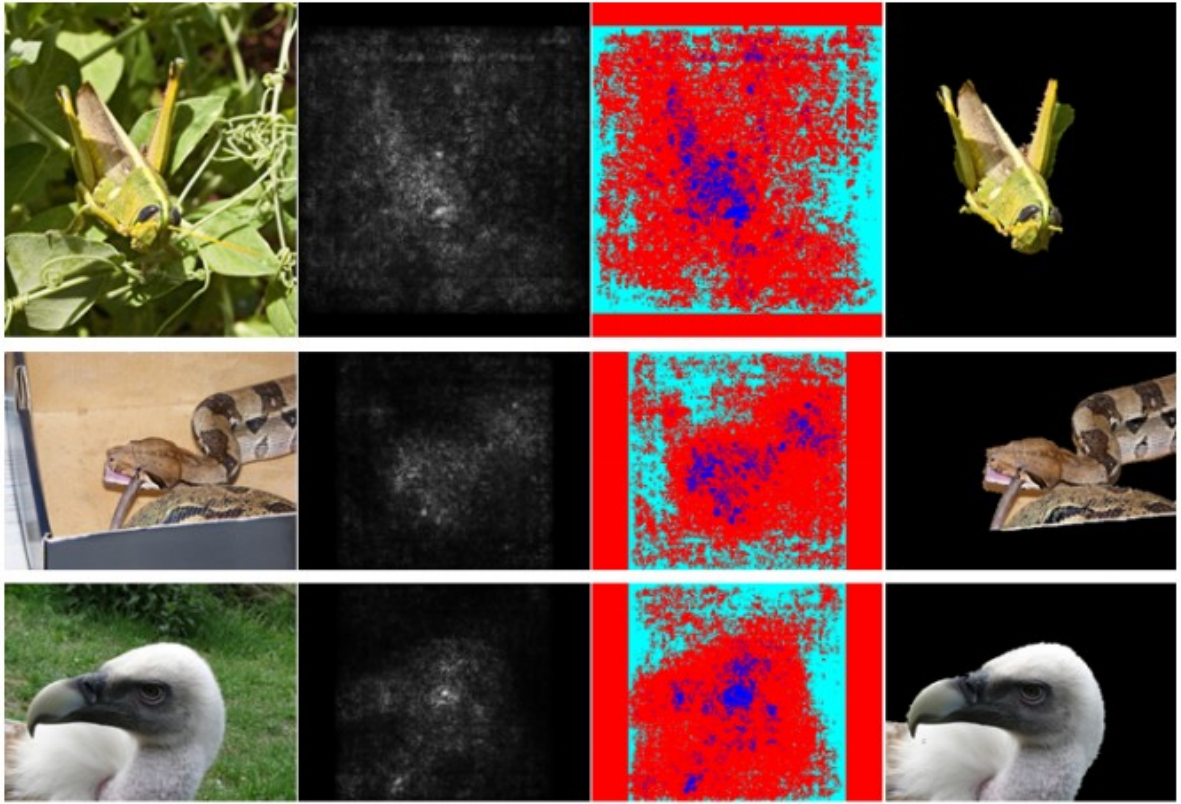
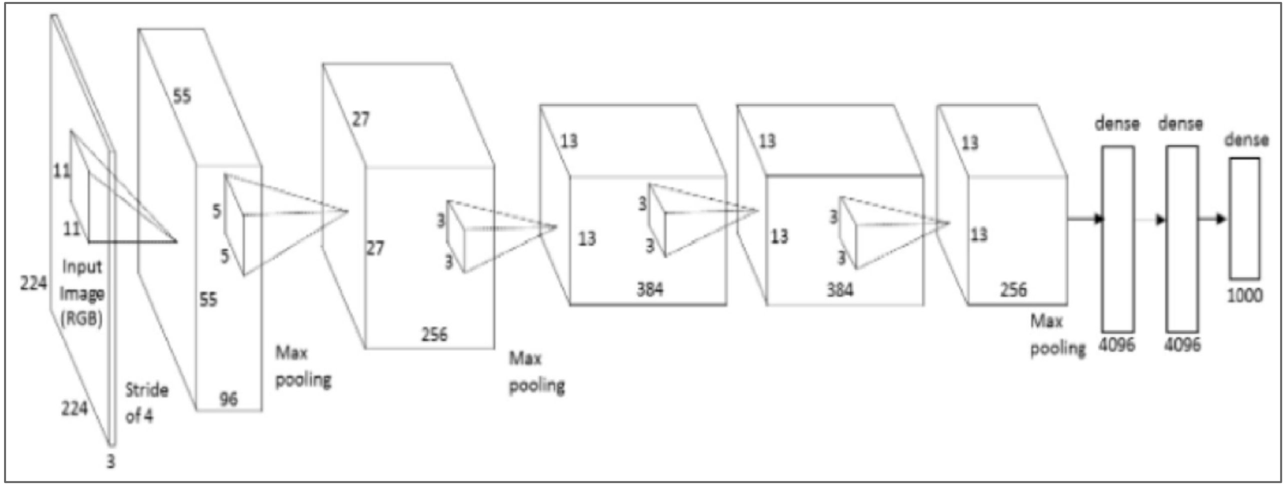


- Use **grabcut** for segmentation



We can in fact do this for arbitrary neurons along the ConvNet



Repeat:

1. Forward an image
2. Set activations in layer of interest to all zero, except for a 1.0 for a neuron of interest
3. Backprop to image
4. Do an “image update”

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

Proposed a different form of regularizing the image

$$\arg\max_{I} S_c(I) - \boxed{\lambda \|I\|_2^2}$$

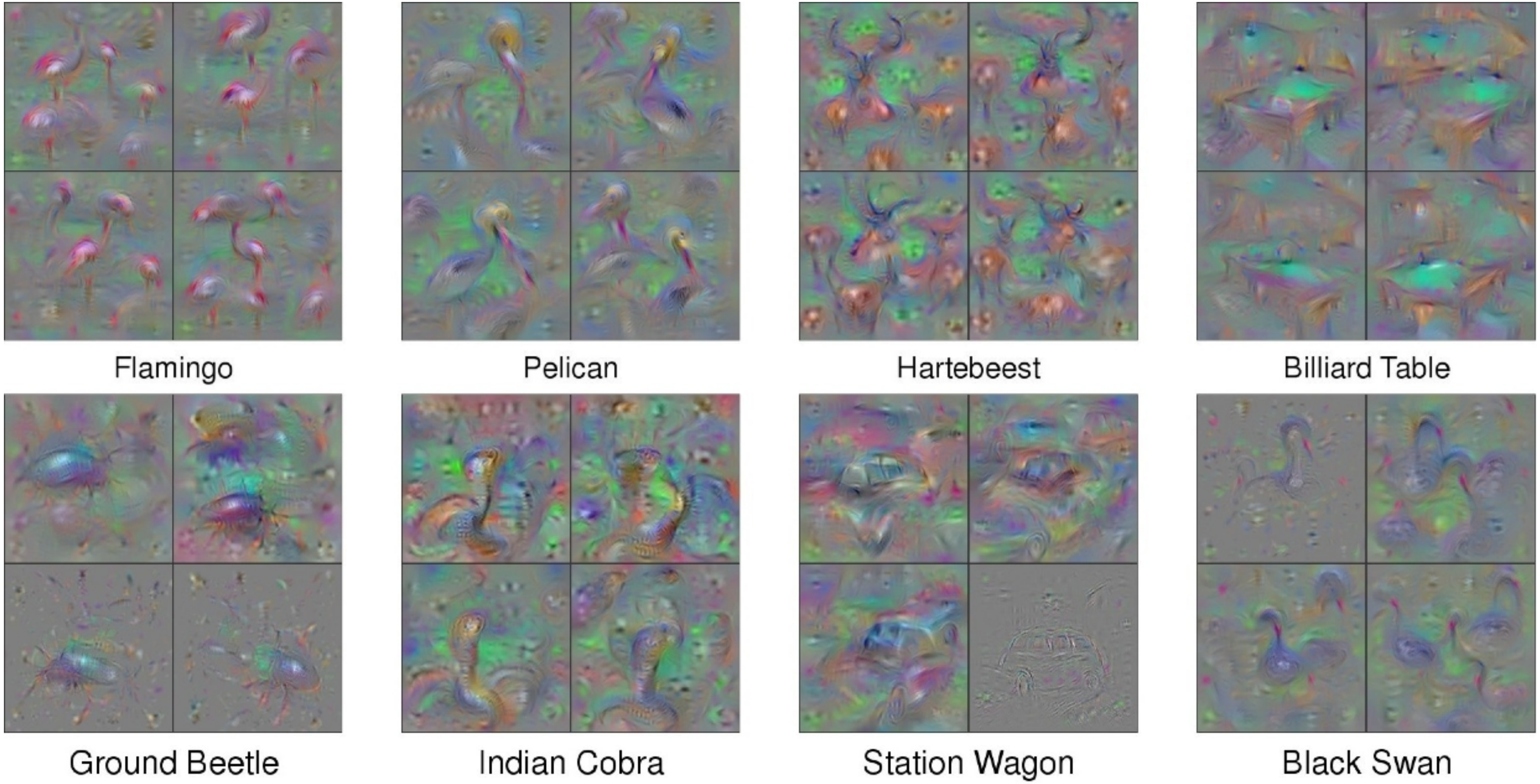
More explicit scheme:

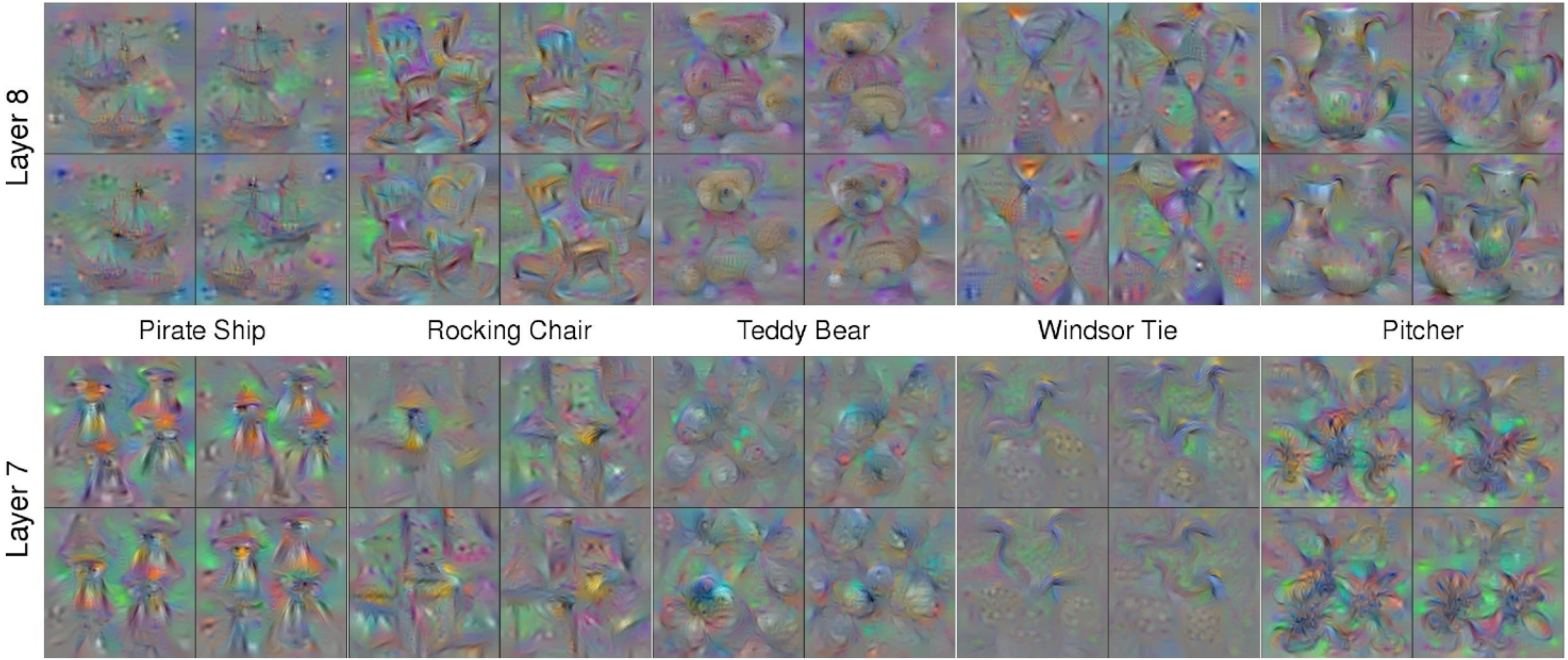
Repeat:

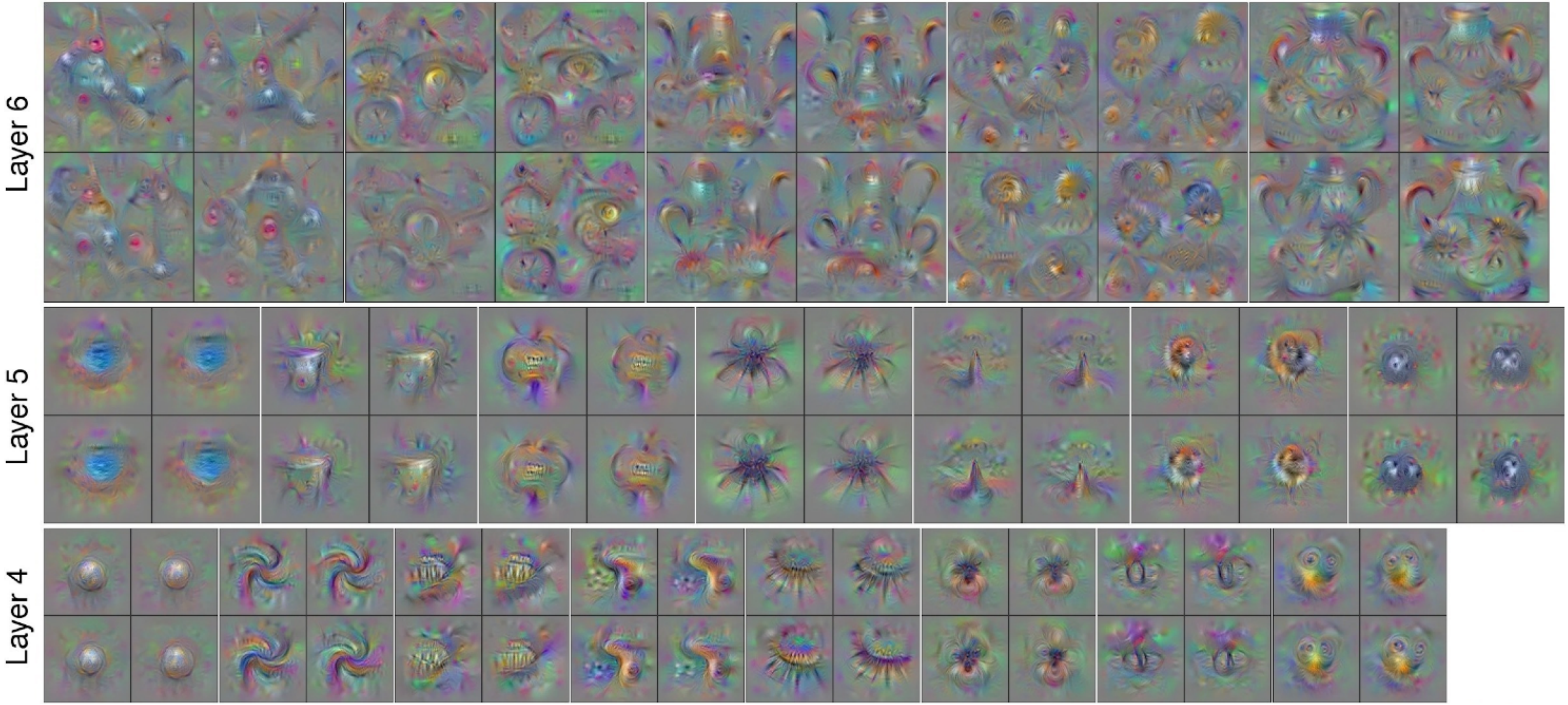
- Update the image **x** with gradient from some unit of interest
- Blur x a bit
- Take any pixel with small norm to zero (to encourage sparsity)

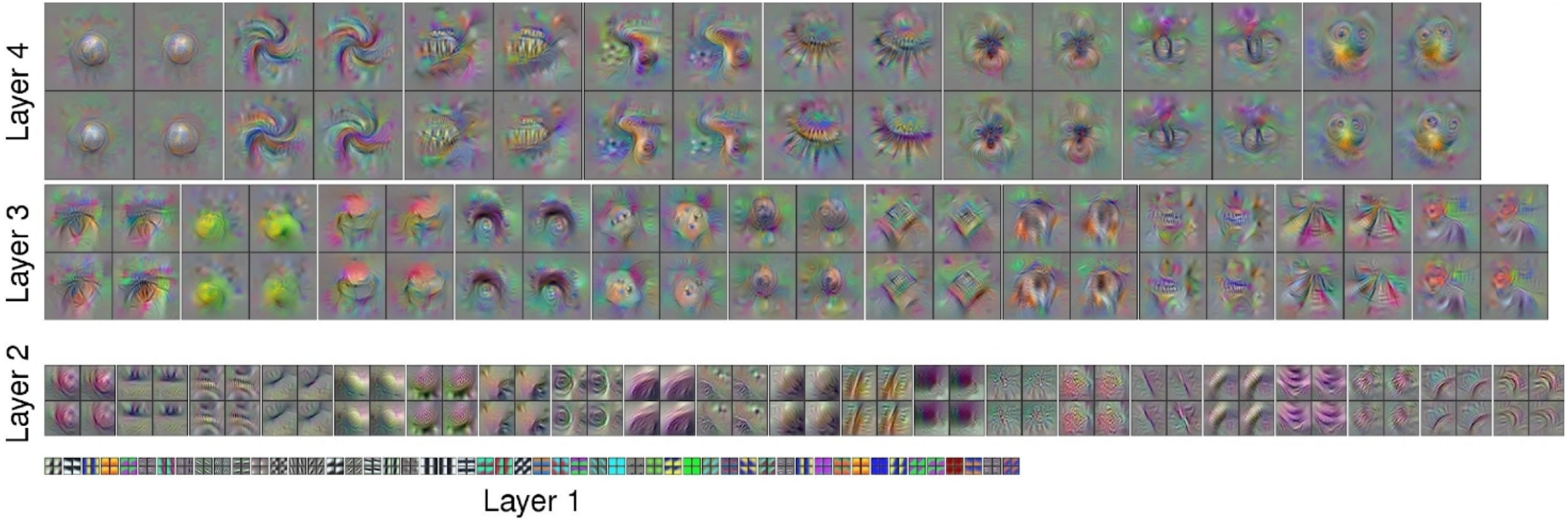
[Understanding Neural Networks Through Deep Visualization, Yosinski et al. , 2015]

http://yosinski.com/deepvis

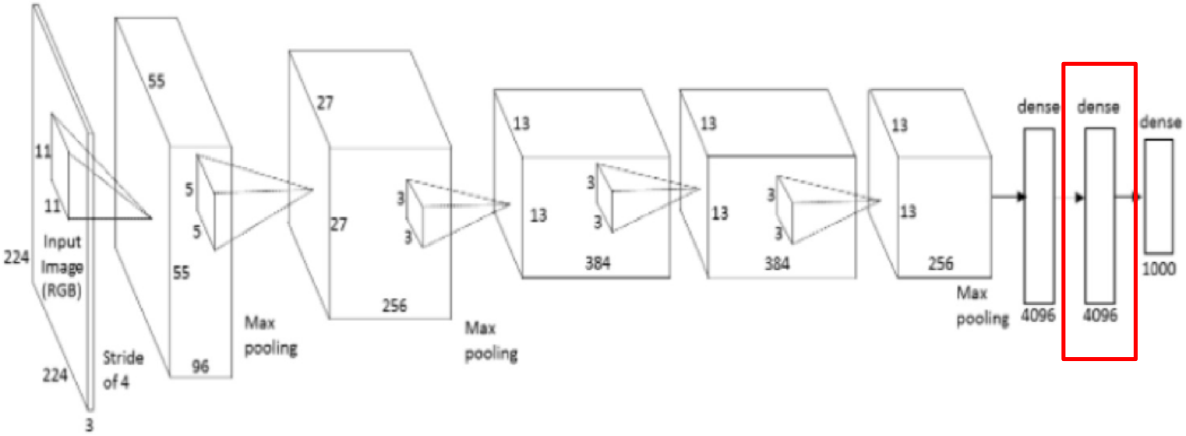



Layer 8
Pirate Ship
Rocking Chair
Teddy Bear
Windsor Tie
Pitcher
Layer 7


Layer 6
Layer 5
Layer 4


Layer 4
Layer 3
Layer 2
Layer 1

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



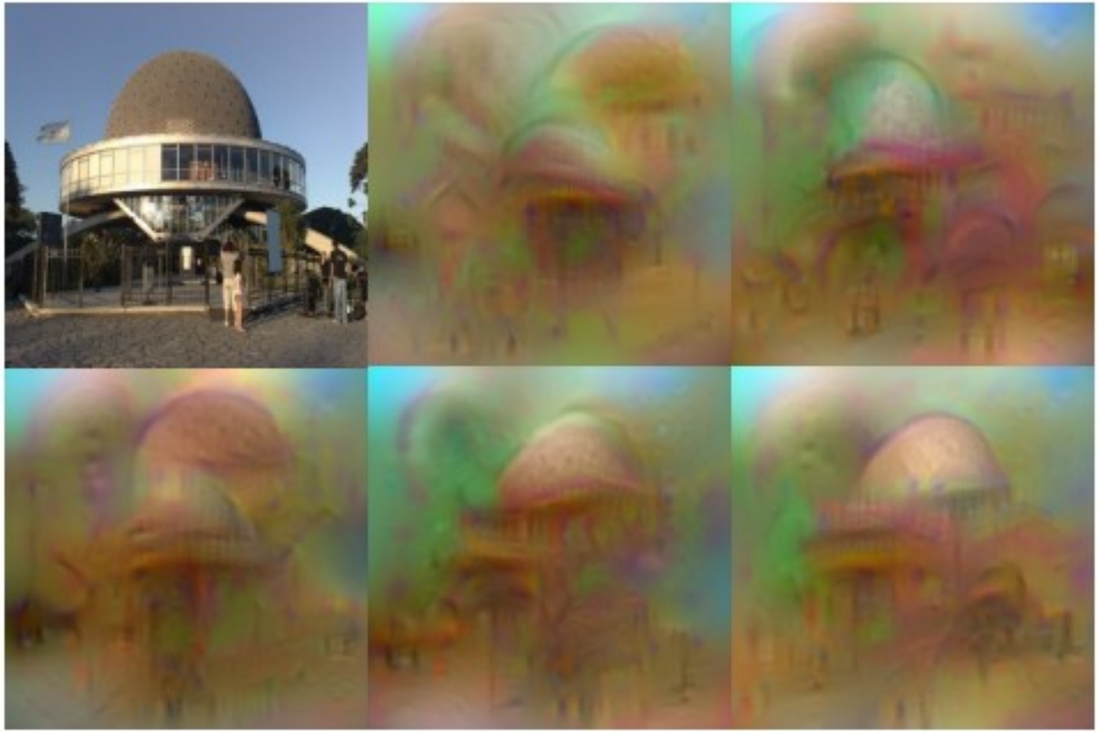
Find an image such that:
- Its code is similar to a given code
- It "looks natural" (image prior regularization)

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

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

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

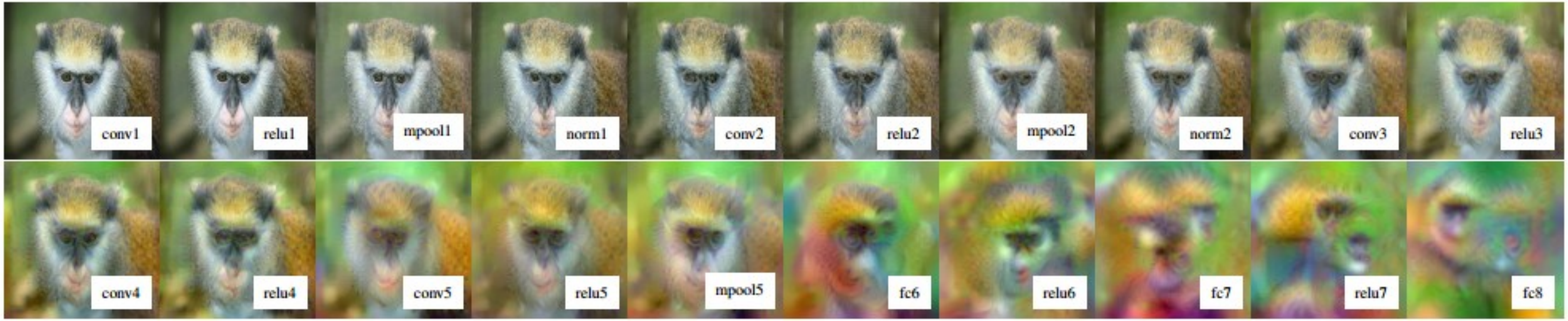
original image

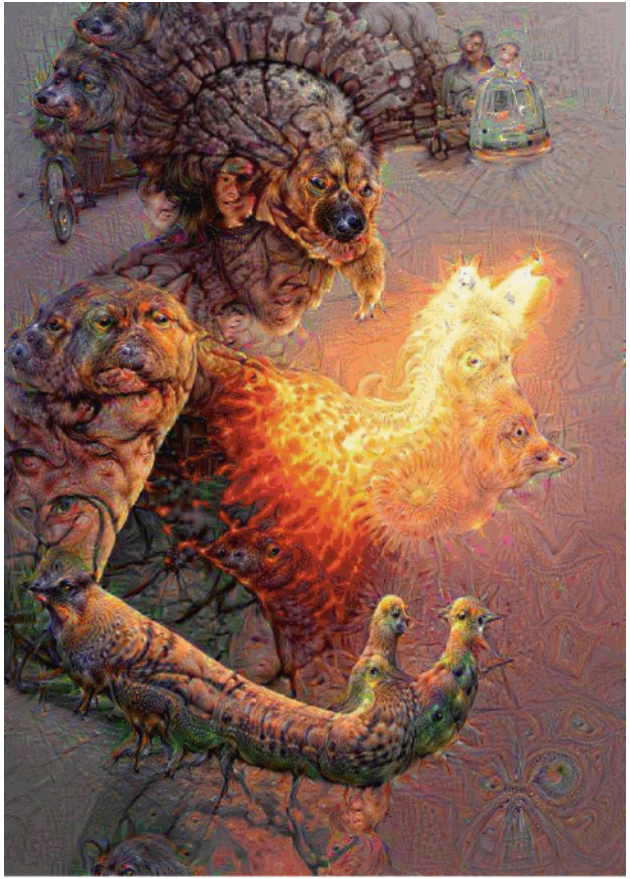


reconstructions from the 1000 log probabilities for ImageNet (ILSVRC) classes

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

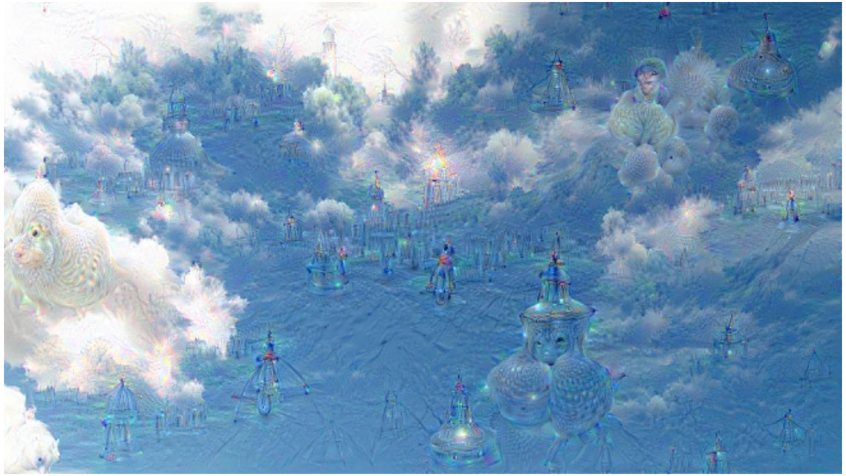
Reconstructions from intermediate layers



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

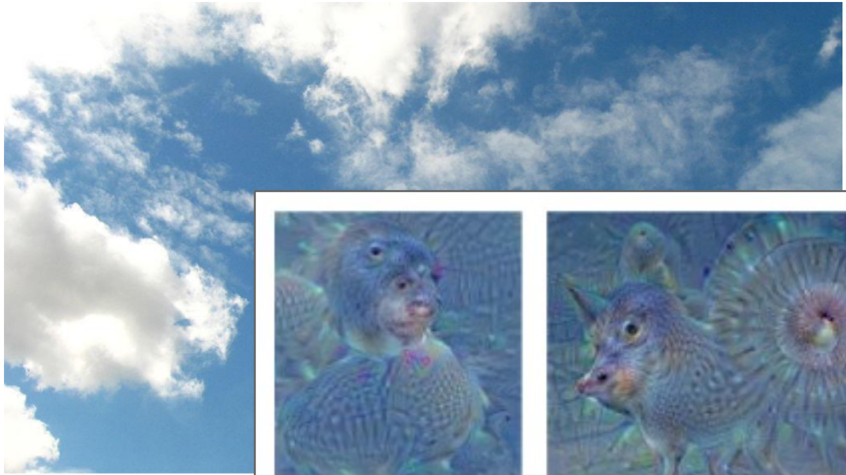
inception_4c/output

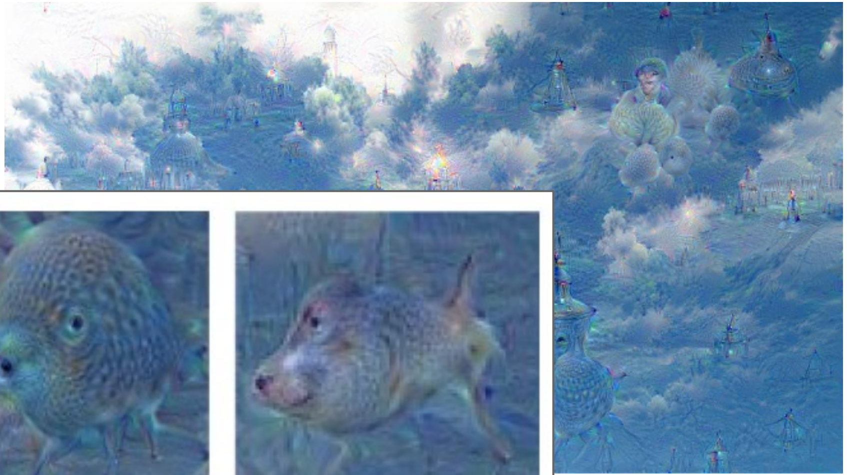


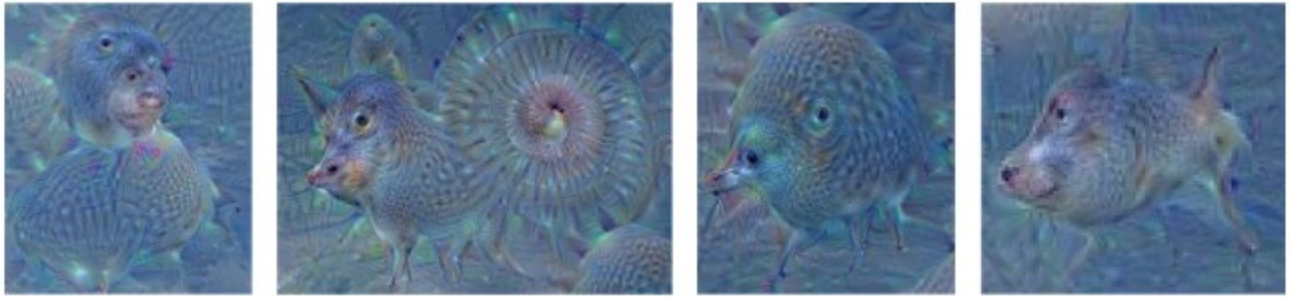
DeepDream modifies the image in a way that "boosts" all activations, at any layer

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

inception_4c/output



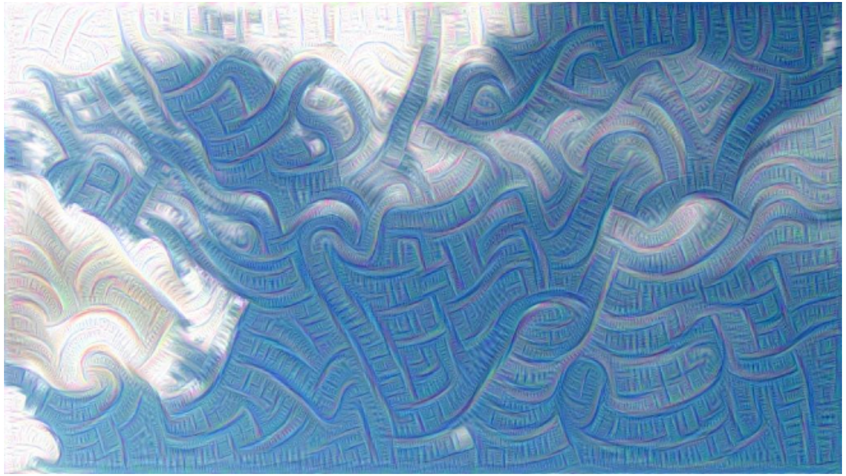




"Admiral Dog!" "The Pig-Snail" "The Camel-Bird" "The Dog-Fish"

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

inception_3b/5x5_reduce



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

```python
def objective_L2(dst):
    dst.diff[:] = dst.data

def make_step(net, step_size=1.5, end='inception_4c/output',
              jitter=32, clip=True, objective=objective_L2):
    '''Basic gradient ascent step.'''

    src = net.blobs['data'] # input image is stored in Net's 'data' blob
    dst = net.blobs[end]

    ox, oy = np.random.randint(-jitter, jitter+1, 2)
    src.data[0] = np.roll(np.roll(src.data[0], ox, -1), oy, -2) # apply jitter shift

    net.forward(end=end)
    objective(dst)  # specify the optimization objective
    net.backward(start=end)
    g = src.diff[0]
    # apply normalized ascent step to the input image
    src.data[:] += step_size/np.abs(g).mean() * g

    src.data[0] = np.roll(np.roll(src.data[0], -ox, -1), -oy, -2) # unshift image

    if clip:
        bias = net.transformer.mean['data']
        src.data[:] = np.clip(src.data, -bias, 255-bias)
```

```python
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```
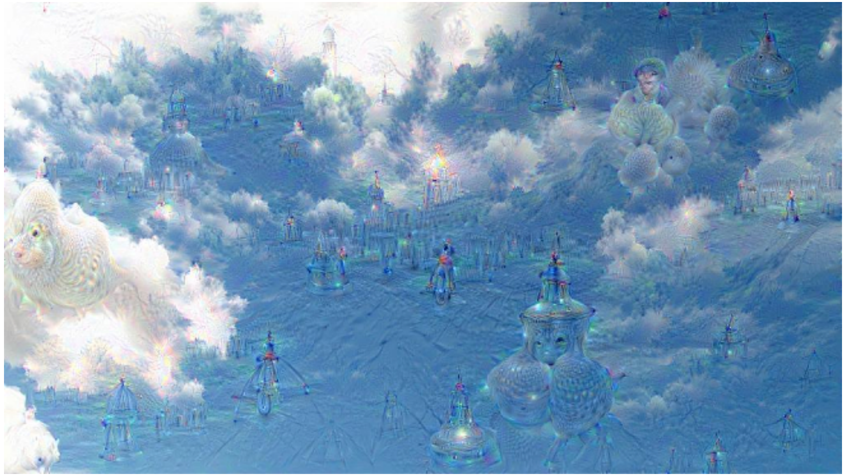

DeepDream: set dx = x :)

jitter regularizer

“image update”

inception_4c/output



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

this creates a <u>feedback loop</u>: e.g. any slightly detected dog face will be made more and more dog like over time

Bonus videos

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

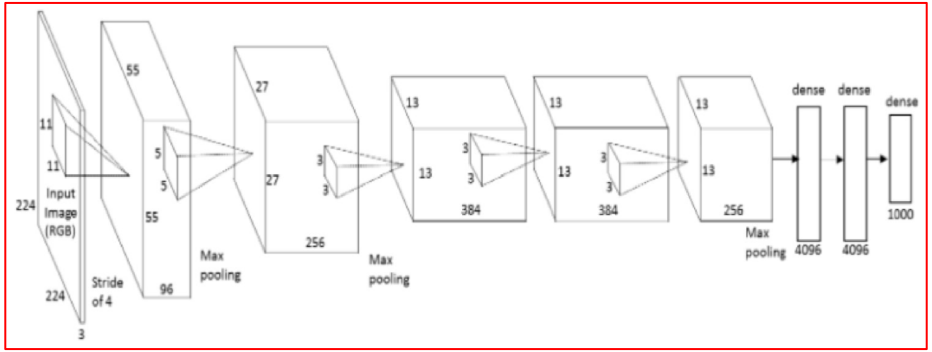
Deep Dreaming Fear & Loathing in Las Vegas: the Great San Francisco Acid Wave
https://www.youtube.com/watch?v=oyxSerkkP4o

NeuralStyle

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

make your own easily on deepart.io

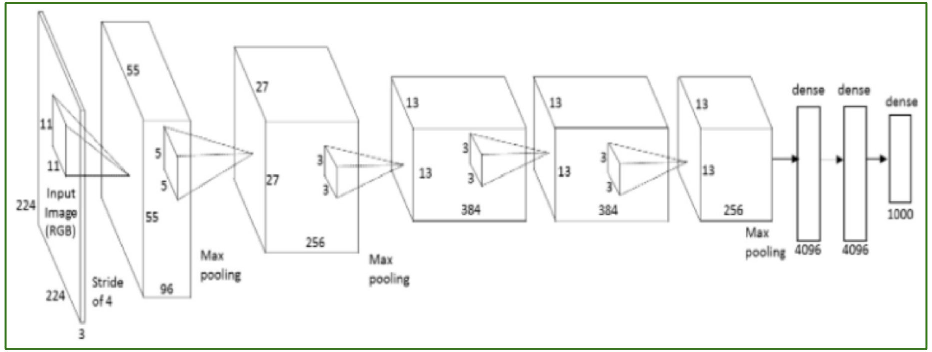
Step 1: Extract **content targets** (ConvNet activations of all layers for the given content image)



content activations

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

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



style gram matrices

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

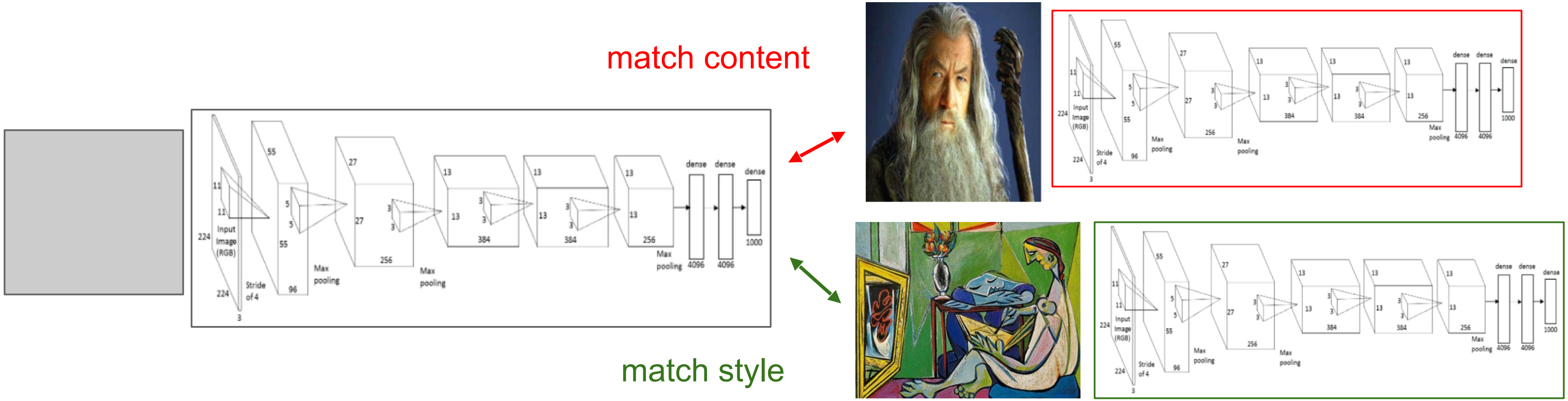
e.g.
at CONV1 layer (with [224x224x64] activations) would give a [64x64] Gram matrix of all pairwise activation covariances (summed across spatial locations)

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)

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

(+Total Variation regularization (maybe))

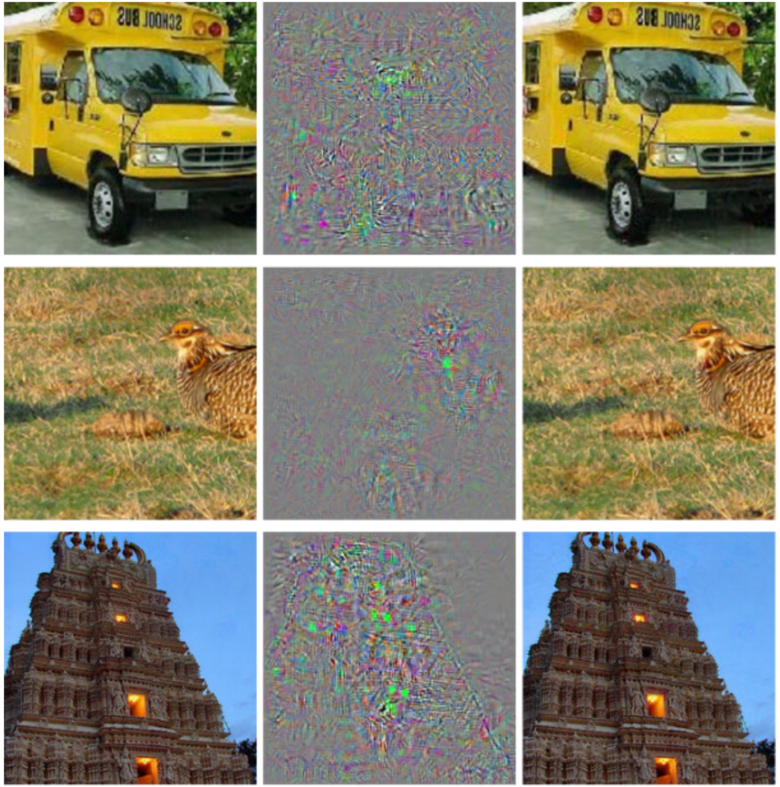


We can pose an optimization over the input image to maximize any class score.
That seems useful.

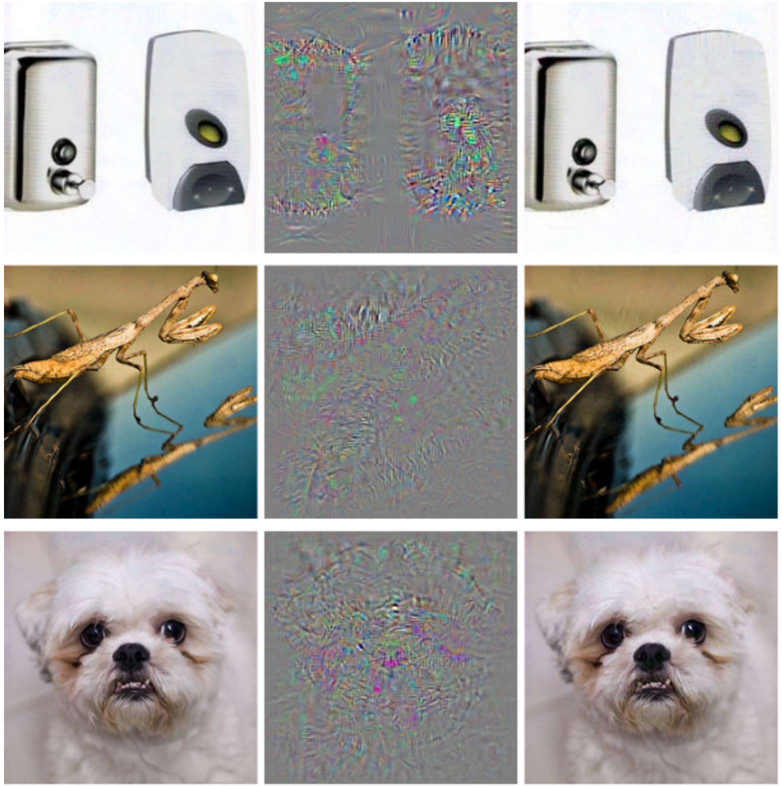
Question: Can we use this to “fool” ConvNets?

spoiler alert: yeah

[Intriguing properties of neural networks, Szegedy et al., 2013]



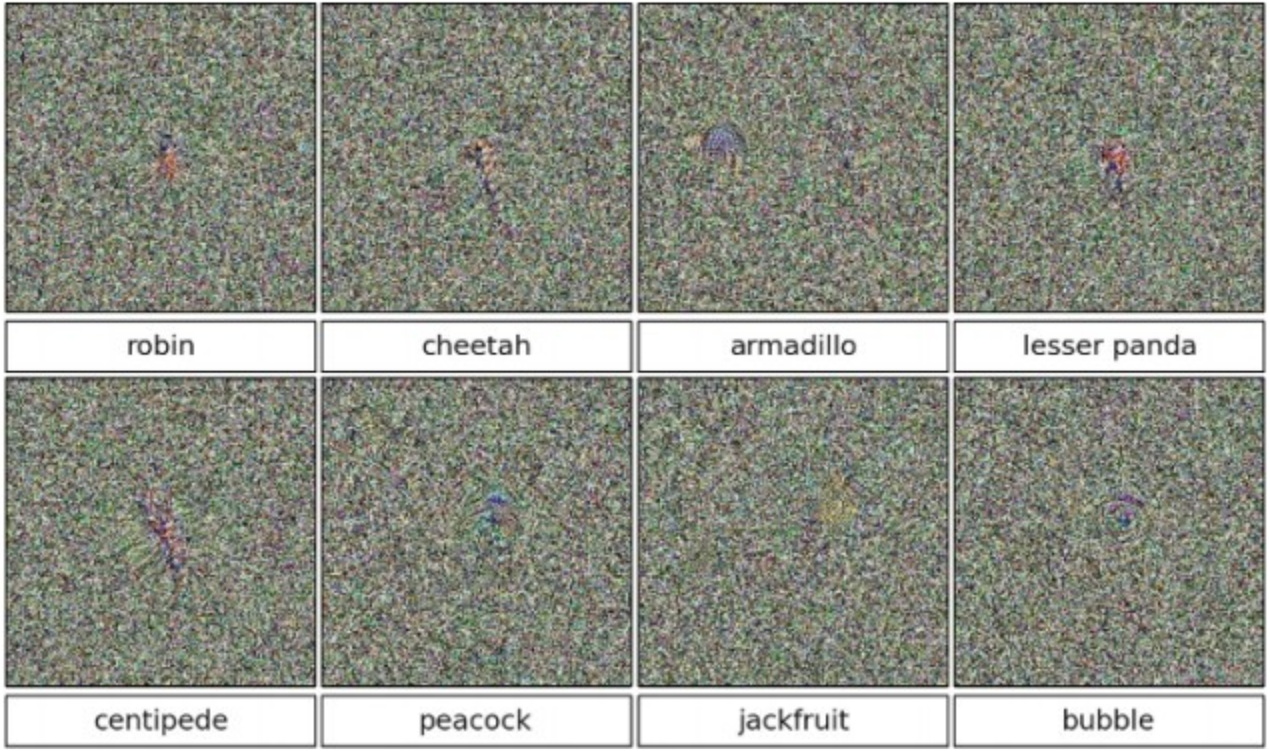
correct +distort ostrich



correct +distort ostrich

[Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images Nguyen, Yosinski, Clune, 2014]

>99.6% confidences



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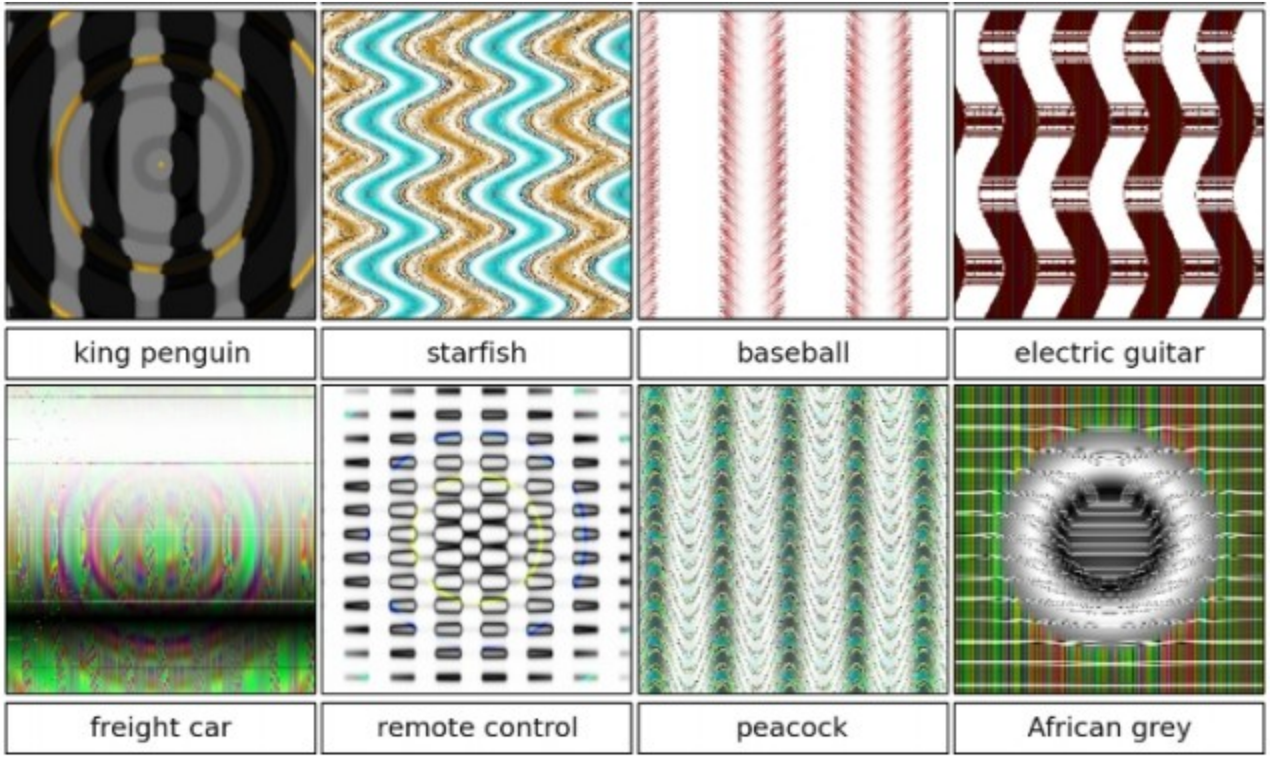
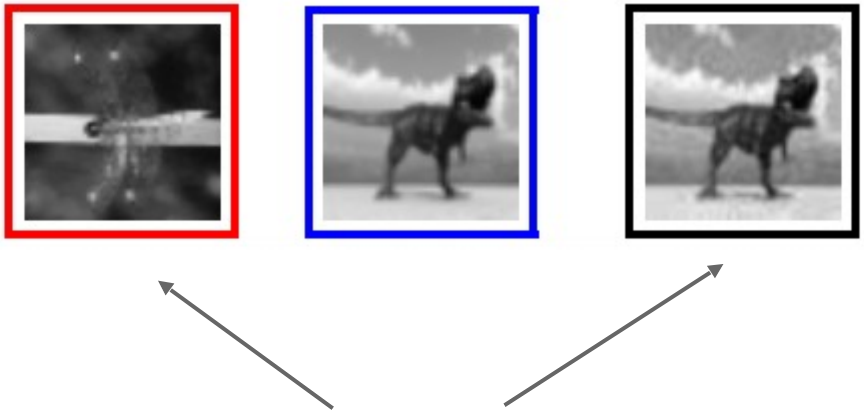
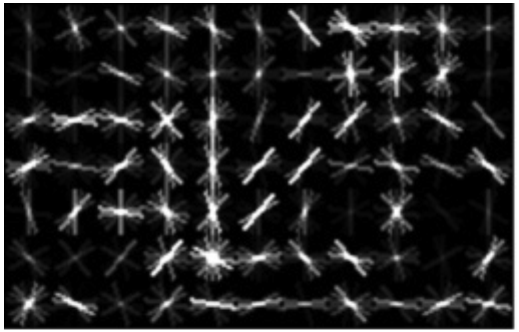


These kinds of results were around even before ConvNets…

[Exploring the Representation Capabilities of the HOG Descriptor, Tatu et al., 2011]

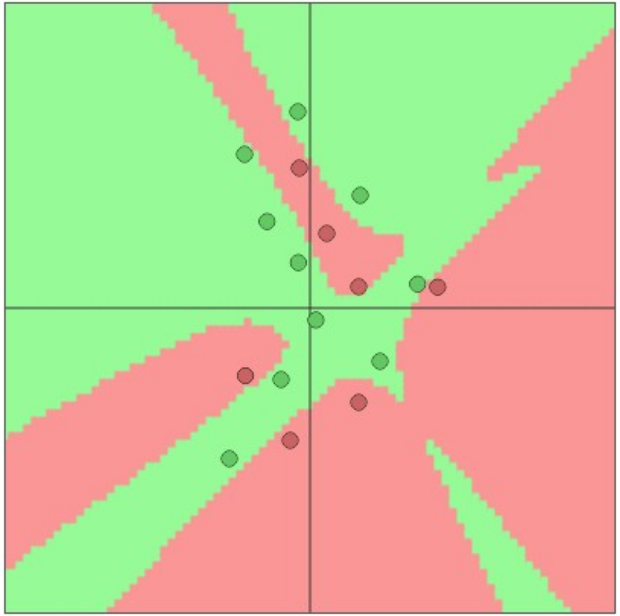




Identical HOG represention

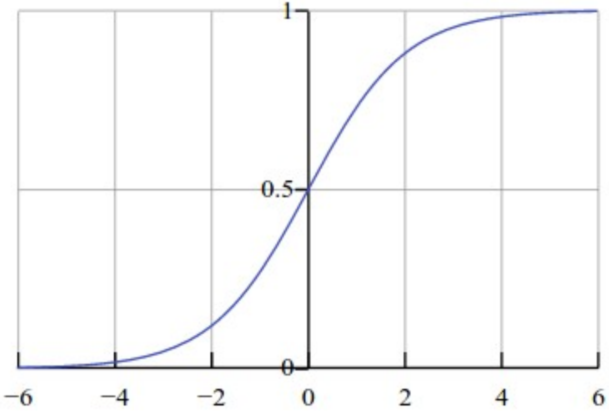
EXPLAINING AND HARNESSING ADVERSARIAL EXAMPLES
[Goodfellow, Shlens & Szegedy, 2014]

“primary cause of neural networks’ vulnerability to adversarial perturbation is their **linear nature**“



Lets fool a binary linear classifier: (logistic regression)

$$P(y=1 \mid x; w, b) = \frac{1}{1+e^{-(w^T x + b)}} = \sigma(w^T x + b)$$



Since the probabilities of class 1 and 0 sum to one, the probability for class 0 is $P(y=0 \mid x; w, b) = 1 - P(y=1 \mid x; w, b)$. Hence, an example is classified as a positive example (y = 1) if $\sigma(w^T x + b) > 0.5$, or equivalently if the score $w^T x + b > 0$.

Lets fool a binary linear classifier:

x	2	-1	3	-2	2	2	1	-4	5	1	← input example
w	-1	-1	1	-1	1	-1	1	1	-1	1	← weights

$$P(y=1 \mid x; w, b) = \frac{1}{1+e^{-(w^T x + b)}} = \sigma(w^T x + b)$$

Lets fool a binary linear classifier:

x	2	-1	3	-2	2	2	1	-4	5	1	← input example
w	-1	-1	1	-1	1	-1	1	1	-1	1	← weights

class 1 score = dot product:
= -2 + 1 + 3 + 2 + 2 - 2 + 1 - 4 - 5 + 1 = -3
=> probability of class 1 is 1/(1+e^(-(-3))) = 0.0474
i.e. the classifier is **95%** certain that this is class 0 example.

$$P(y=1 \mid x; w, b) = \frac{1}{1+e^{-(w^T x + b)}} = \sigma(w^T x + b)$$

Lets fool a binary linear classifier:

x	2	-1	3	-2	2	2	1	-4	5	1	← input example
w	-1	-1	1	-1	1	-1	1	1	-1	1	← weights
adversarial x	?	?	?	?	?	?	?	?	?	?	

class 1 score = dot product:
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Lets fool a binary linear classifier:

x	2	-1	3	-2	2	2	1	-4	5	1	← input example
w	-1	-1	1	-1	1	-1	1	1	-1	1	← weights
adversarial x	1.5	-1.5	3.5	-2.5	2.5	1.5	1.5	-3.5	4.5	1.5	

class 1 score before:
-2 + 1 + 3 + 2 + 2 - 2 + 1 - 4 - 5 + 1 = -3
=> probability of class 1 is 1/(1+e^(-(-3))) = 0.0474

-1.5+1.5+3.5+2.5+2.5-1.5+1.5-3.5-4.5+1.5 = 2
=> probability of class 1 is now 1/(1+e^(-(2))) = 0.88
i.e. we improved the class 1 probability from 5% to 88%

$$P(y=1 \mid x; w, b) = \frac{1}{1+e^{-(w^T x + b)}} = \sigma(w^T x + b)$$

Lets fool a binary linear classifier:

x	2	-1	3	-2	2	2	1	-4	5	1	← input example
w	-1	-1	1	-1	1	-1	1	1	-1	1	← weights
adversarial x	1.5	-1.5	3.5	-2.5	2.5	1.5	1.5	-3.5	4.5	1.5	

class 1 score before:
-2 + 1 + 3 + 2 + 2 - 2 + 1 - 4 - 5 + 1 = -3
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-1.5+1.5+3.5+2.5+2.5-1.5+1.5-3.5-4.5+1.5 = 2
=> probability of class 1 is now 1/(1+e^(-(2))) = 0.88
i.e. we improved the class 1 probability from 5% to 88%

This was only with 10 input dimensions. A 224x224 input image has 150,528.

(It's significantly easier with more numbers, need smaller nudge for each)