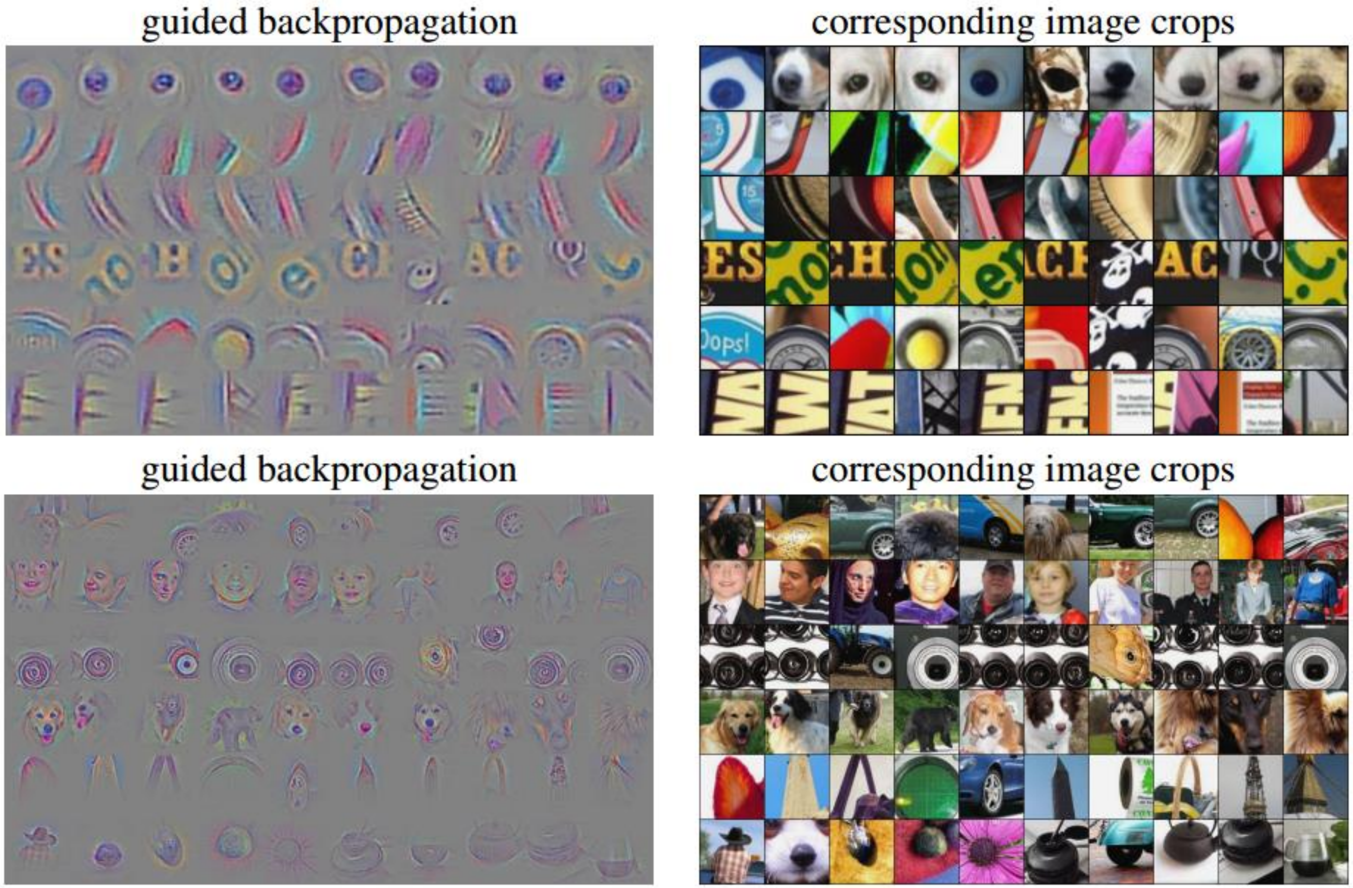
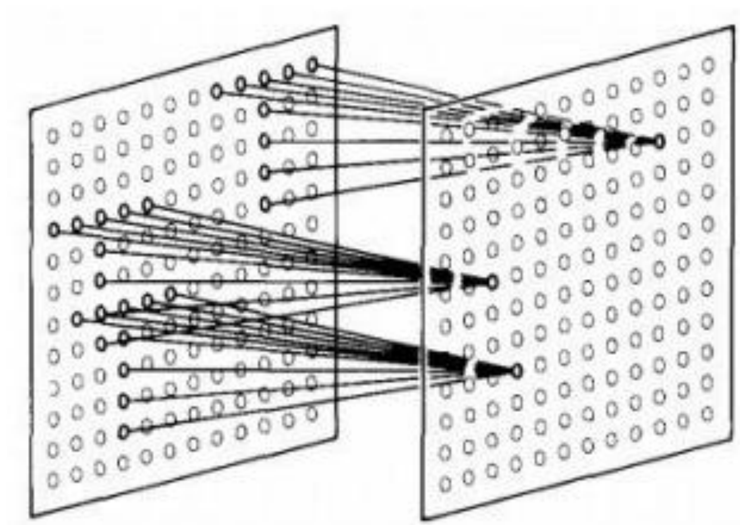
Understanding How ConvNets See



Springerberg et al, Striving for Simplicity: The All Convolutional Net (ICLR 2015 workshops)

What Does a Neuron Do in a ConvNet? (1)

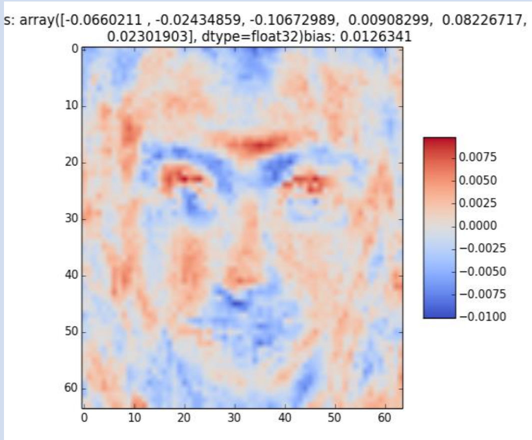
- A neuron in the first hidden layer computes a weighted sum of pixels in a patch of the image for which it is responsible



K. Fukushima, "Neurocognitron: A self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position" (Biol. Cybernetics 1980)

What Does a Neuron Do in a ConvNet? (2)

- For Neurons in the first hidden layer, we can visualize the weights.

<table>
<tr><th>Example weights for fully-connected single-hidden layer network for faces, for one neuron</th><th>Weights for 9 features in the first convolutional layer of a layer for classifying ImageNet images</th></tr>
<tr><td>


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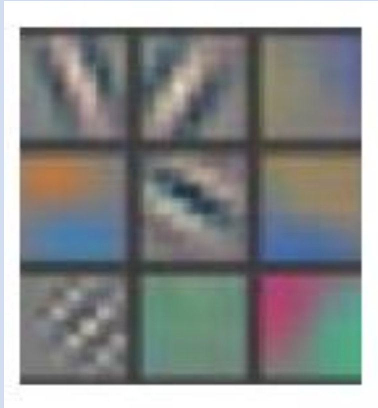
Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks"
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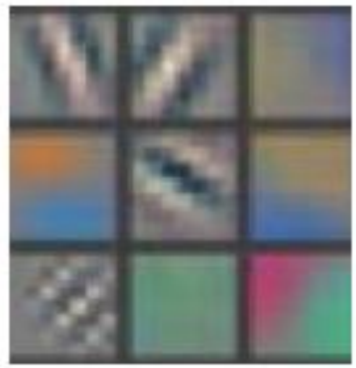
What Does a Neuron Do in a ConvNet? (3)



- **The neuron would be activated the most if the input looks like the weight matrix**
- These are called “Gabor-like filters”
- The colour is due to the input being 3D. We visualize the strength of the weight going from each of the R, G, and B components

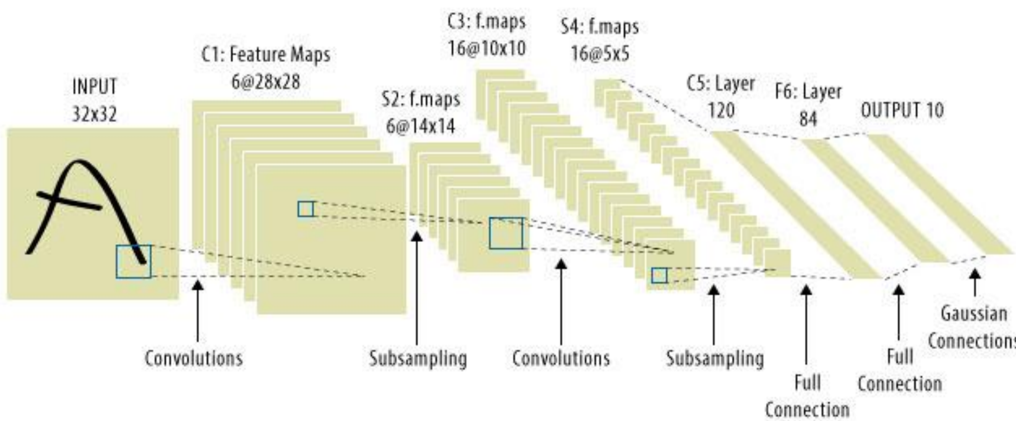
What Does a Neuron Do in a ConvNet (4)

- Another to figuring out what kind of images active the neuron: just try lots of images in a dataset, and see which ones active the neuron the most

For each feature, fine the 9 images that produce the highest activations for the neuron, and crop out the relevant patch

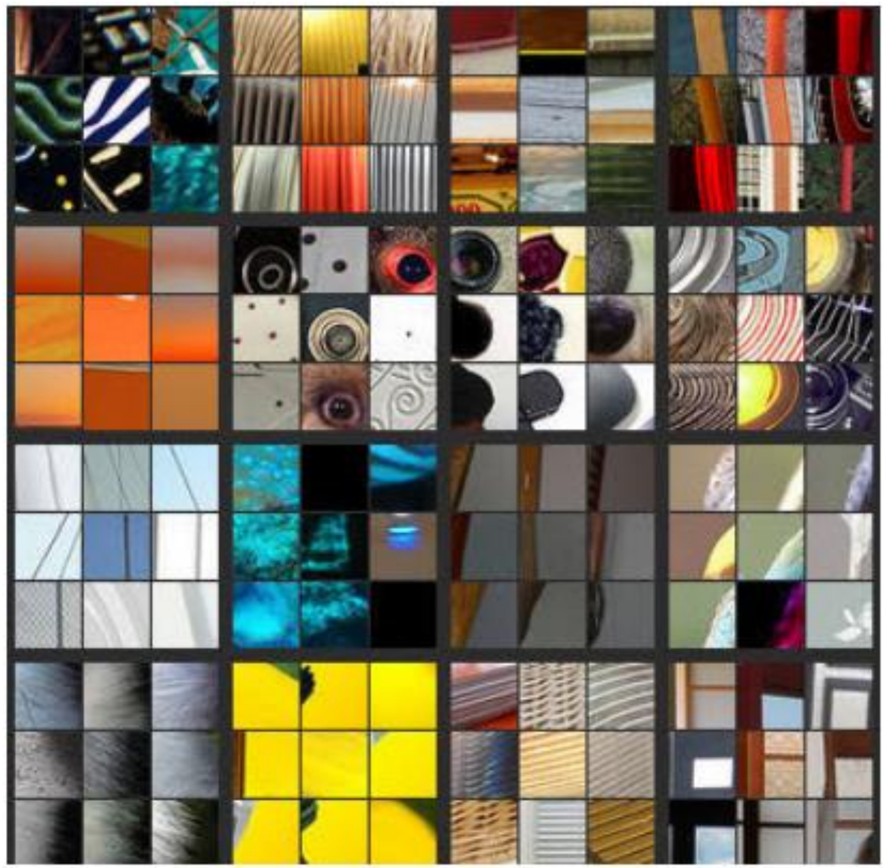
Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks"

Aside: Relevant Patch?



- Each neuron is affected by some small patch in the layer below
- Can recursively figure out what patch in the input layer each neuron is affected
- Neurons in the top layers are affected by (almost) the entire image

This allows us to look at layers besides the first one: layer 3



Layer 4

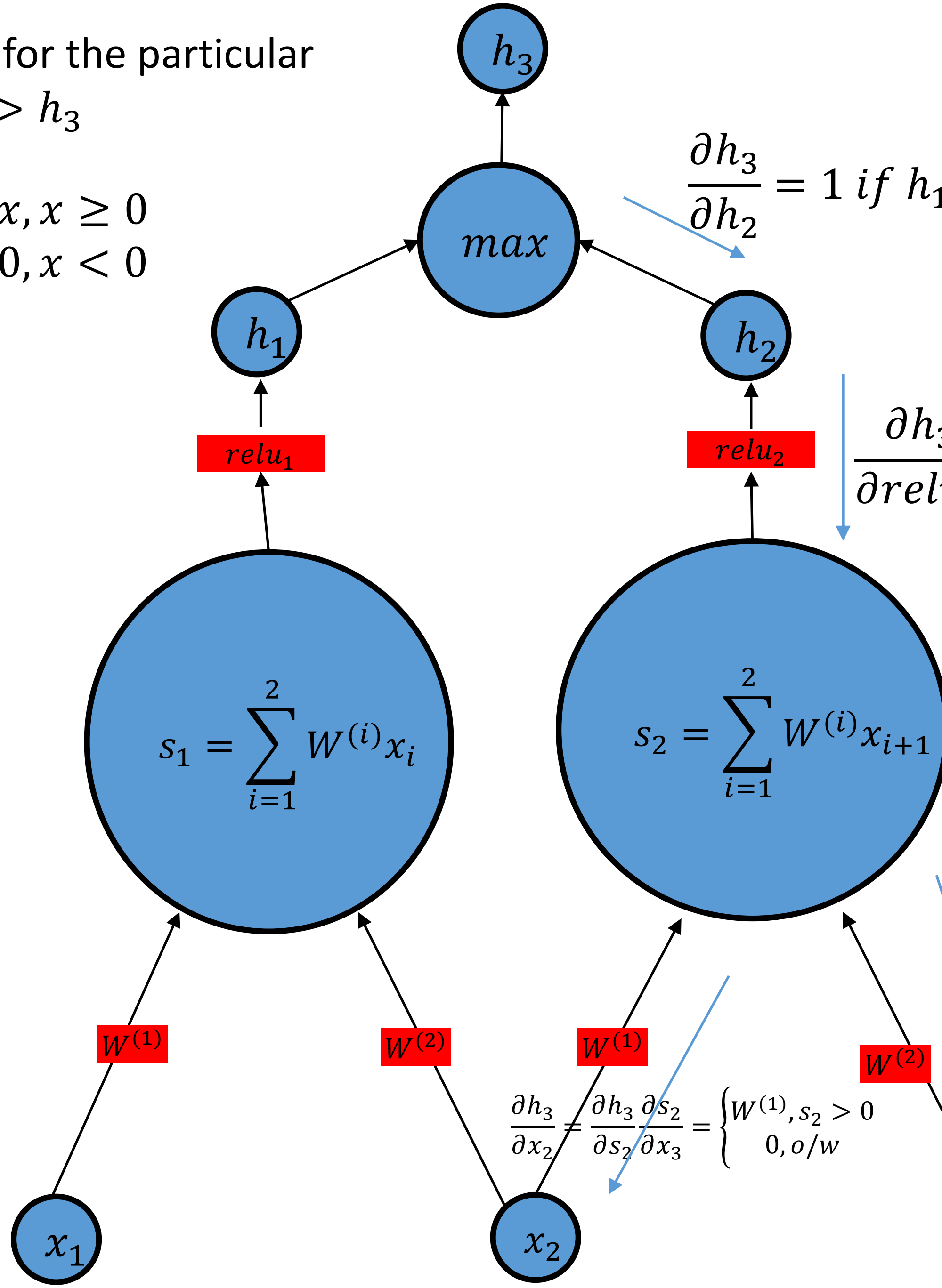
Layer 5

Which Pixels in the Input Affect the Neuron the Most?

- Rephrased: which pixels would make the neuron not turn on if they had been different?
- In other words, for which inputs is $\frac{\partial neuron}{\partial x_i}$ large?

Assume that for the particular image x, $h_2 > h_3$

$$relu(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases}$$



$$\frac{\partial h_3}{\partial h_2} = 1 \; if \; h_1 < h_2$$

$$\frac{\partial h_3}{\partial relu_2} = \frac{\partial h_3}{\partial h_2}\frac{\partial h_2}{\partial relu_2} = \begin{cases} 1, s_2 > 0 \\ 0, o/w \end{cases}$$

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$$\frac{\partial h_3}{\partial x_2} = \frac{\partial h_3}{\partial s_2}\frac{\partial s_2}{\partial x_3} = \begin{cases} W^{(1)}, s_2 > 0 \\ 0, o/w \end{cases}$$

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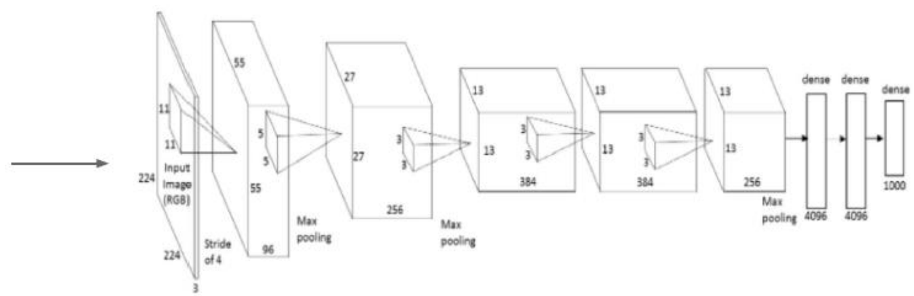
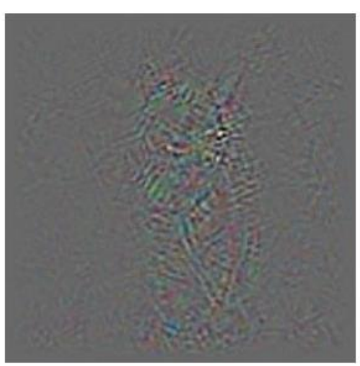
Typical Gradient of a Neuron

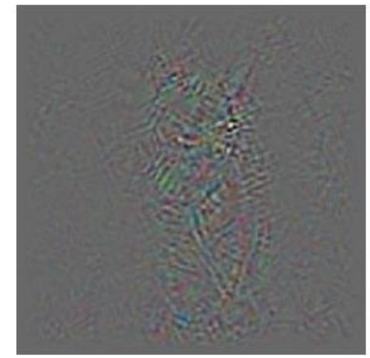
- Visualize the gradient of a particular neuron with respect to the input *x*
- Do a forward pass:



- Compute the gradient of a particular neuron using backprop:

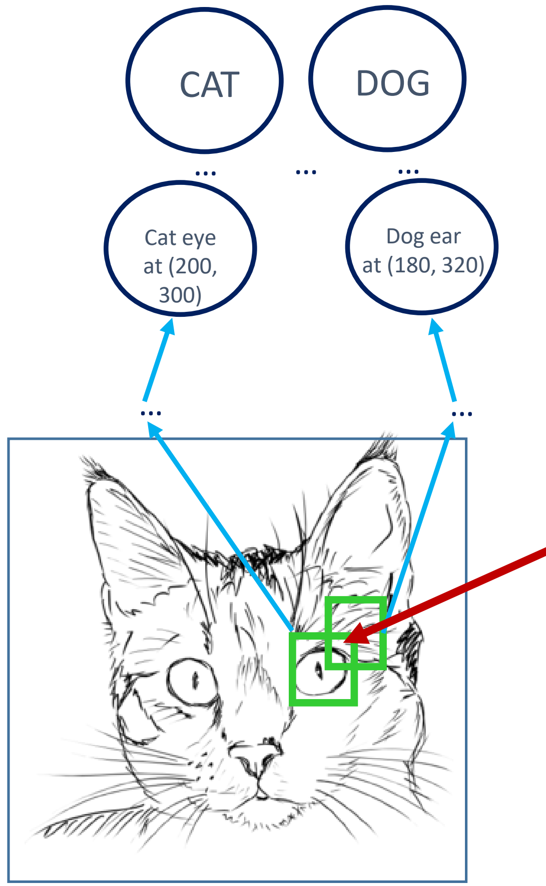


Typical Gradient of a Neuron



- Mostly zero away from the object, but the results are not very satisfying
- Every pixel influences the neuron via multiple hidden neurons.
  The network is trying to detect kittens everywhere, and the same pixel could fit a kitten in one location but not another, leading to its overall effect on the kitten neuron to be 0

Typical Gradient of a Neuron



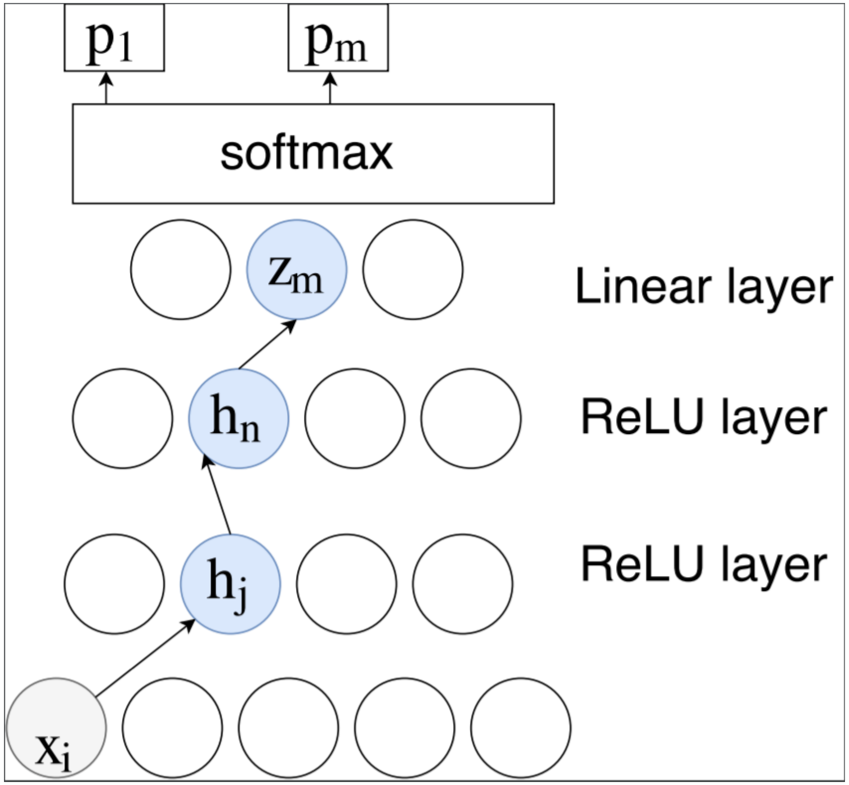
Pixel provides both positive (via a cat eye detection) and negative (via absence of cat eye detection) evidence for a cat in the image

Guided Backpropagation

- Idea: neurons act like detectors of particular image features
- We are only interested in what image features the neuron detects, not in what kind of stuff it *doesn't* detect

Guided Backpropagation

- Instead of computing $\frac{\partial p_m}{\partial x}$, only consider paths from x to p_m where the weights are positive and all the units are positive (and greater than 0). Compute this modified version of $\frac{\partial p_m}{\partial x}$
- Only consider evidence for neurons being active, discard evidence for neurons having to be not active



Guided Backpropagation: Computation

- When performing the backward pass we already know "$\frac{\partial neuron}{\partial h^{(l,i)}}$" for every i
- If $\frac{\partial h^{(l,i)}}{\partial h^{(l,-1\ j)}} < 0$, set it to 0
- Compute "$\frac{\partial neuron}{\partial h^{(l-1,j)}}$" $= = \sum_i$ "$\frac{\partial neuron}{\partial h^{(l,i)}}$""$\frac{\partial h^{(l,i)}}{\partial h^{(l,-1\ j)}}$"
- Repeat
- If a path contains negative weights, it will be ignored, since a negative weight corresponds to a negative $\frac{\partial h^{(l,i)}}{\partial h^{(l,-1\ j)}}$

Guided Backpropagation

Compute gradient, zero out negatives, backpropagate

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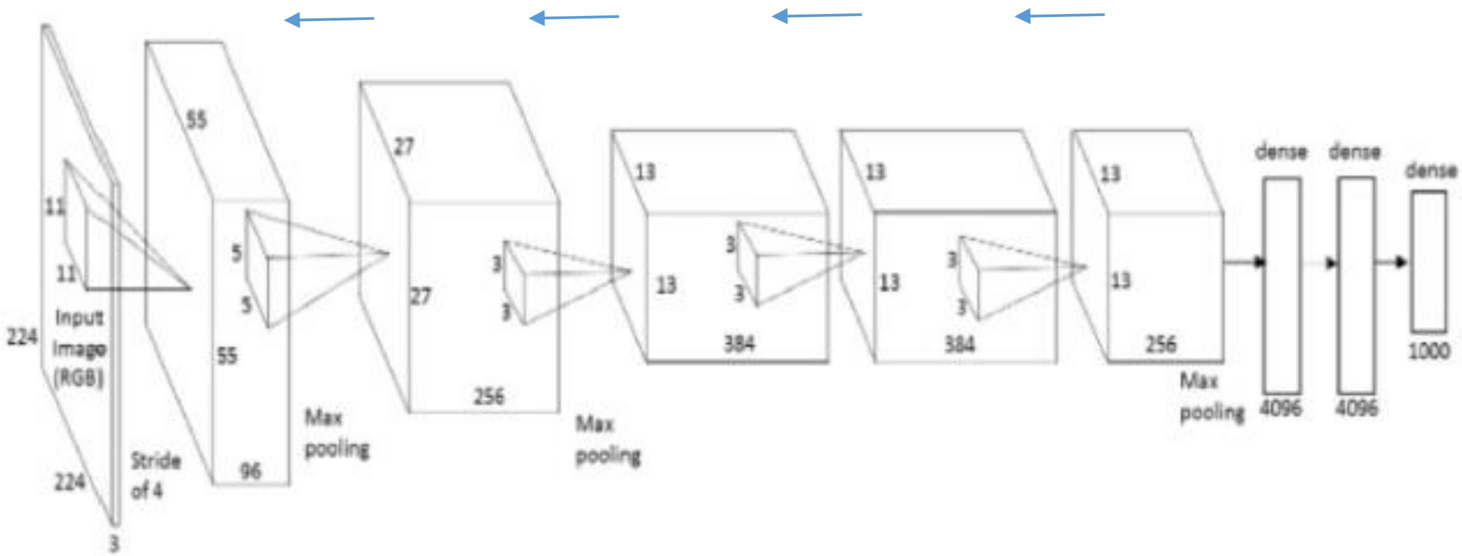

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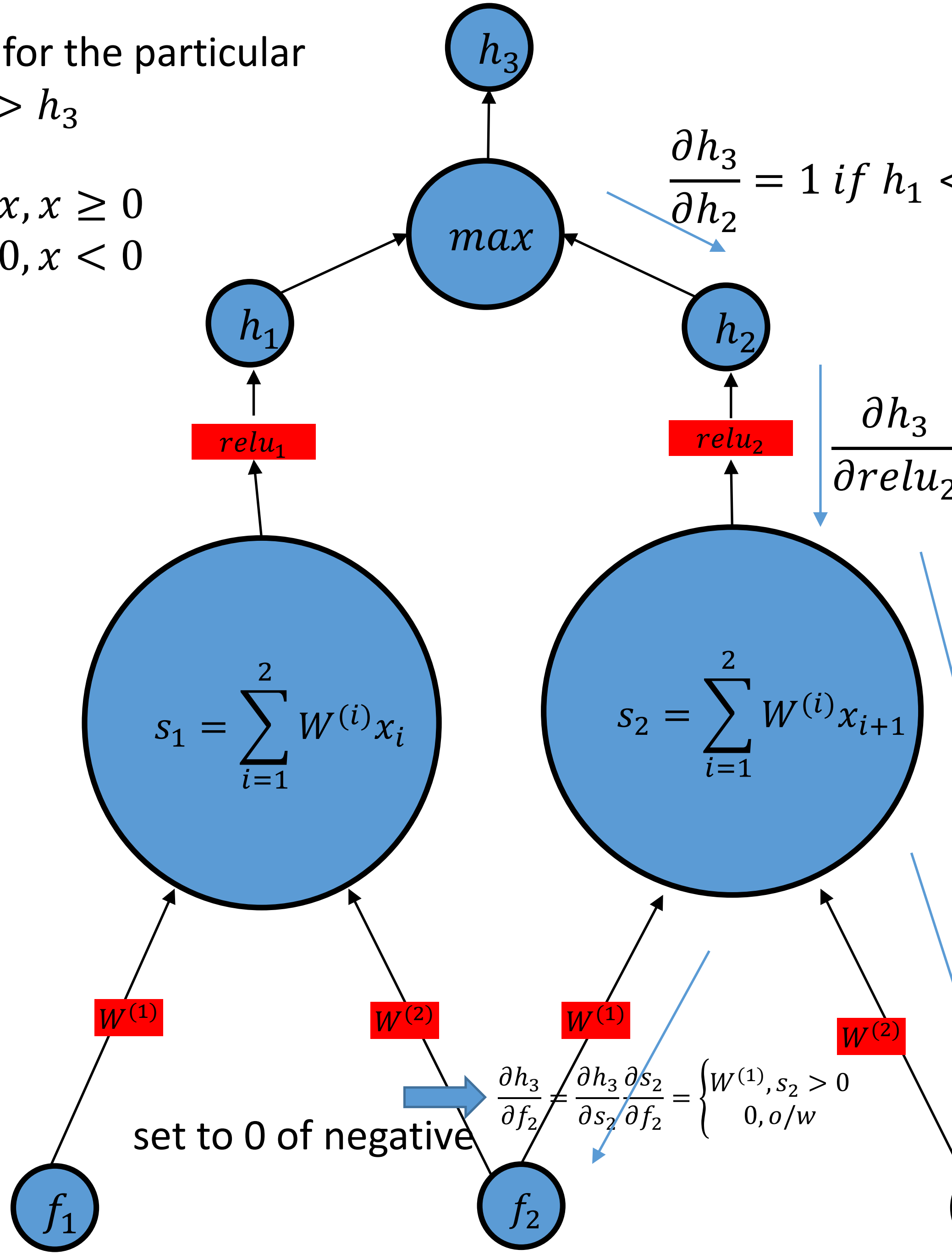

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set to 0 if negative

$$\frac{\partial h_3}{\partial f_3} = \frac{\partial h_3}{\partial s_2} \frac{\partial s_2}{\partial f_3} = \begin{cases} W^{(2)}, s_2 > 0 \\ 0, o/w \end{cases}$$

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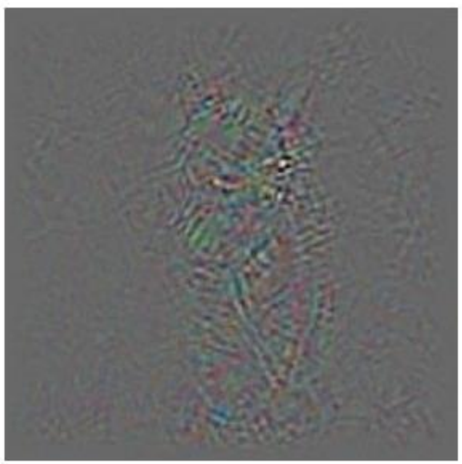
$$\frac{\partial h_3}{\partial f_2} = \frac{\partial h_3}{\partial s_2} \frac{\partial s_2}{\partial f_2} = \begin{cases} W^{(1)}, s_2 > 0 \\ 0, o/w \end{cases}$$

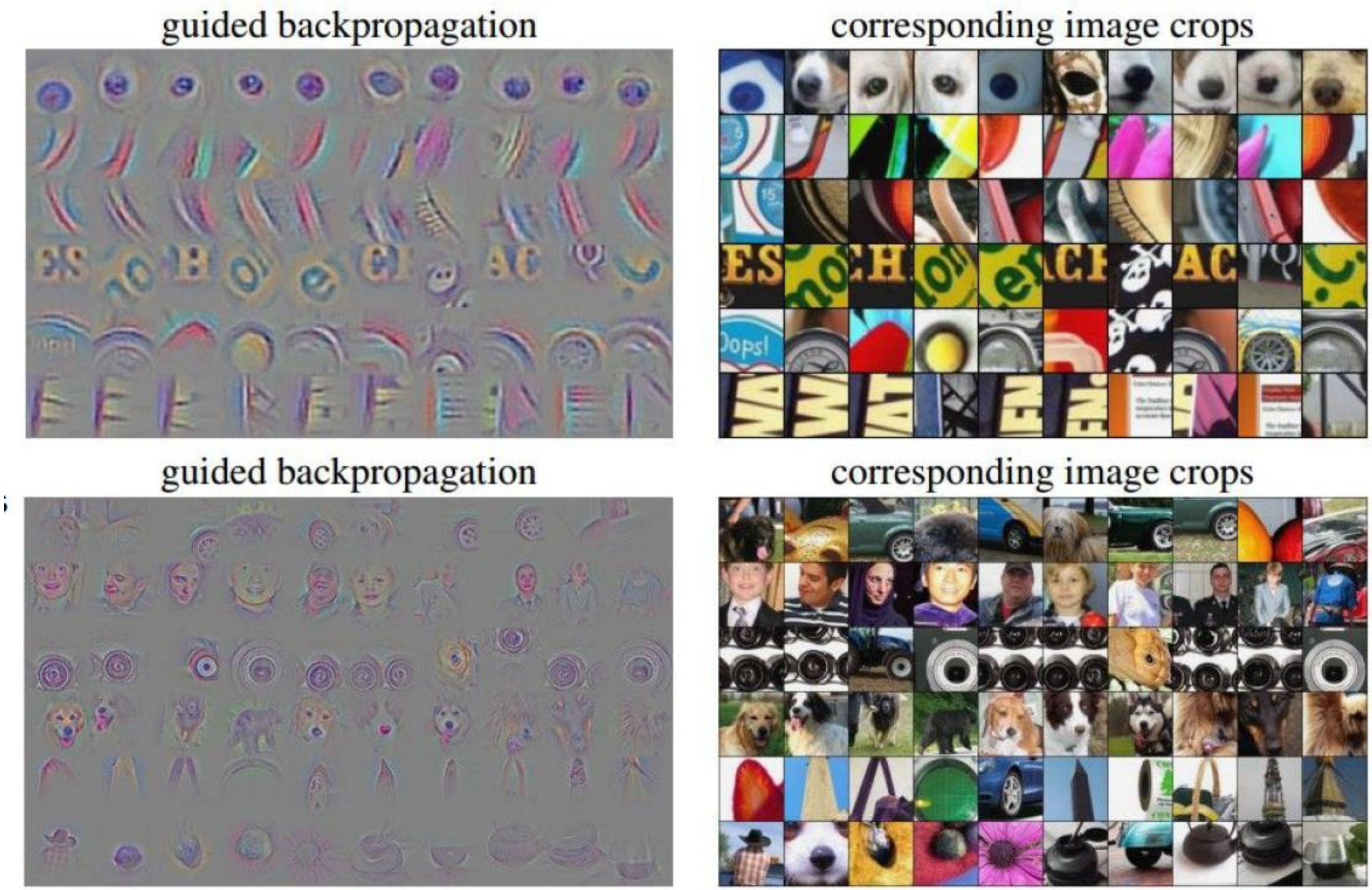
Guided Backpropagation



Backprop

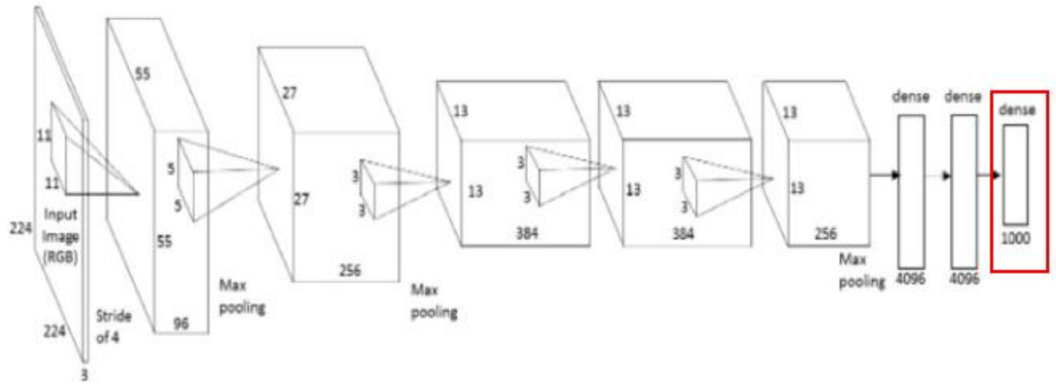
Guided Backprop

Guided Backpropagation

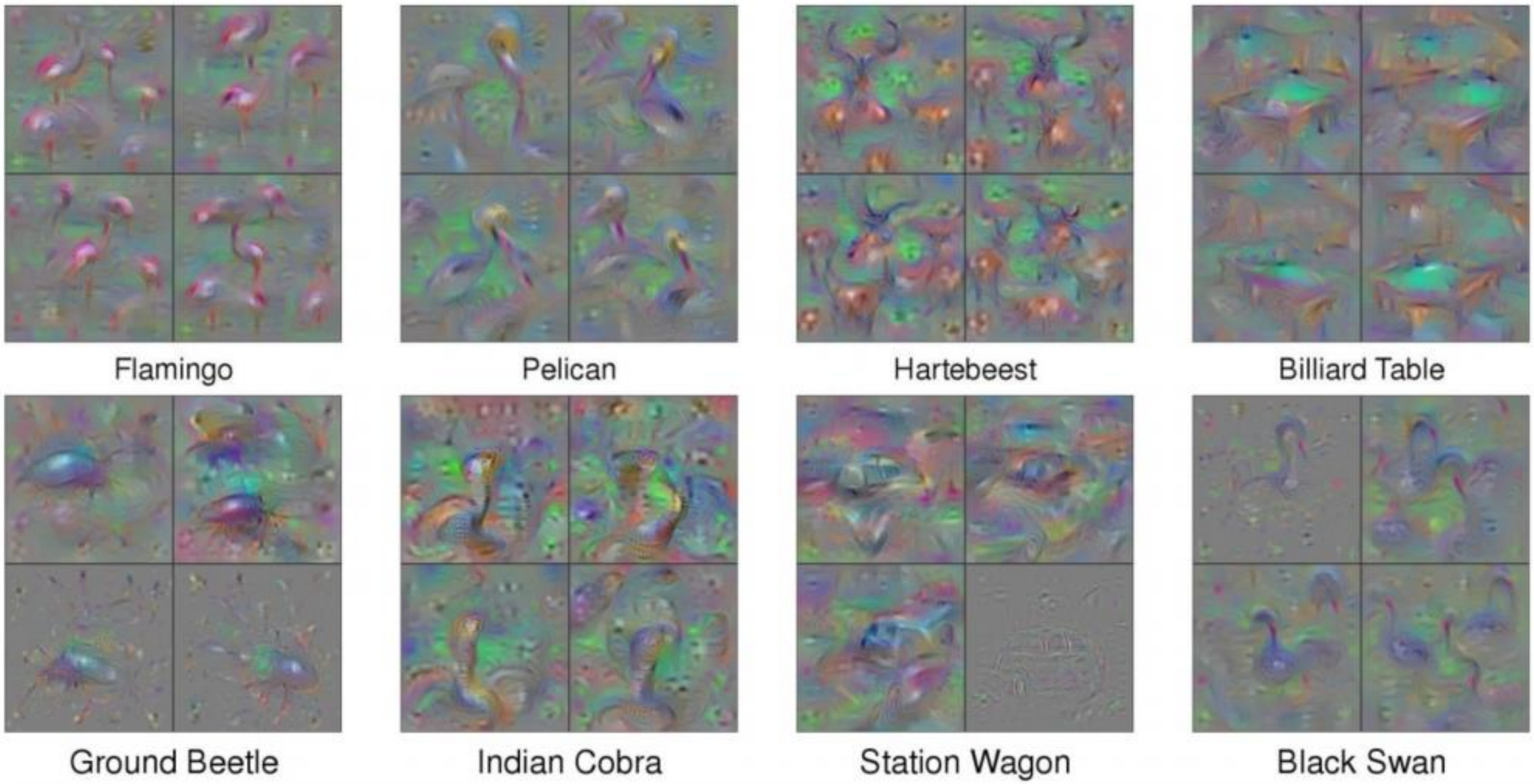


Springerberg et al, Striving for Simplicity: The All Convolutional Net (ICLR 2015 workshops)

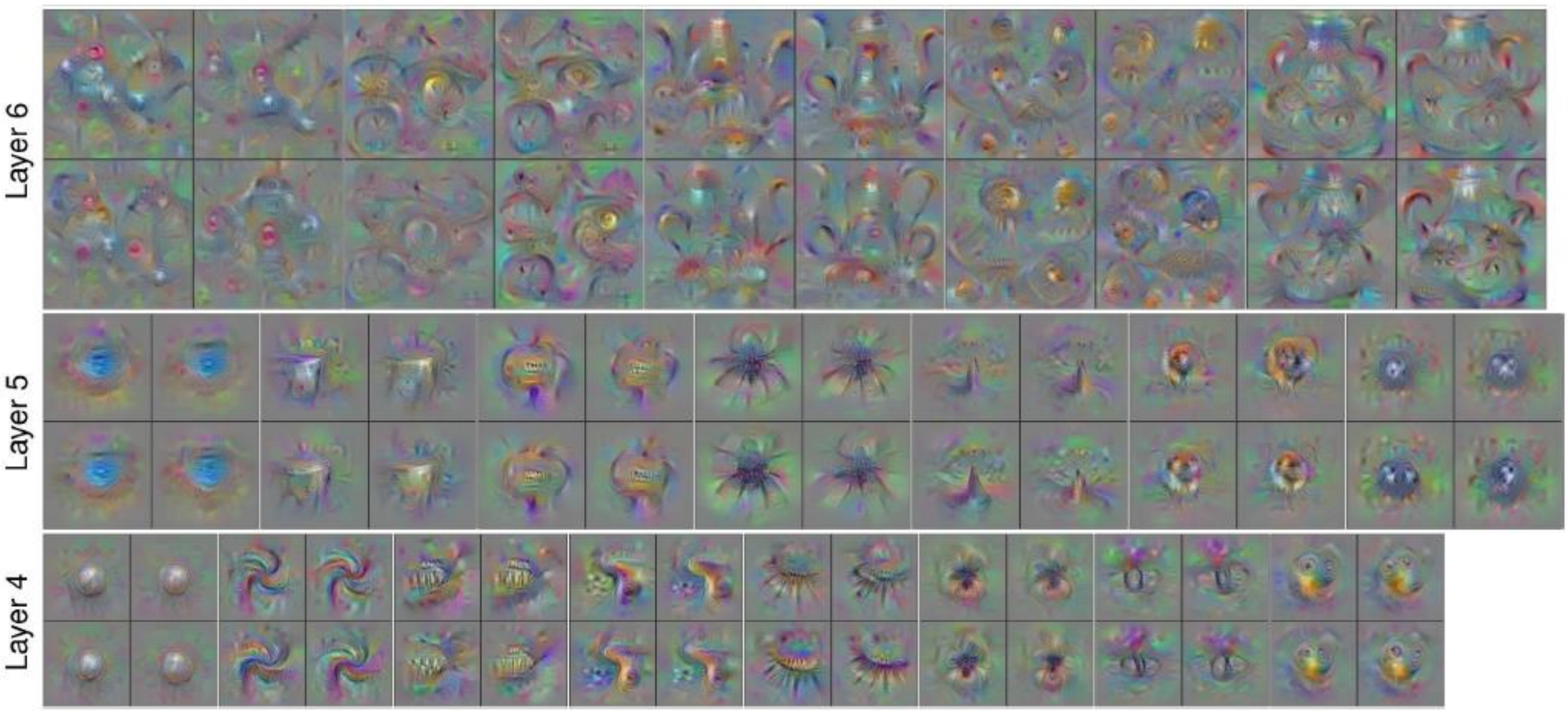
What About Doing Gradient Ascent?

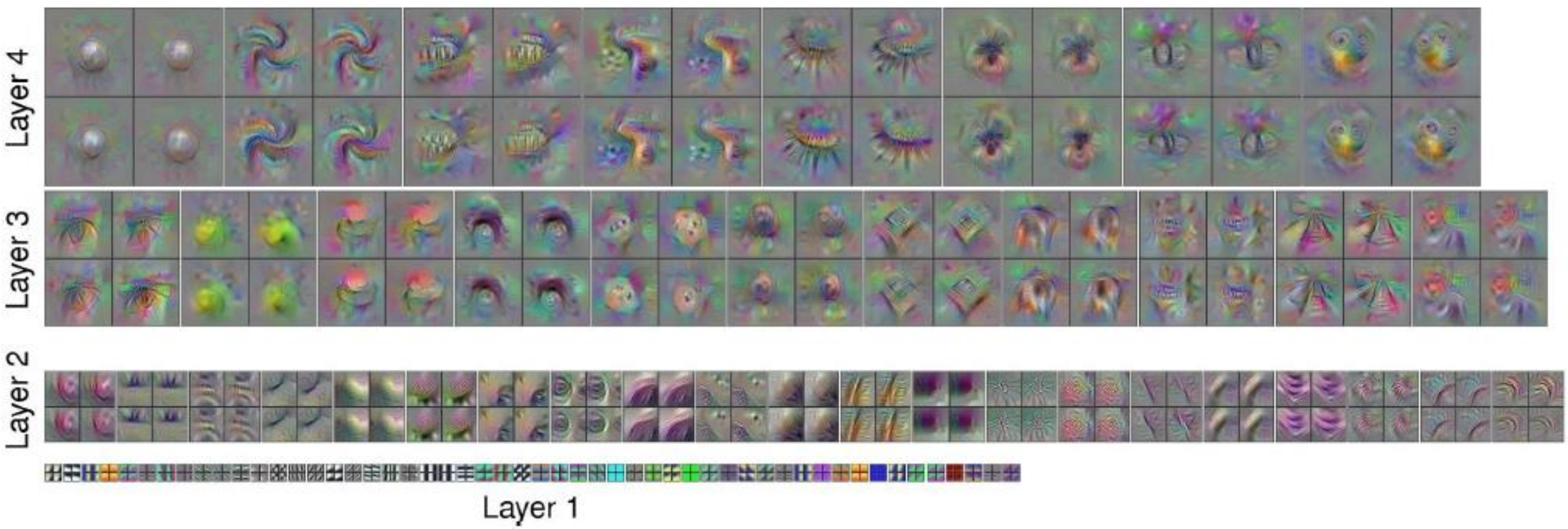


- Want to maximize the i-th output of the softmax
- Can compute the gradient of the i-th output of the softmax with respect to the *input x* (the W's and b's are fixed to make classification as good as possible)
- Perform gradient ascent on the *input*



Yosinski et al, Understanding Neural Networks Through Deep Visualization (ICML 2015)


Layer 6
Layer 5
Layer 4


Layer 4
Layer 3
Layer 2
Layer 1

(A Small Tweak For the Gradient Descent Algorithm)

- Doing gradient ascent can lead to things that don't look like images at all, and yet maximize the output
- To keep images from looking like white noise, do the following:
  - Update the image x using a gradient ascent step
  - Blur the image x
  - In a Bayesian framework: higher prior probabilities assigned to 2D arrays which look like they were blurred
    - (There is no exact equivalence – but there are versions of this where the equivalence can be made precise.)