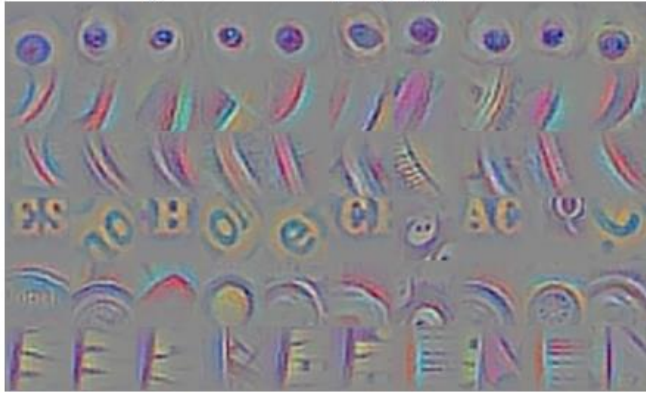


# Understanding How ConvNets See

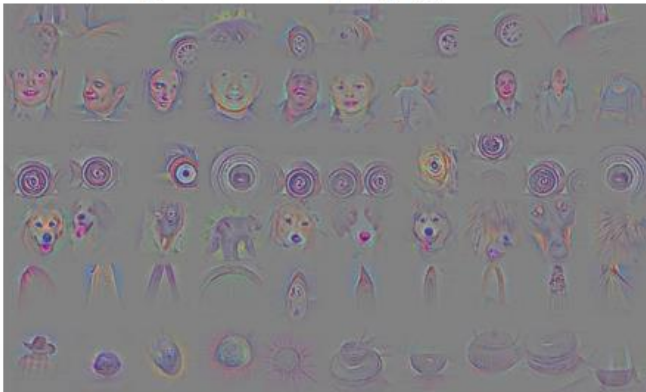
guided backpropagation



corresponding image crops



guided backpropagation



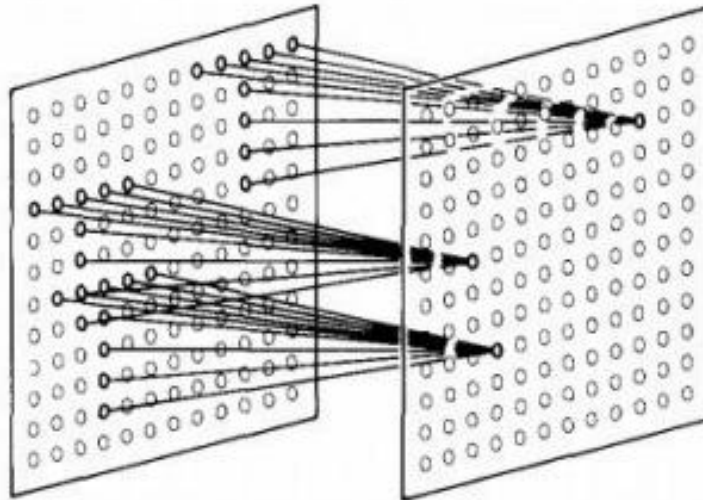
corresponding image crops



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

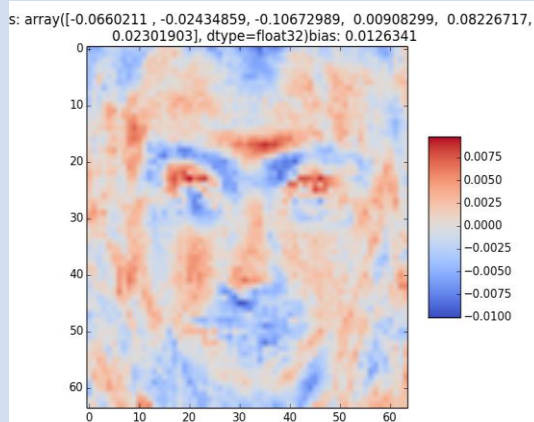


K. Fukushima, "Neurocognitron: A self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position" (Biol. Cybernetics 1980)

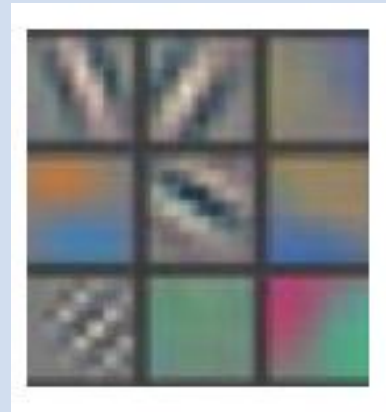
# What Does a Neuron Do in a ConvNet? (2)

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

Example weights for fully-connected single-hidden layer network for faces, for one neuron

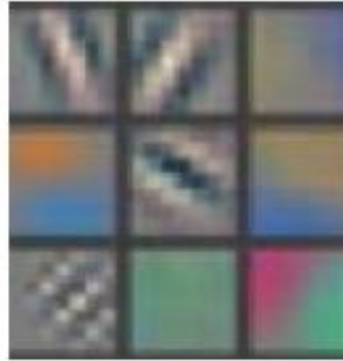


Weights for 9 features in the first convolutional layer of a layer for classifying ImageNet images



Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks"

## 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 activate the neuron: just try lots of images in a dataset, and see which ones activate the neuron the most

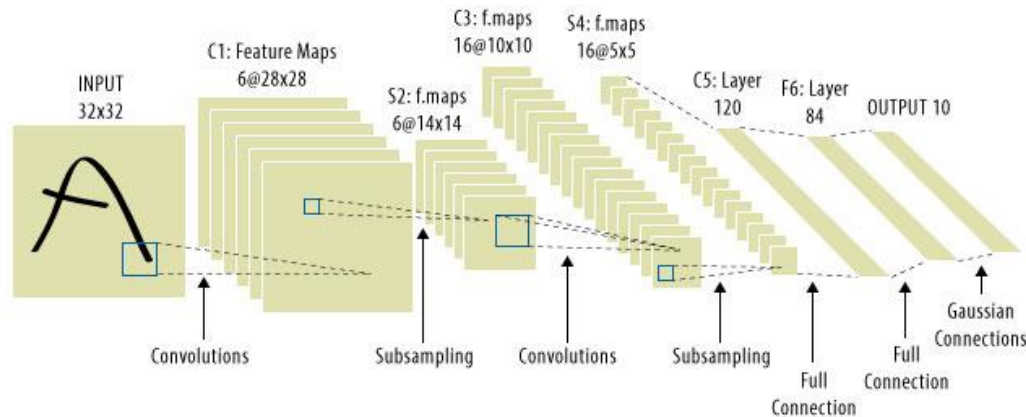


For each feature, find the 9 images that produce the highest activations for the neuron, and crop out the relevant patch



Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks"

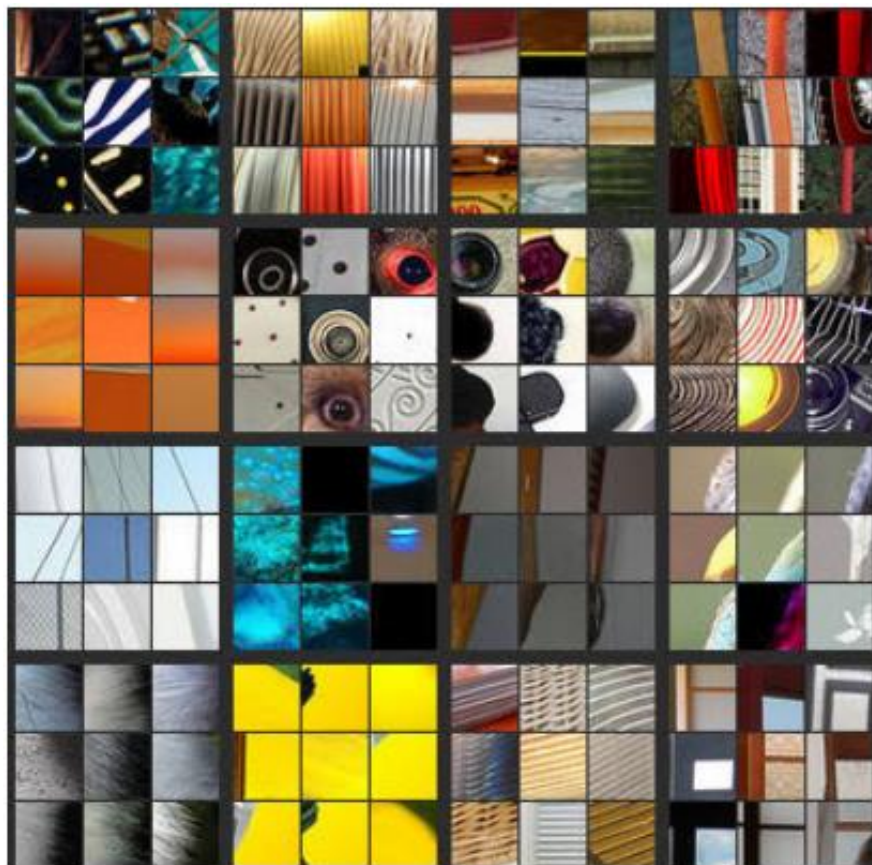
# Aside: Relevant Patch?



- 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

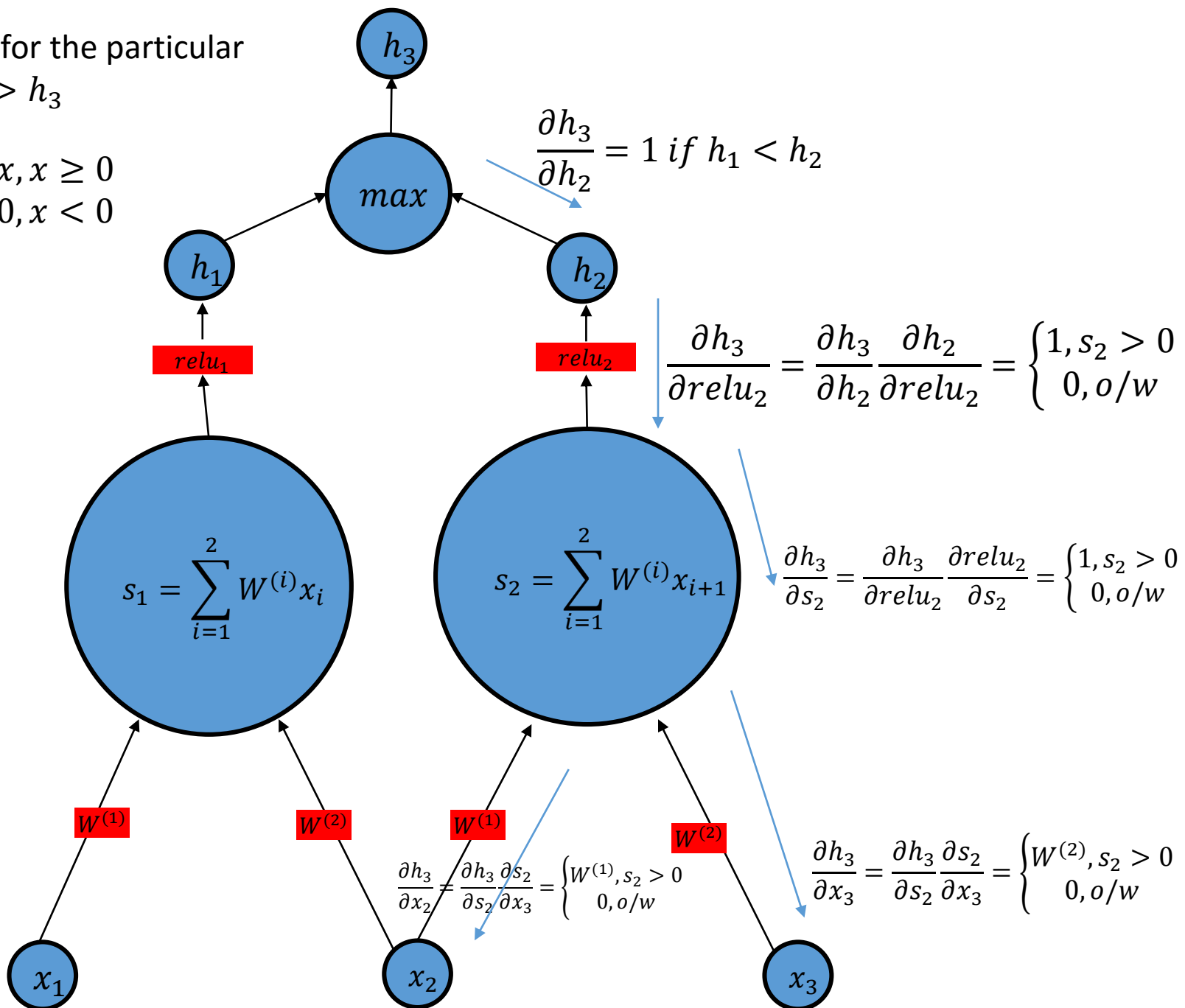


# Which Pixels in the Input Affect the Neuron the Most?

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

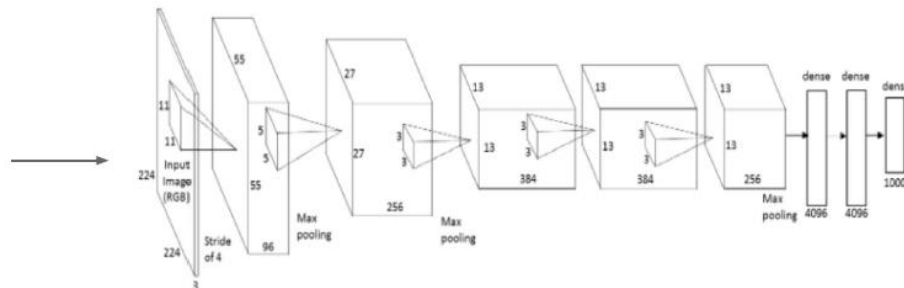
Assume that for the particular image  $x$ ,  $h_2 > h_3$

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

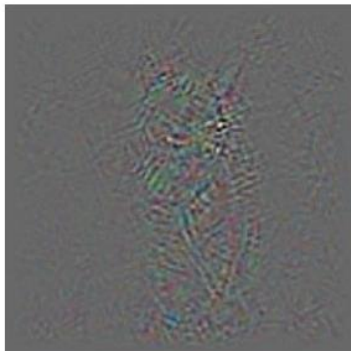


# Typical Gradient of a Neuron

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

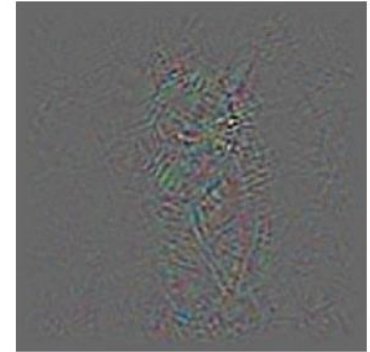


- Compute the gradient of a particular neuron using backprop:



# 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  
(Explanation on the board)

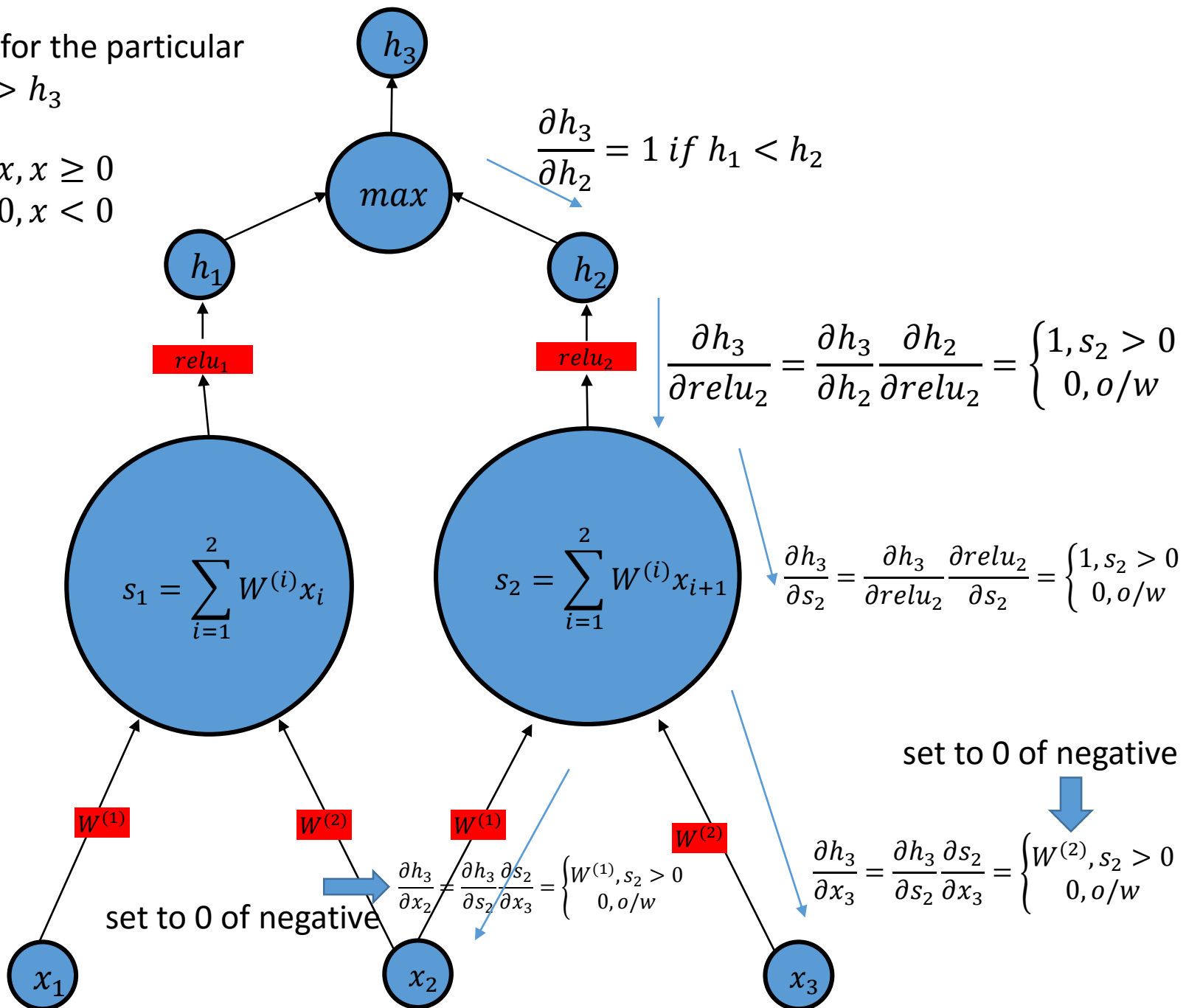
# “Guided Backpropagation”

- 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
- So when propagating the gradient, we set all the negative gradients to 0
  - We don't care if a pixel “suppresses” a neuron somewhere along the path to our neuron

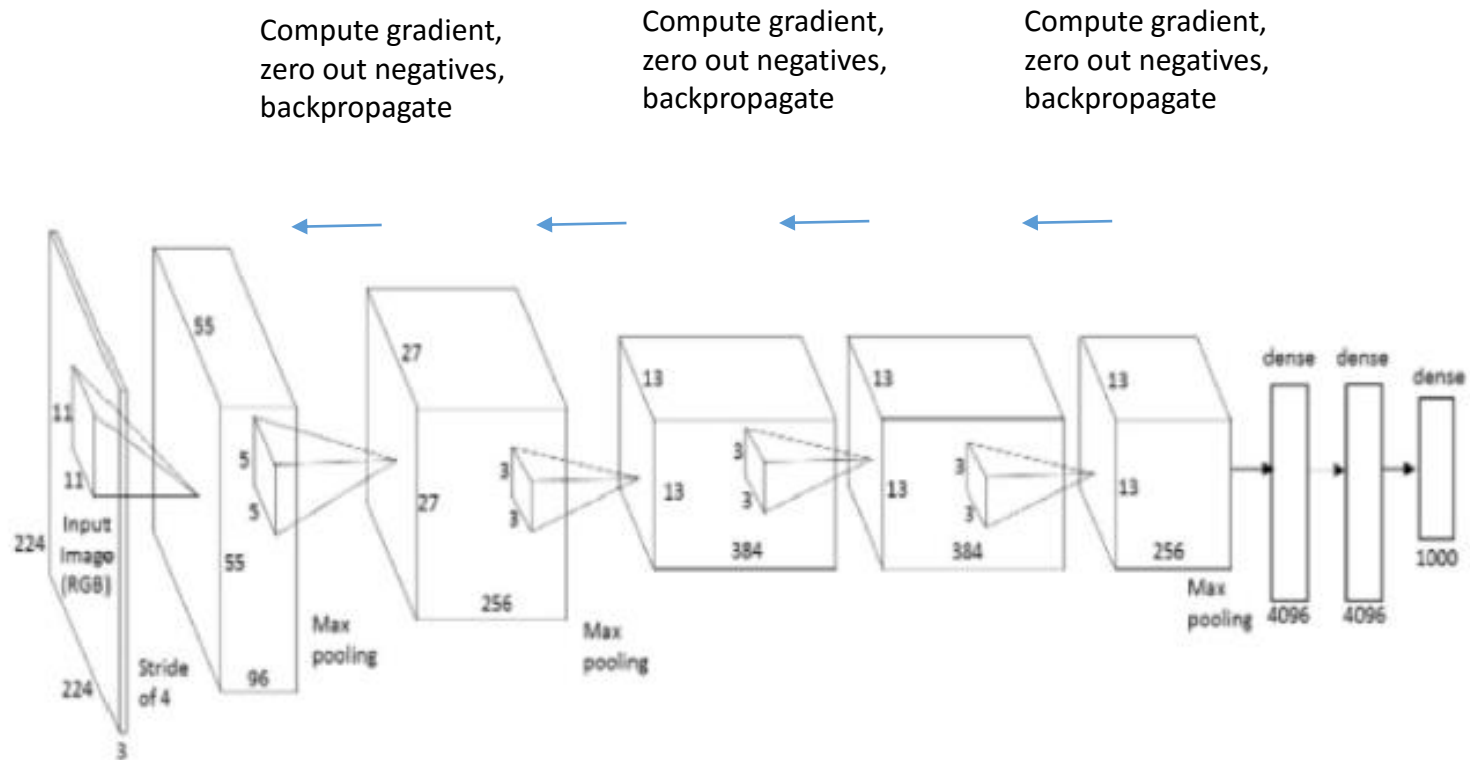


Assume that for the particular image  $x$ ,  $h_2 > h_3$

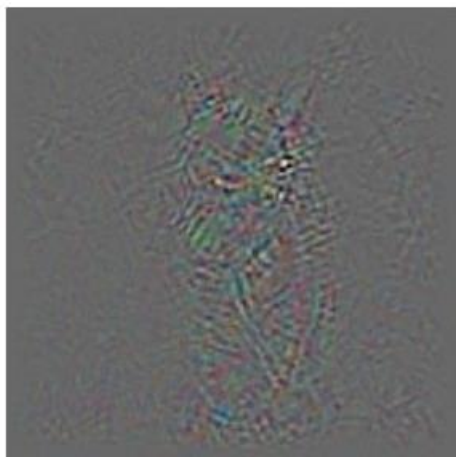
$$\text{relu}(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases}$$



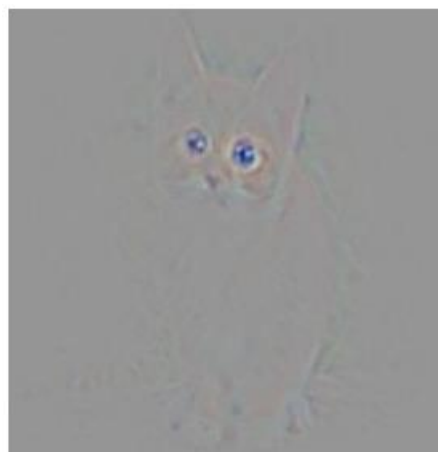
# Guided Backpropagation



# Guided Backpropagation



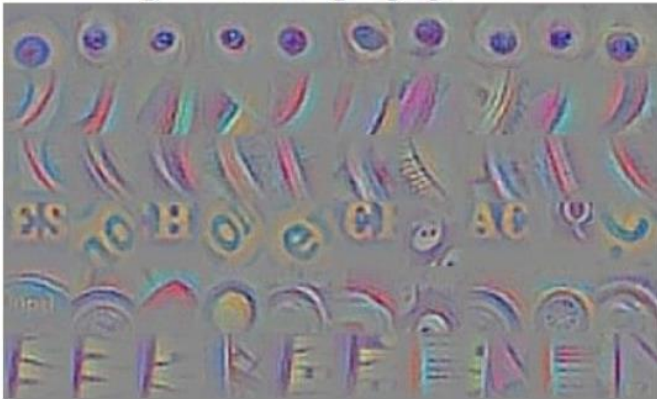
Backprop



Guided Backprop

# Guided Backpropagation

guided backpropagation



corresponding image crops



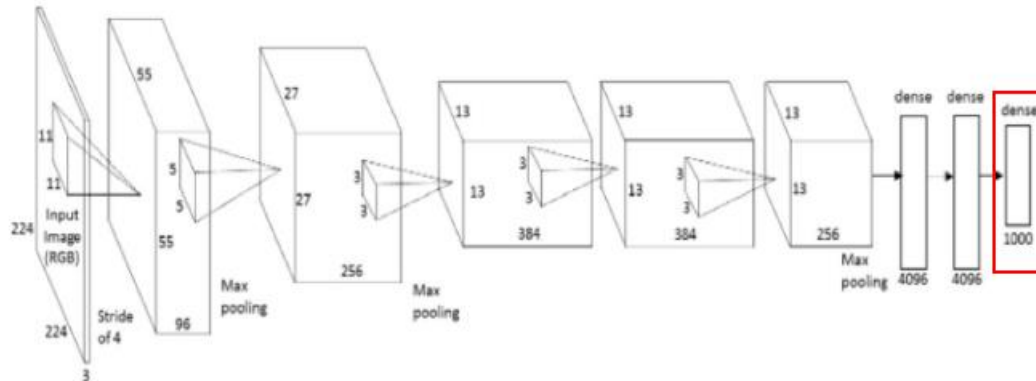
guided backpropagation



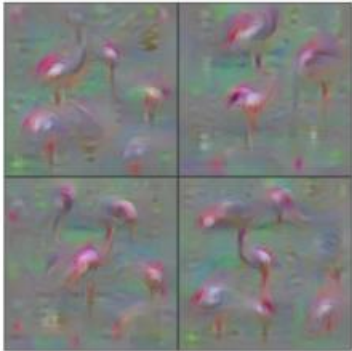
corresponding image crops



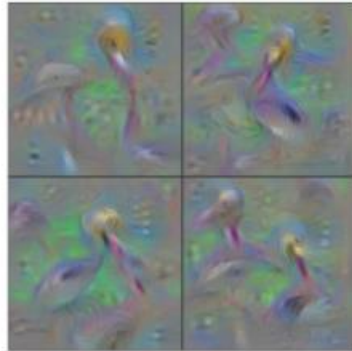
# What About Doing Gradient Descent?



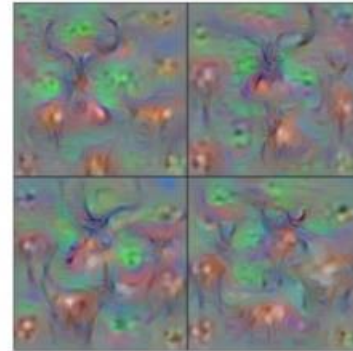
- What to maximize the  $i$ -th output of the softmax
- Can compute the gradient of the  $i$ -th output of the softmax with respect to the *input*  $x$  (the  $W$ 's and  $b$ 's are fixed to make classification as good as possible)
- Perform gradient descent on the *input*



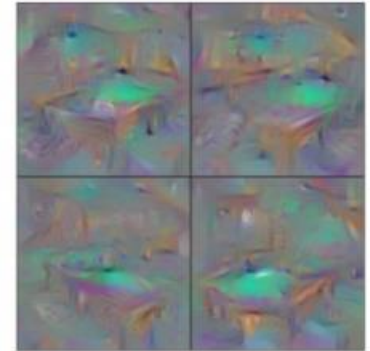
Flamingo



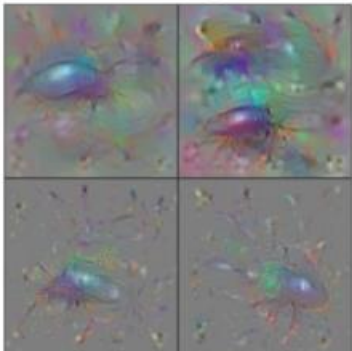
Pelican



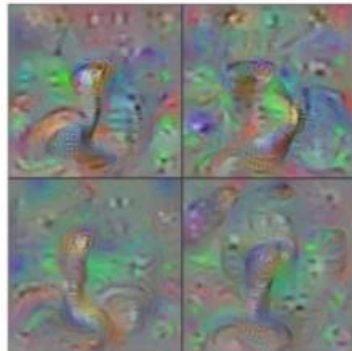
Hartebeest



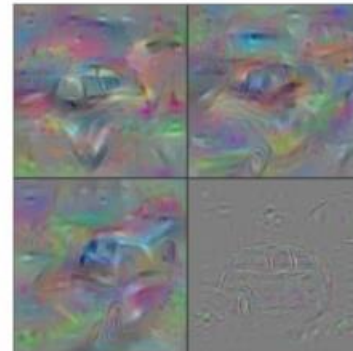
Billiard Table



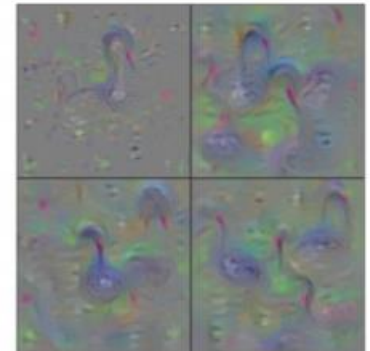
Ground Beetle



Indian Cobra



Station Wagon



Black Swan

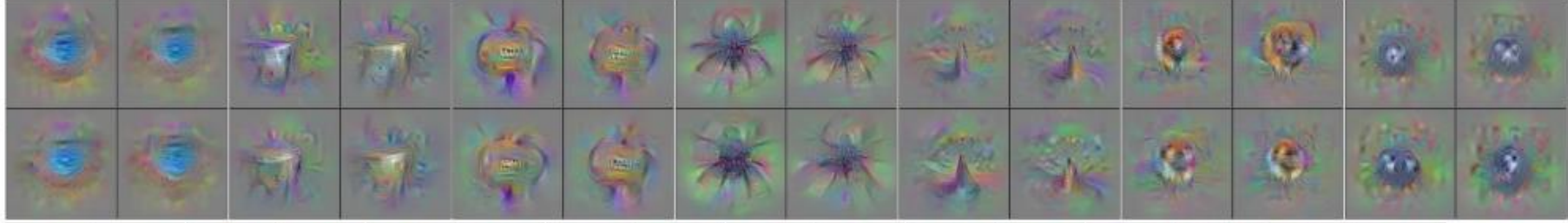
Yosinski et al, Understanding Neural Networks Through Deep Visualization (ICML 2015)



Layer 6

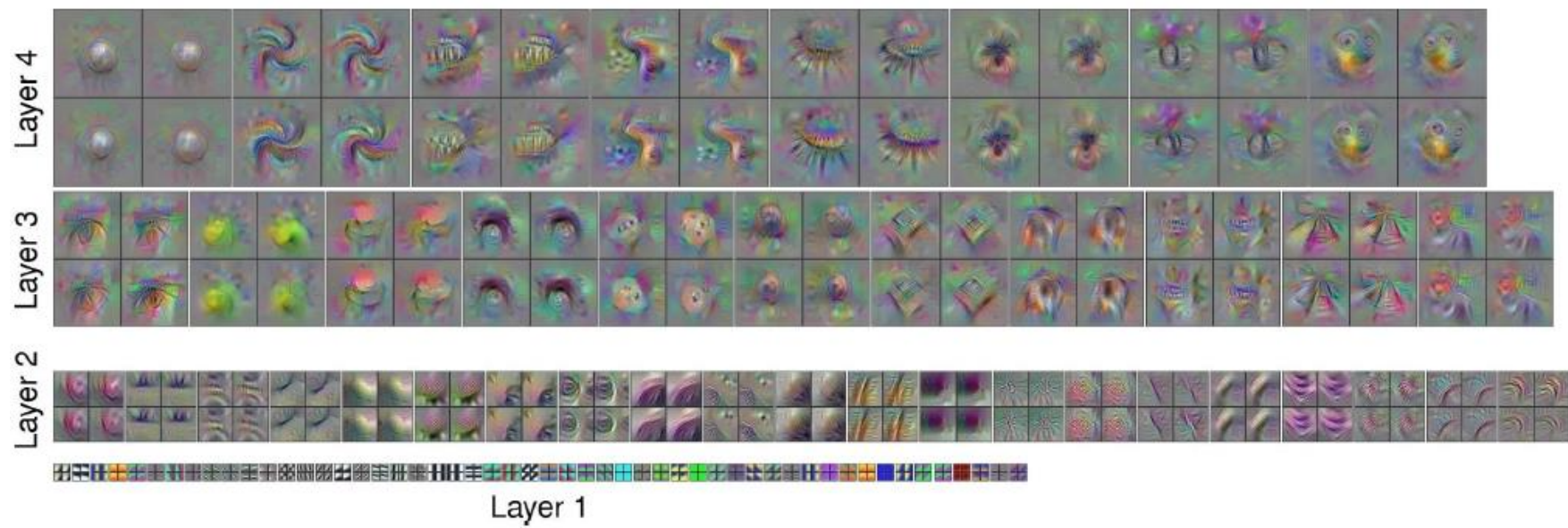


Layer 5



Layer 4





## (A Small Tweak For the Gradient Descent Algorithm)

- Doing gradient descent 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 descent step
  - Blur the image  $x$