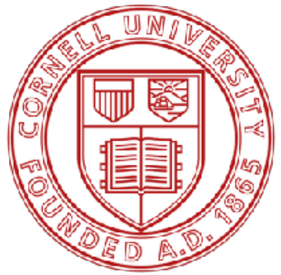
Lecture 9: Convolutional networks

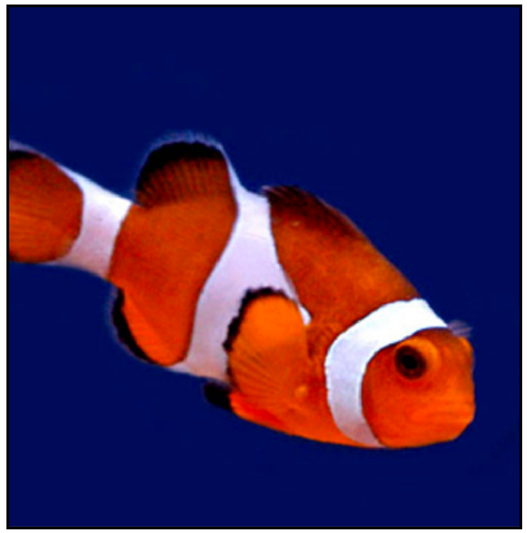
CS 5670: Introduction to Computer Vision



Announcements

- PS2 due on Monday
- PyTorch tutorial link (from Justin Johnson)
- PS1 grades back in ~2 weeks
- Thoughts on PS1?

Image classification



Classifier

"Fish"

image **x**

label y

Source: Isola, Torralba, Freeman

Image classification

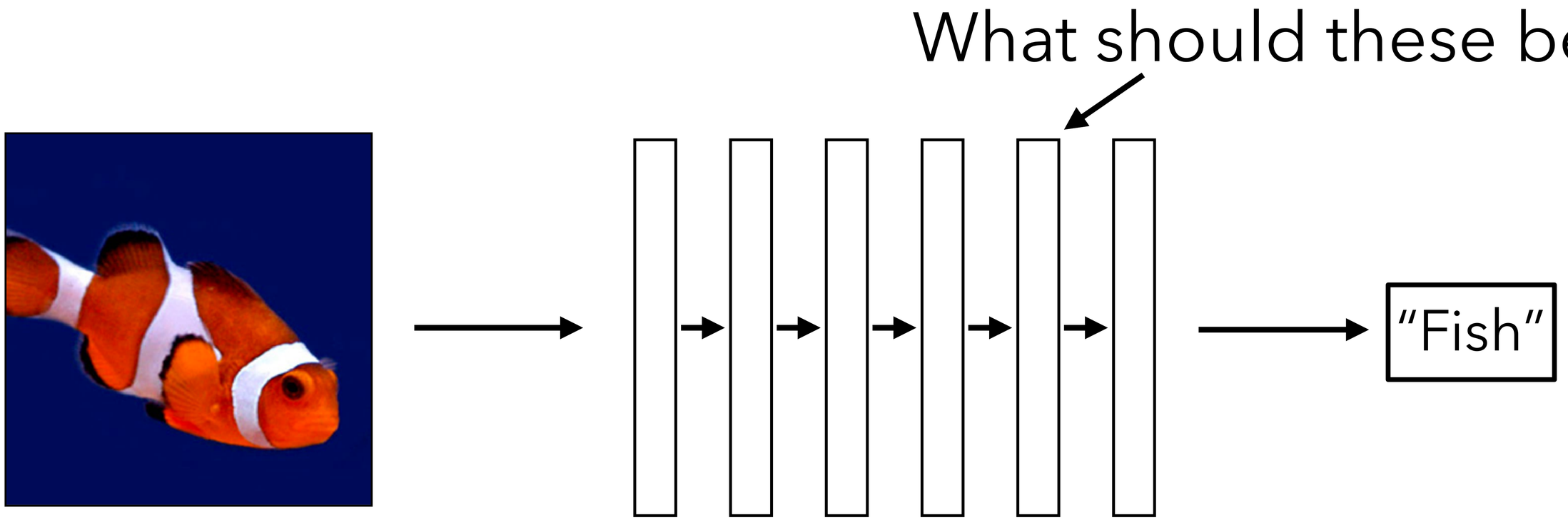


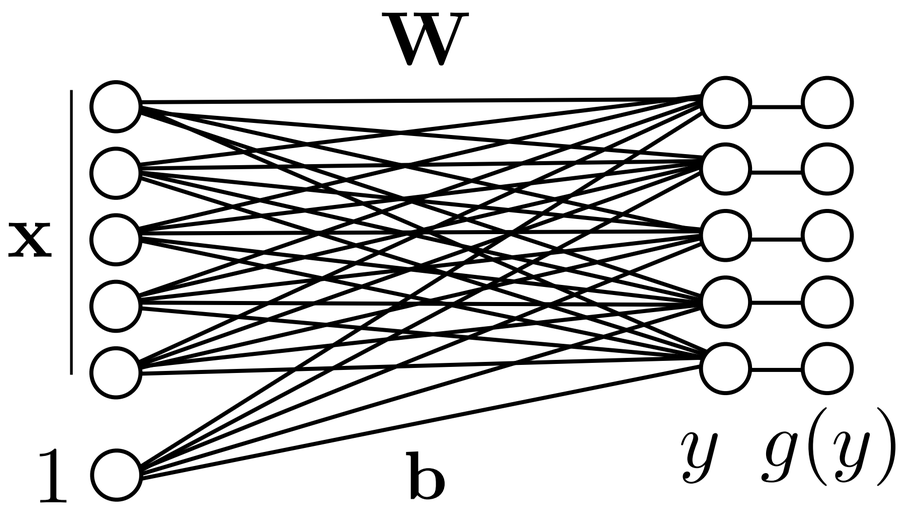
image **x**

label y

Source: Isola, Torralba, Freeman

Idea #1: Fully-connected network

Fully-connected (a.k.a. linear) layer

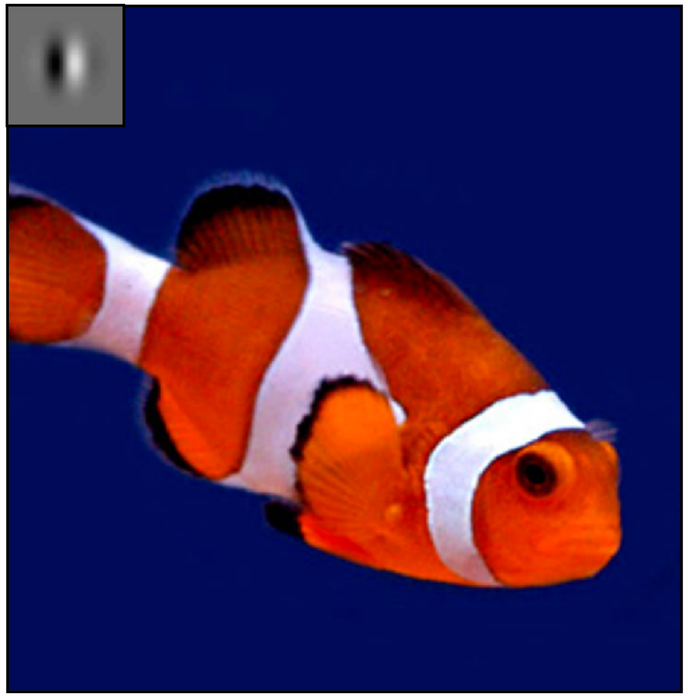


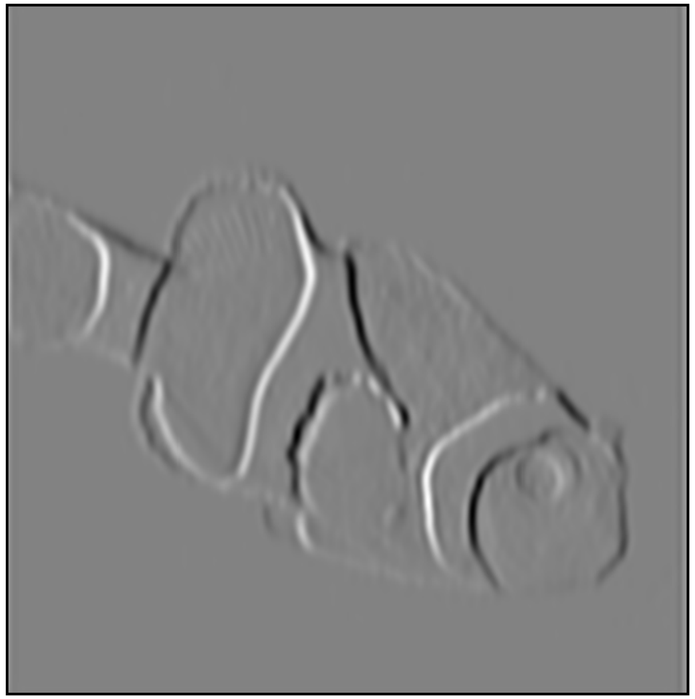
$\mathbf{x} =$ 

But $\mathbf{x}$ is really big!

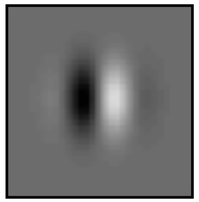
Say, 256 x 256 x 3 = 197k

Can we use convolution in a neural network?



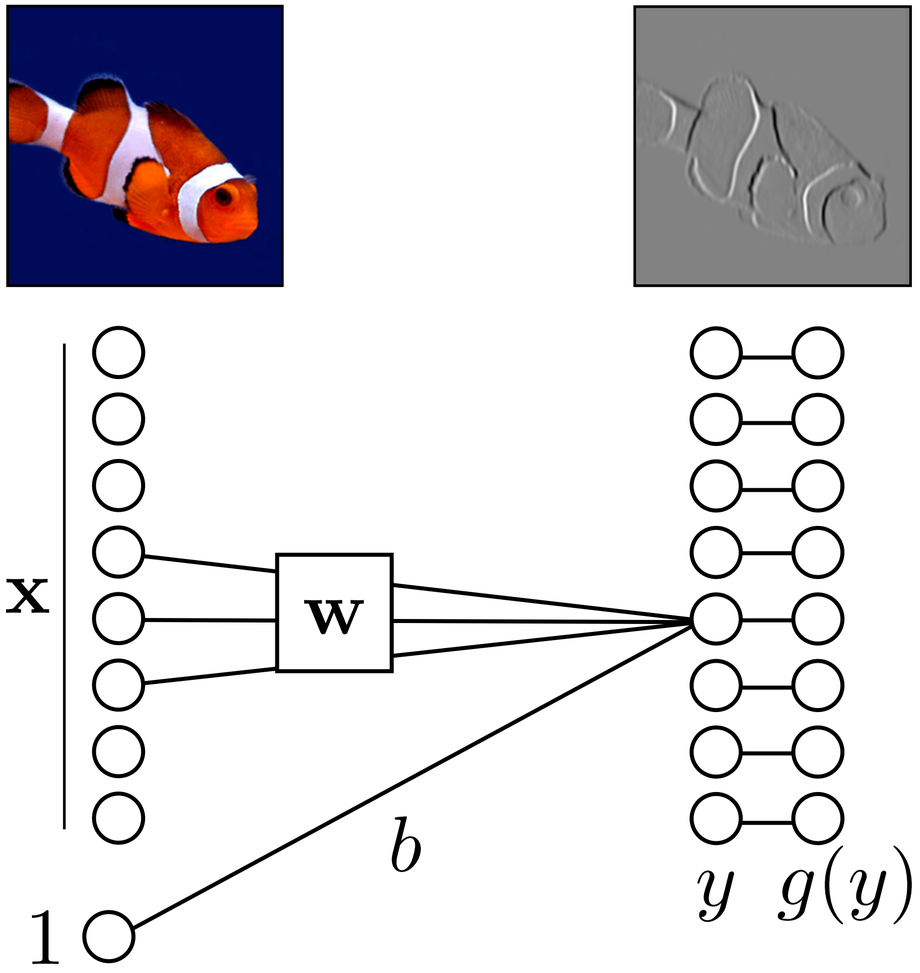


filter



Source: Isola, Torralba, Freeman

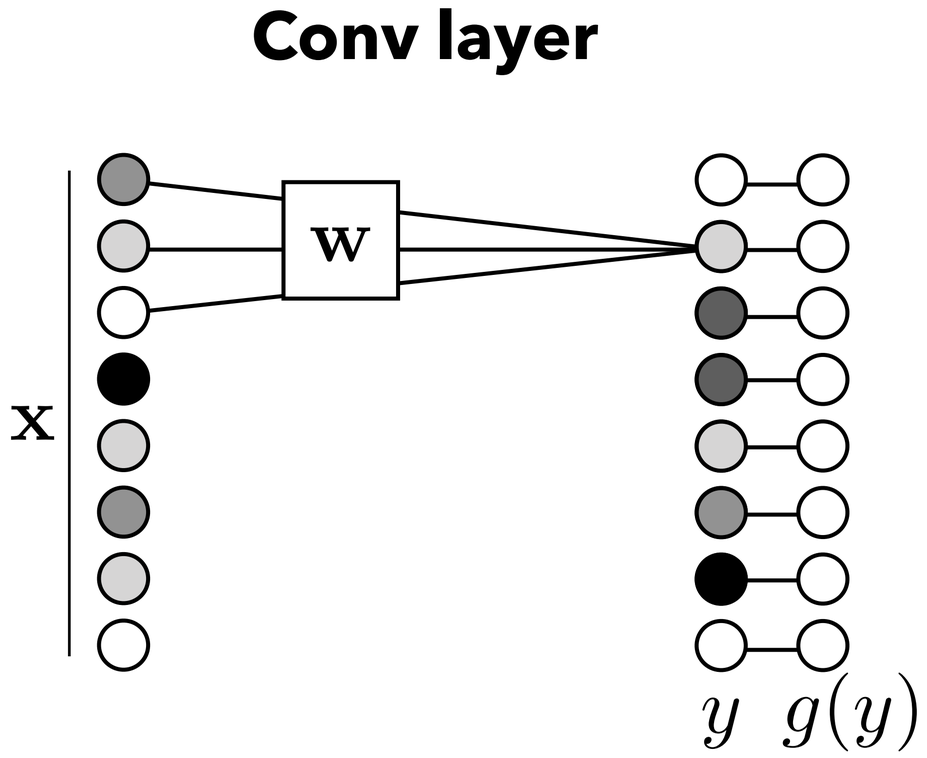
Sparsely connected network



Each unit is connected to a subset of the units in the previous layer.

Source: Isola, Torralba, Freeman

Convolutional neural network



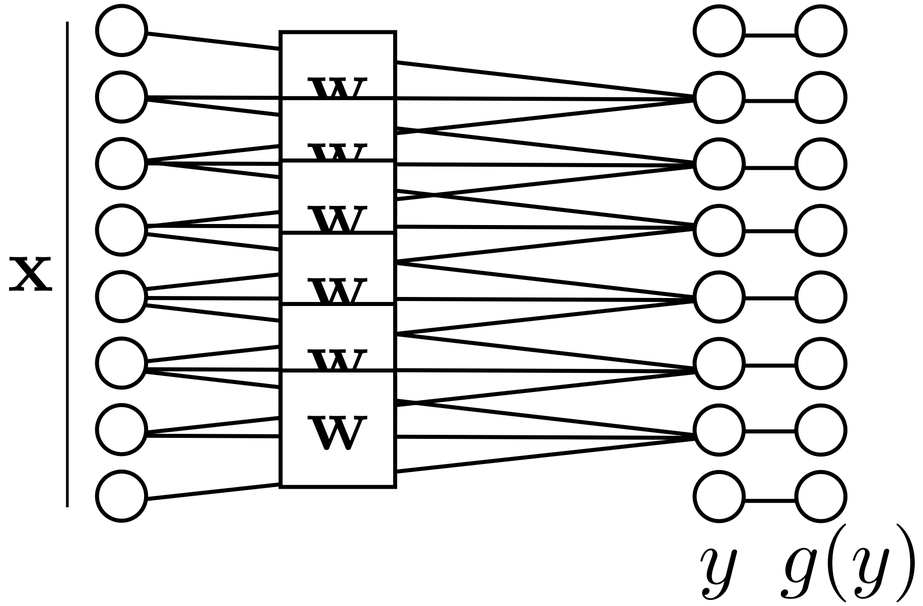
Each output unit is computed from an image patch.

a.k.a. CNN or ConvNet

Source: Isola, Torralba, Freeman

Weight sharing

Conv layer

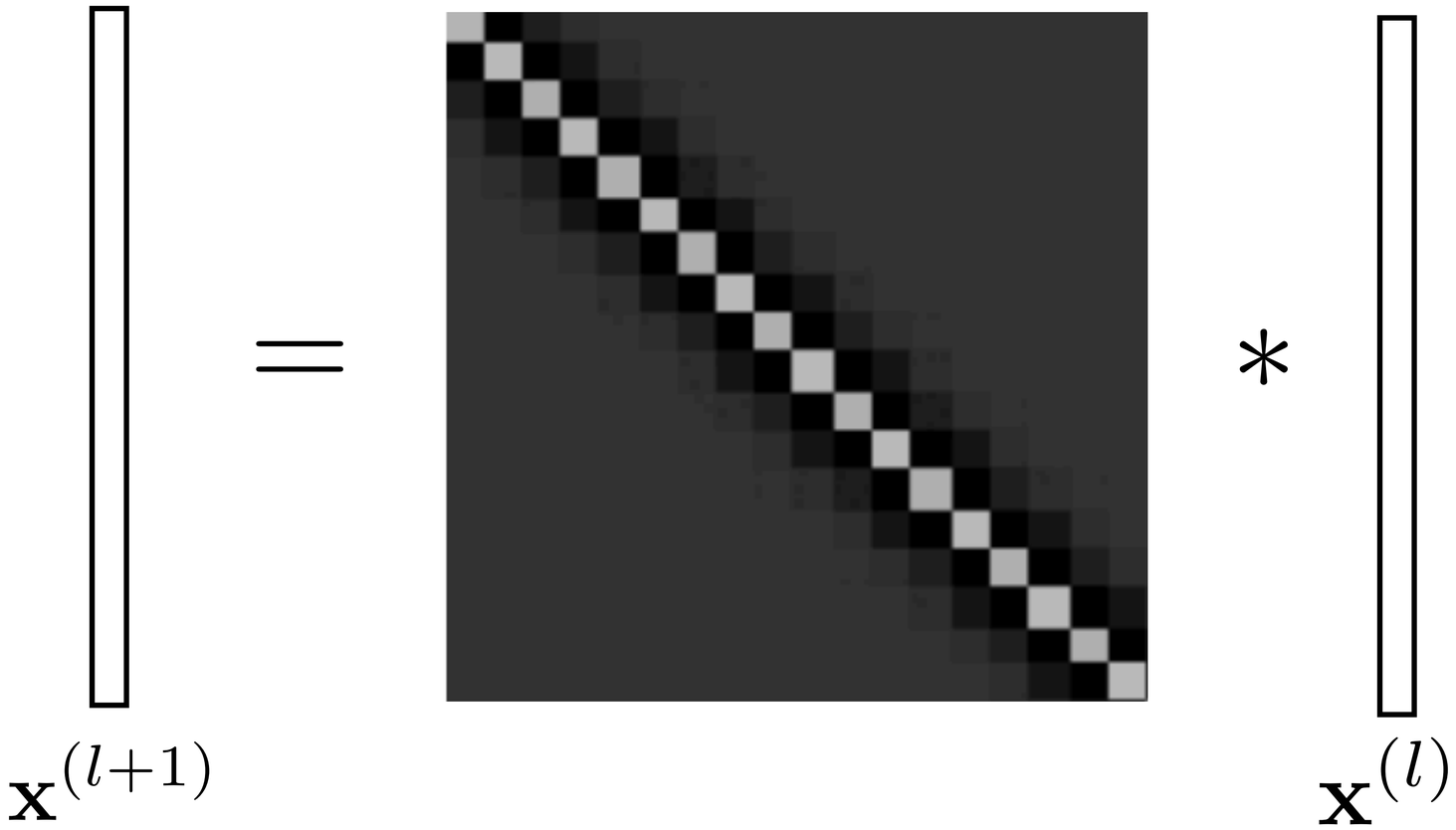


We “share” weights for each patch.

If a feature is useful in one position, it should be useful in others, too.

Source: Isola, Torralba, Freeman

Convolution is a linear function



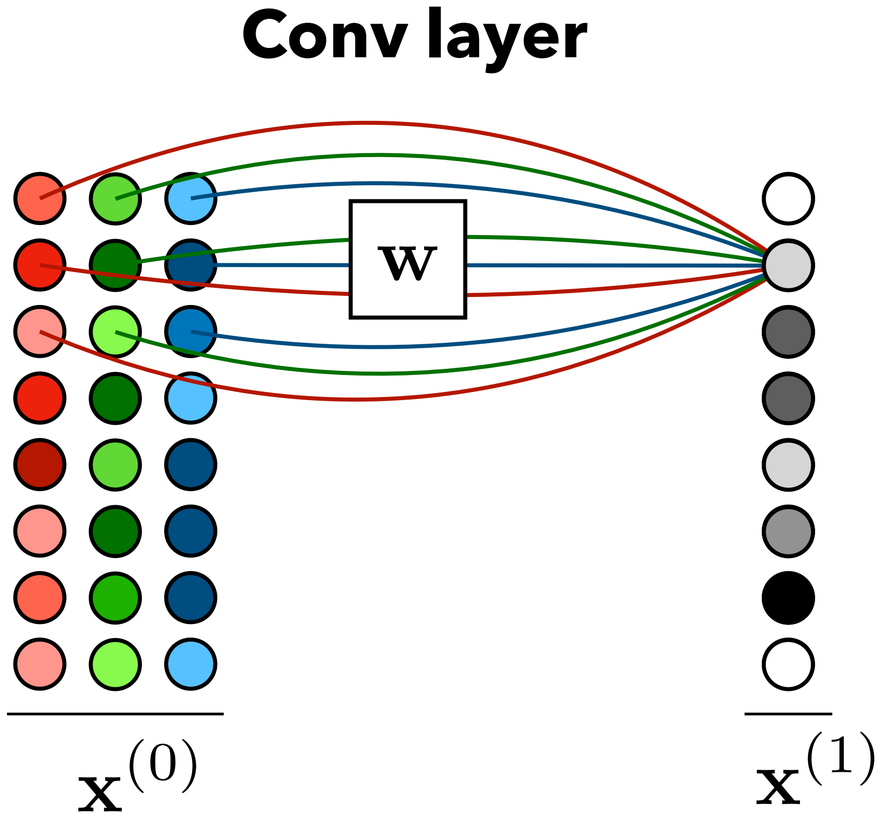
- Constrained linear layer

e.g., image

- Fewer parameters: easier to learn, less overfitting
- Usually use zero padding

Source: Isola, Torralba, Freeman

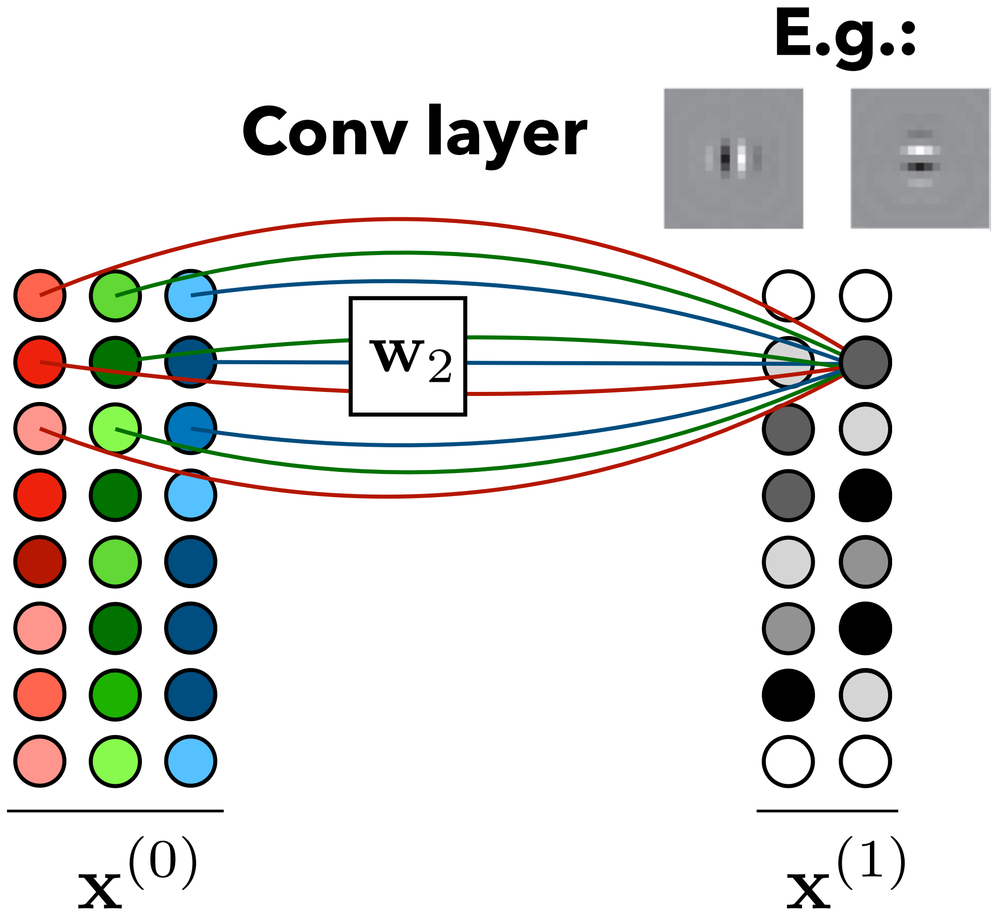
Multiple input channels



$$\mathbb{R}^{N \times C} \rightarrow \mathbb{R}^{N \times 1}$$

Source: Isola, Torralba, Freeman

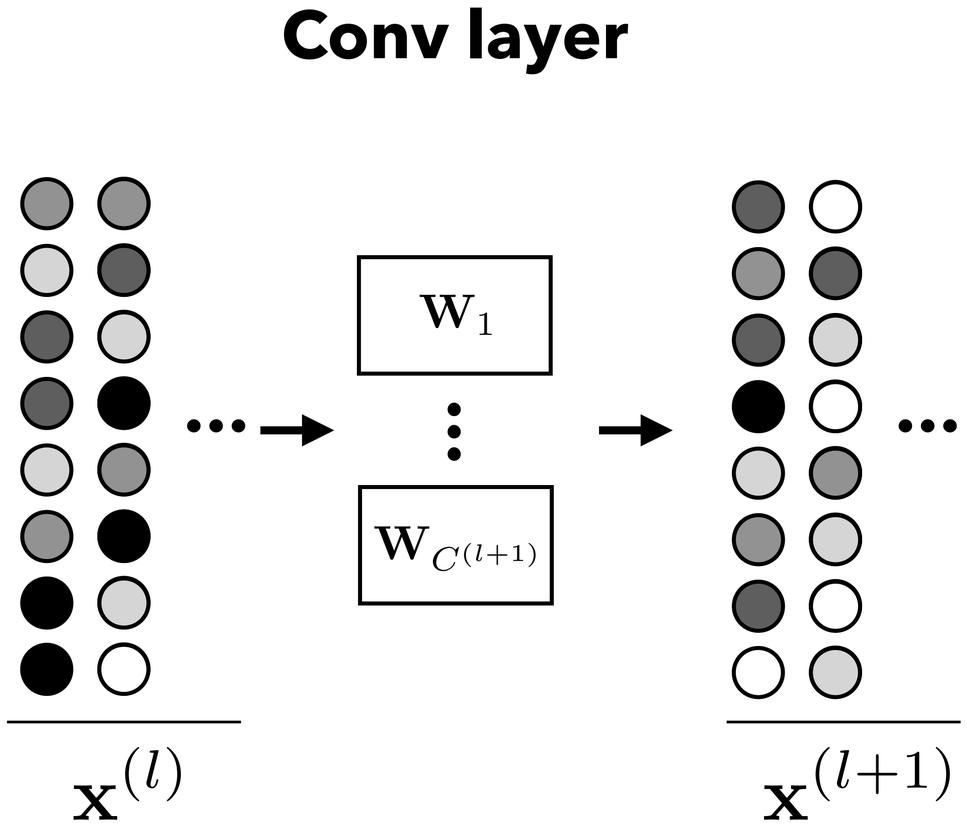
Multiple output channels



$$\mathbb{R}^{N \times C^{(0)}} \rightarrow \mathbb{R}^{N \times C^{(1)}}$$

Source: Isola, Torralba, Freeman

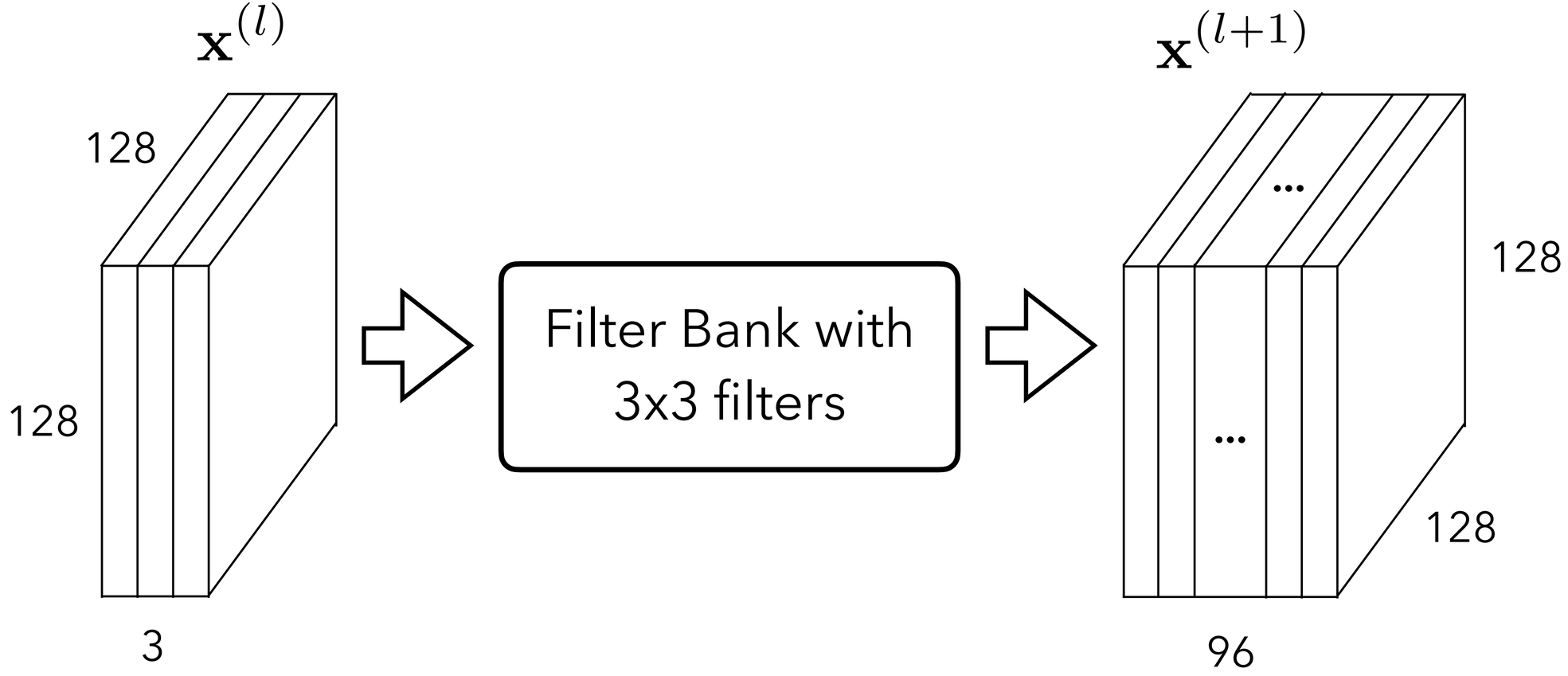
Multiple input and output channels



$$\mathbb{R}^{N \times C^{(l)}} \rightarrow \mathbb{R}^{N \times C^{(l+1)}}$$

Source: Isola, Torralba, Freeman

Multiple channels: Example

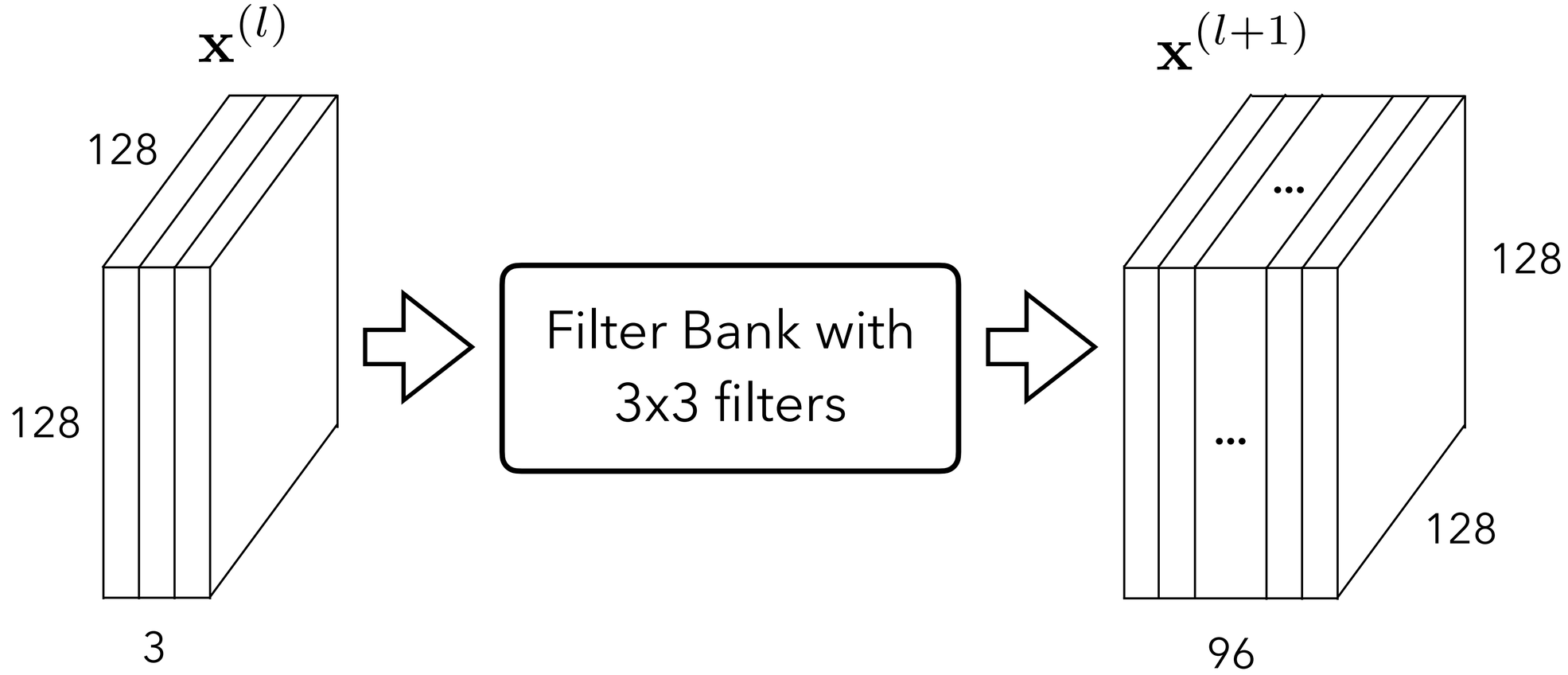


How many parameters does *each filter* have?

(a) 9 (b) 27 (c) 96 (d) 2592

Source: Isola, Torralba, Freeman

Multiple channels: Example



How many parameters *total* does this layer have?

(a) 9 (b) 27 (c) 96 (d) 2592

Image classification

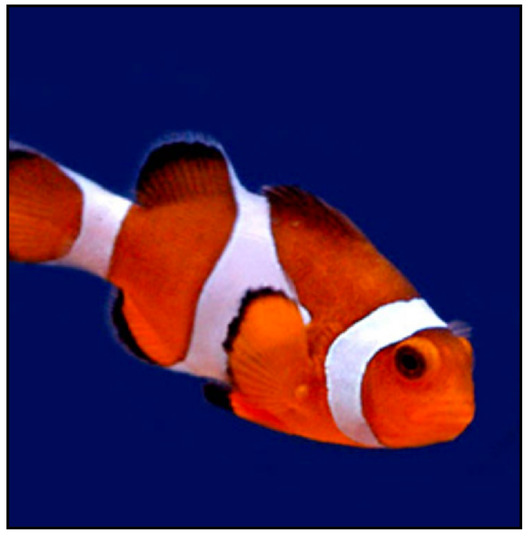
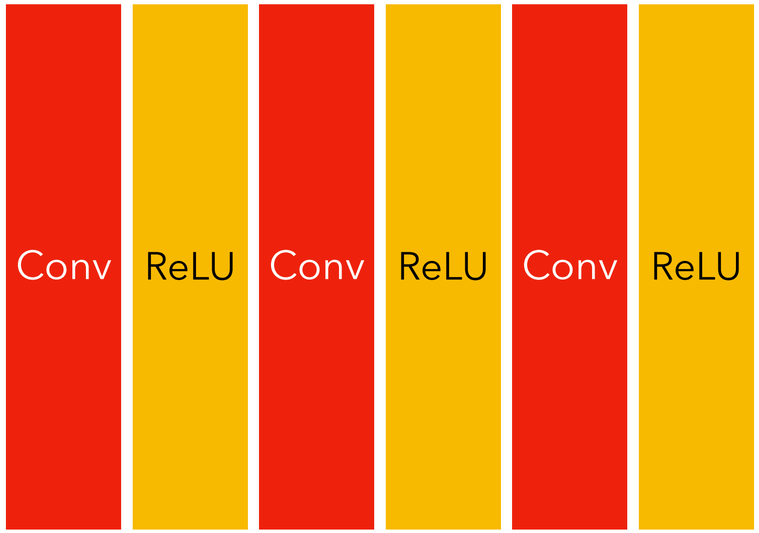


image **x**



"Fish"

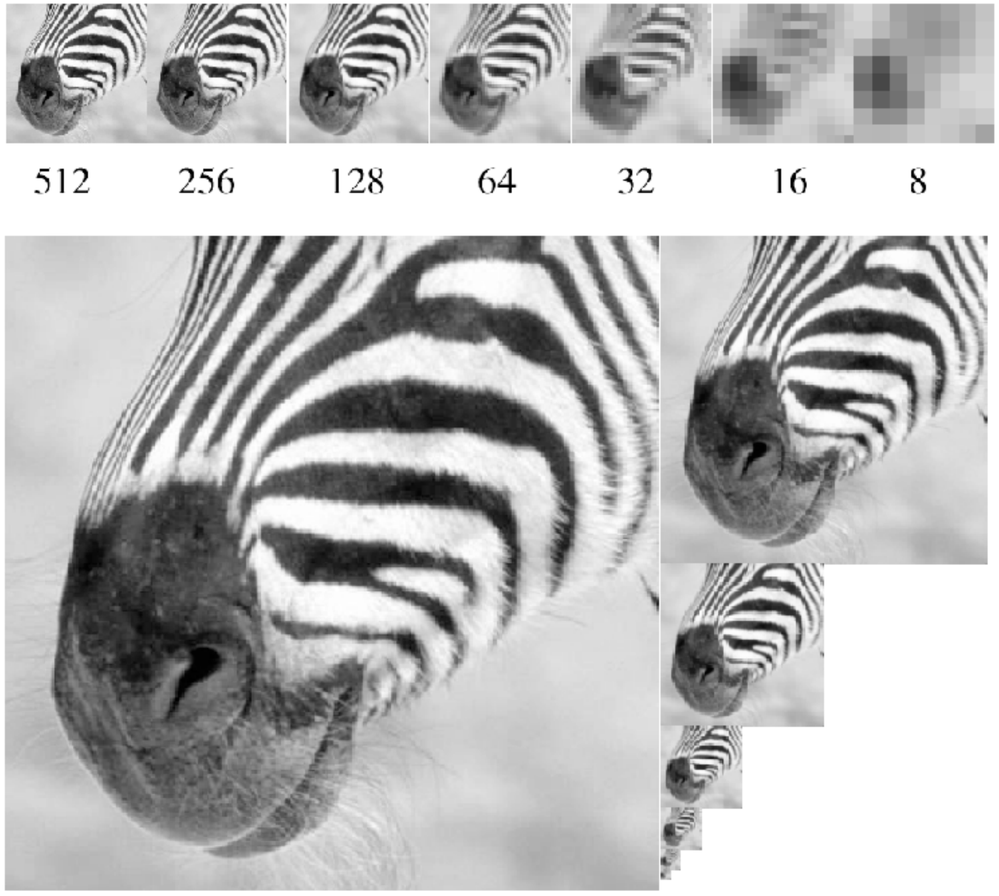
label y

Problems with this idea:

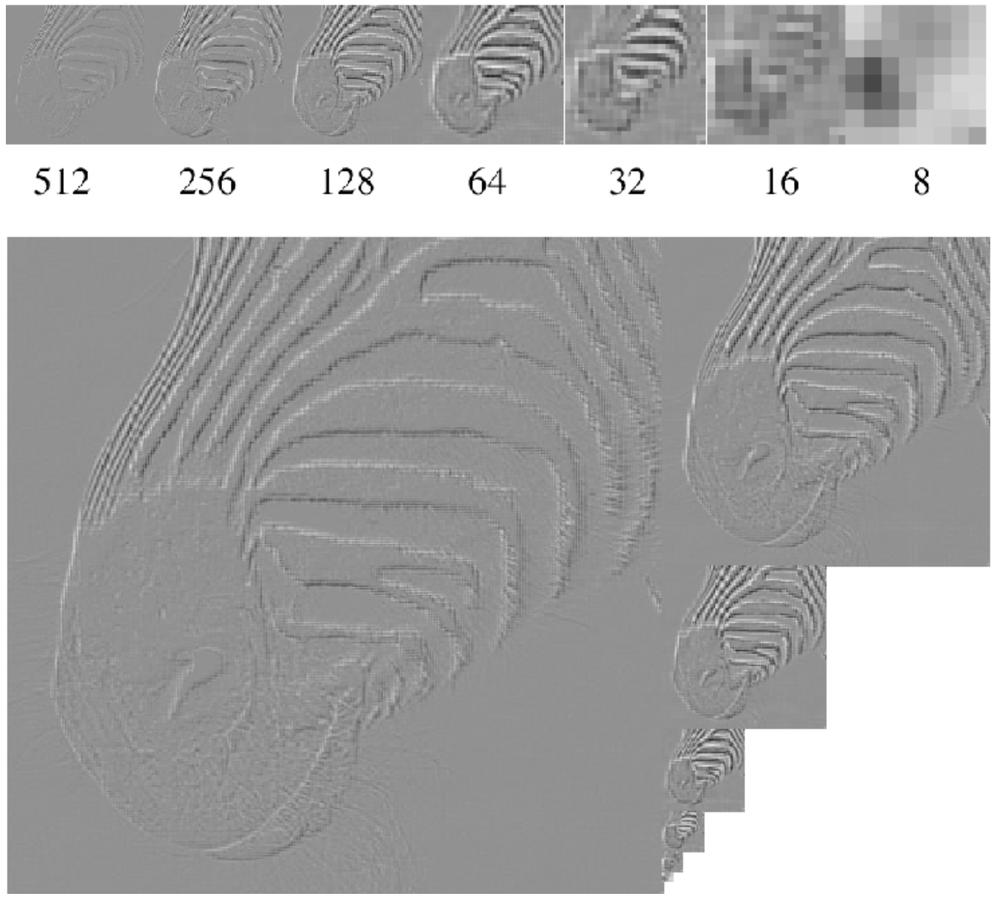
1. No "global" processing.
2. How do you get the final label?

Source: Isola, Torralba, Freeman

Recall: pyramid representations



Gaussian Pyramid

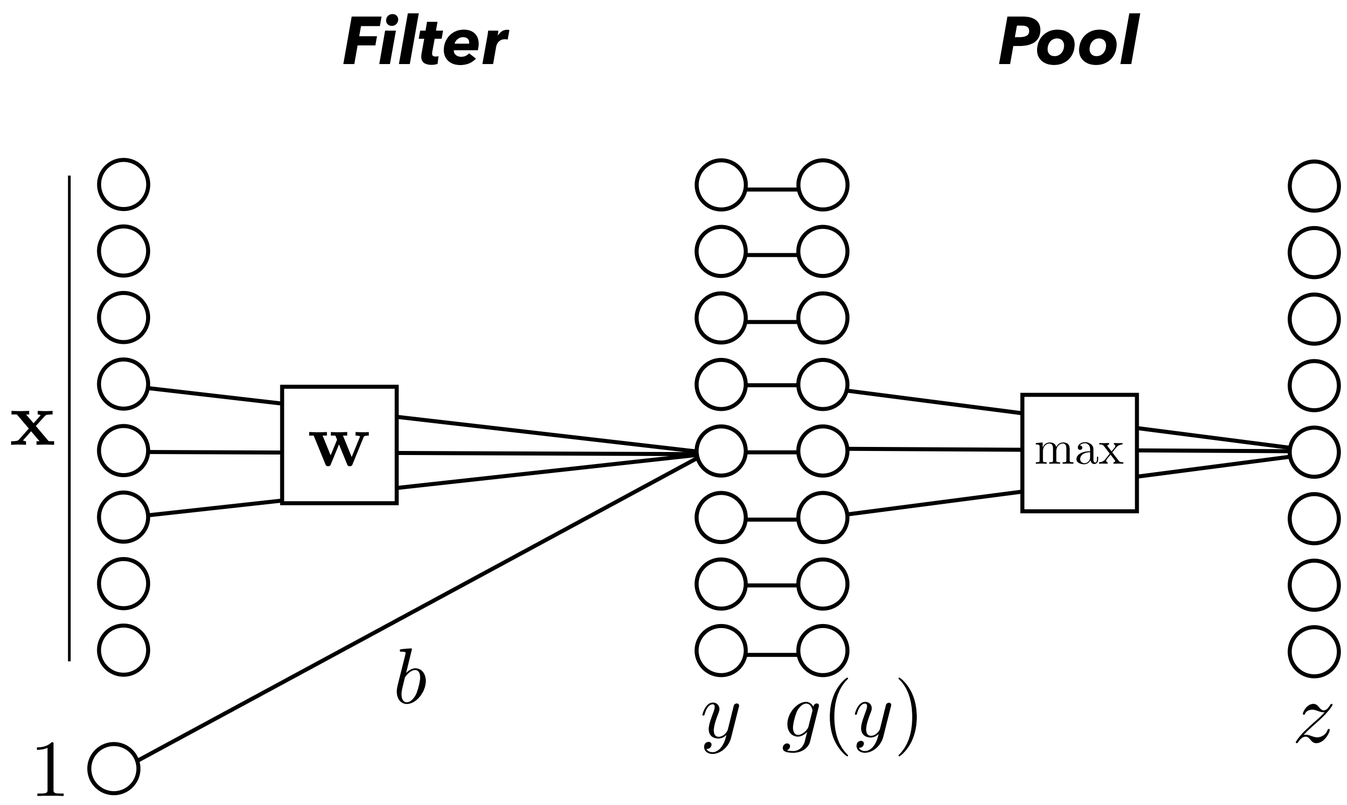


Laplacian Pyramid

Can we use a similar idea in CNNs?

Source: Isola, Torralba, Freeman

Pooling

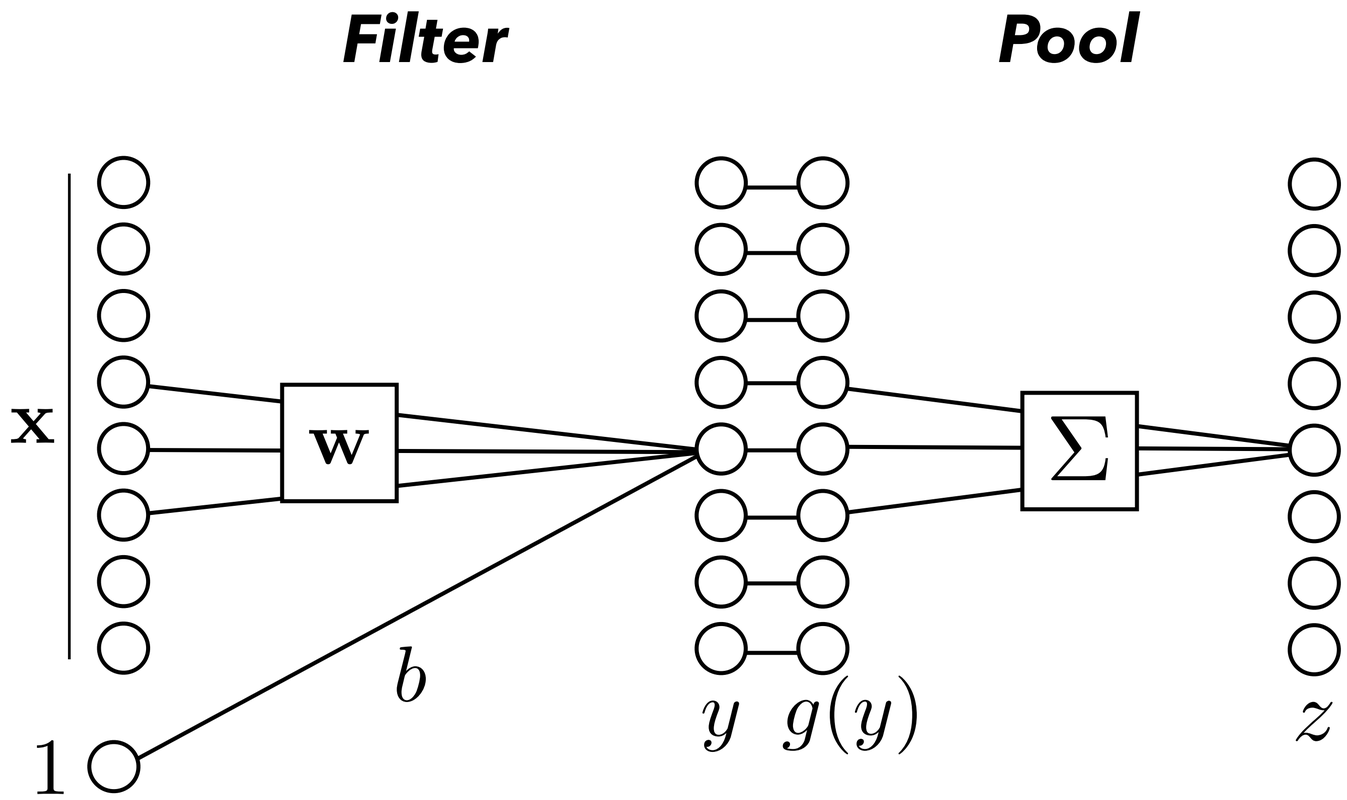


Max pooling

$$z_k = \max_{j \in \mathcal{N}(j)} g(y_j)$$

Source: Isola, Torralba, Freeman

Pooling



Max pooling

$$z_k = \max_{j \in \mathcal{N}(j)} g(y_j)$$

Mean pooling

$$z_k = \frac{1}{|\mathcal{N}|} \sum_{j \in \mathcal{N}(j)} g(y_j)$$

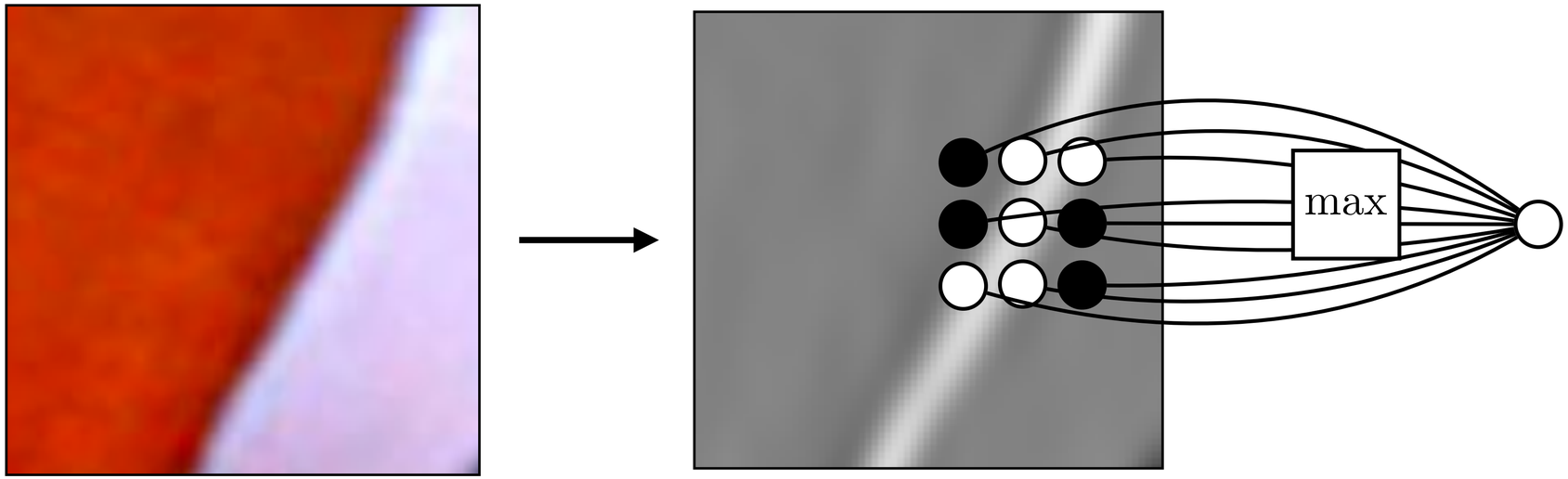
Blurring [Zhang 2019]

$$z = \text{conv}(y, \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix})$$

Adapted from: Isola, Torralba, Freeman

Pooling – Why?

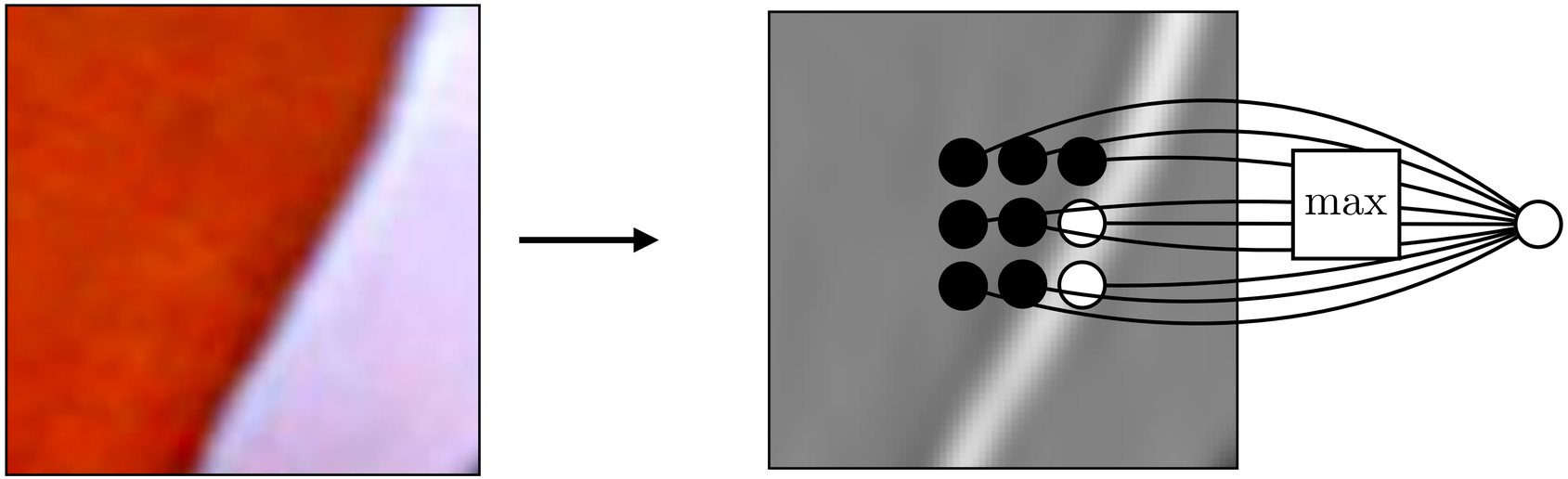
Pooling across spatial locations achieves stability w.r.t. small translations:



Source: Isola, Torralba, Freeman

Pooling – Why?

Pooling across spatial locations achieves stability w.r.t. small translations:

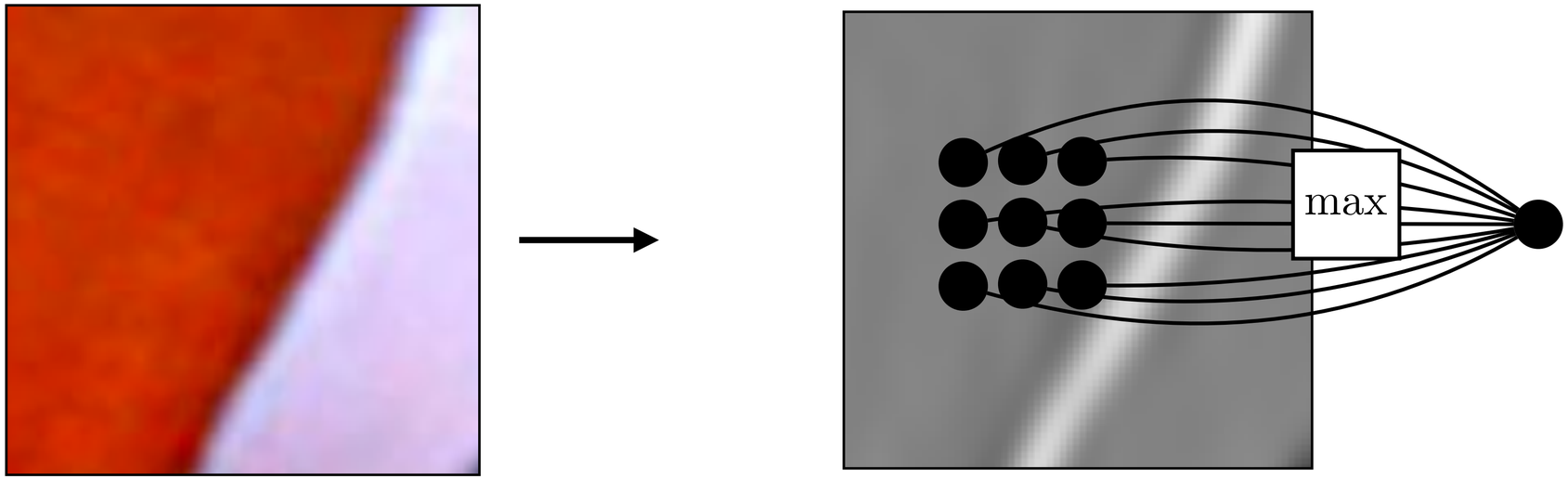


same large response regardless of exact position of edge

Source: Isola, Torralba, Freeman

Pooling – Why?

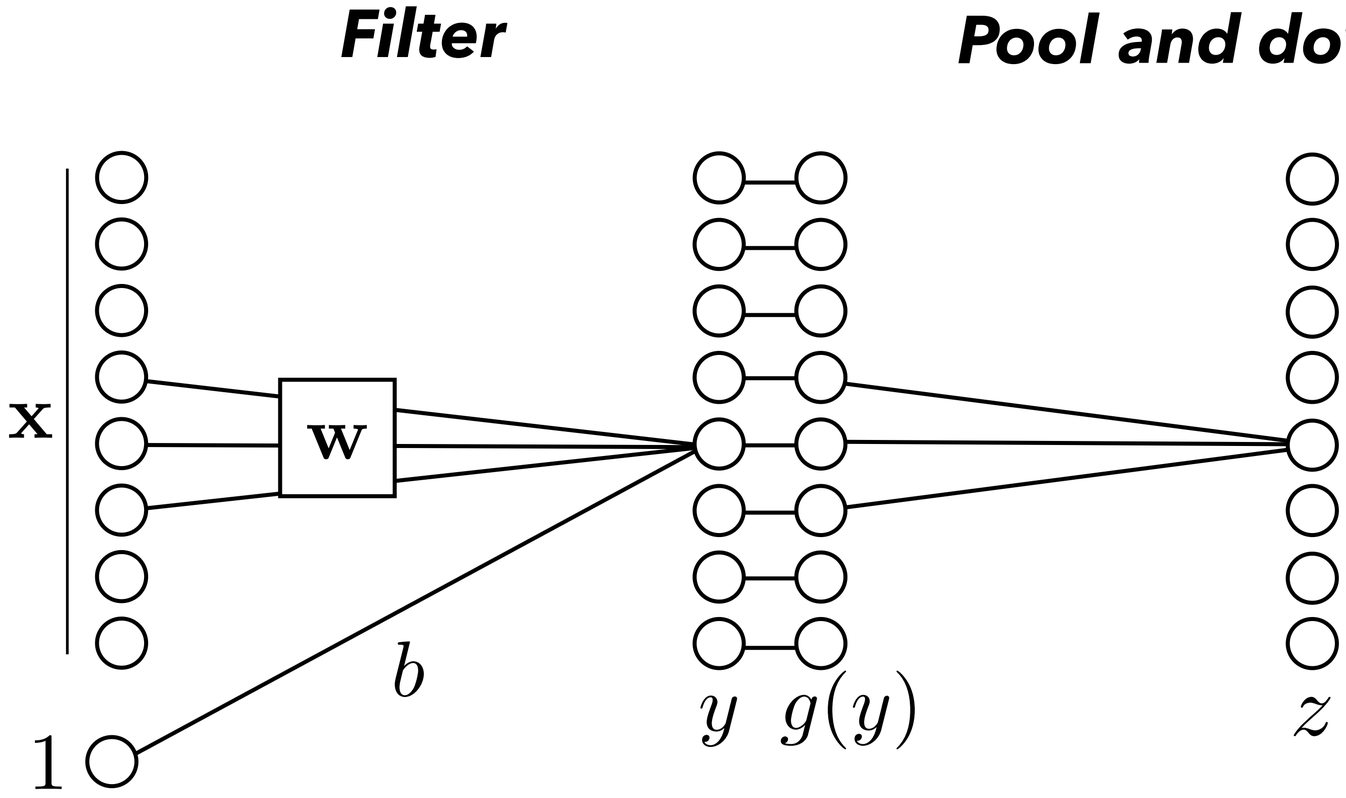
Pooling across spatial locations achieves stability w.r.t. small translations:



however, if the image is translated a lot…

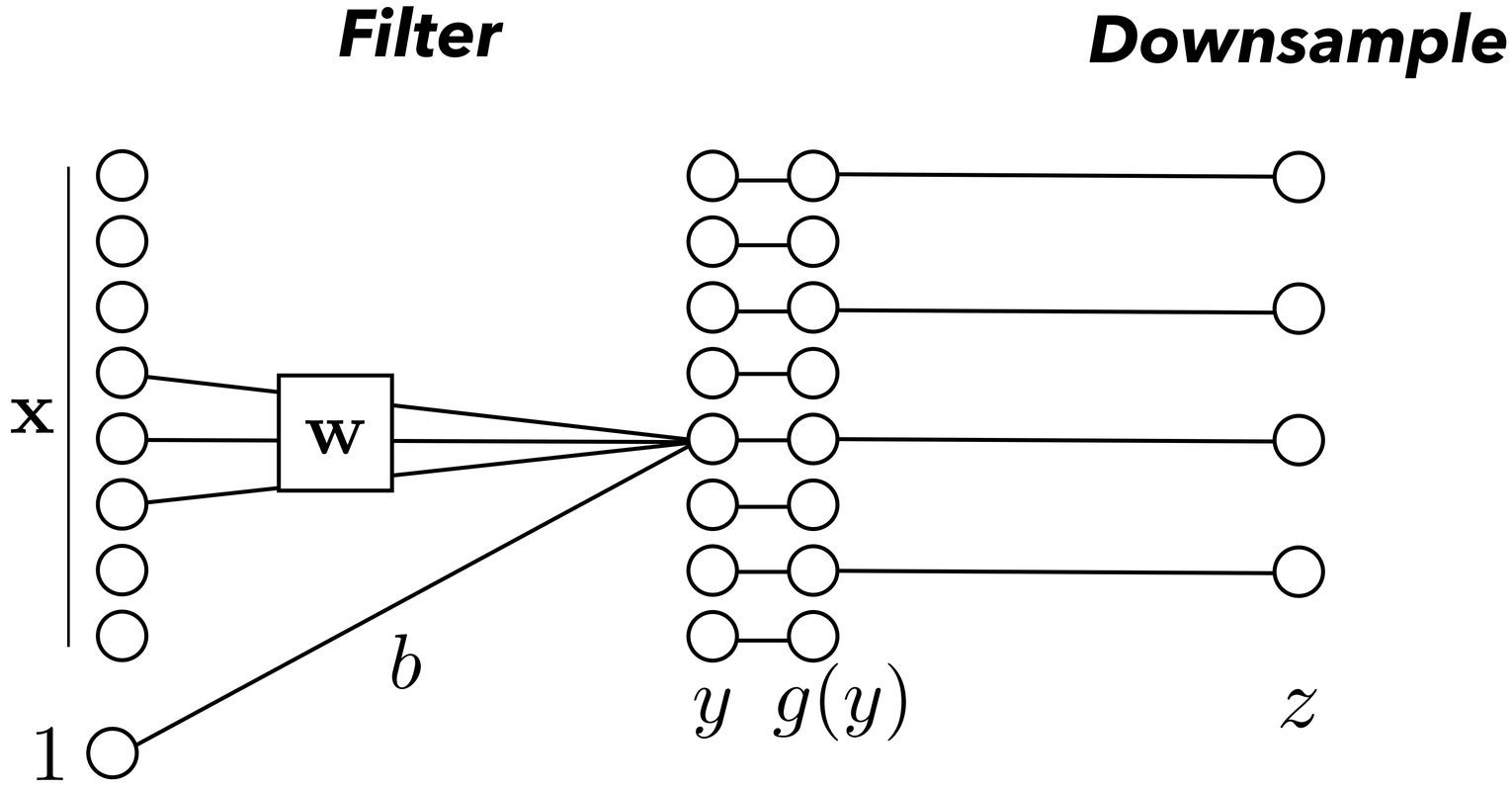
Source: Isola, Torralba, Freeman

Downsampling



Source: Isola, Torralba, Freeman

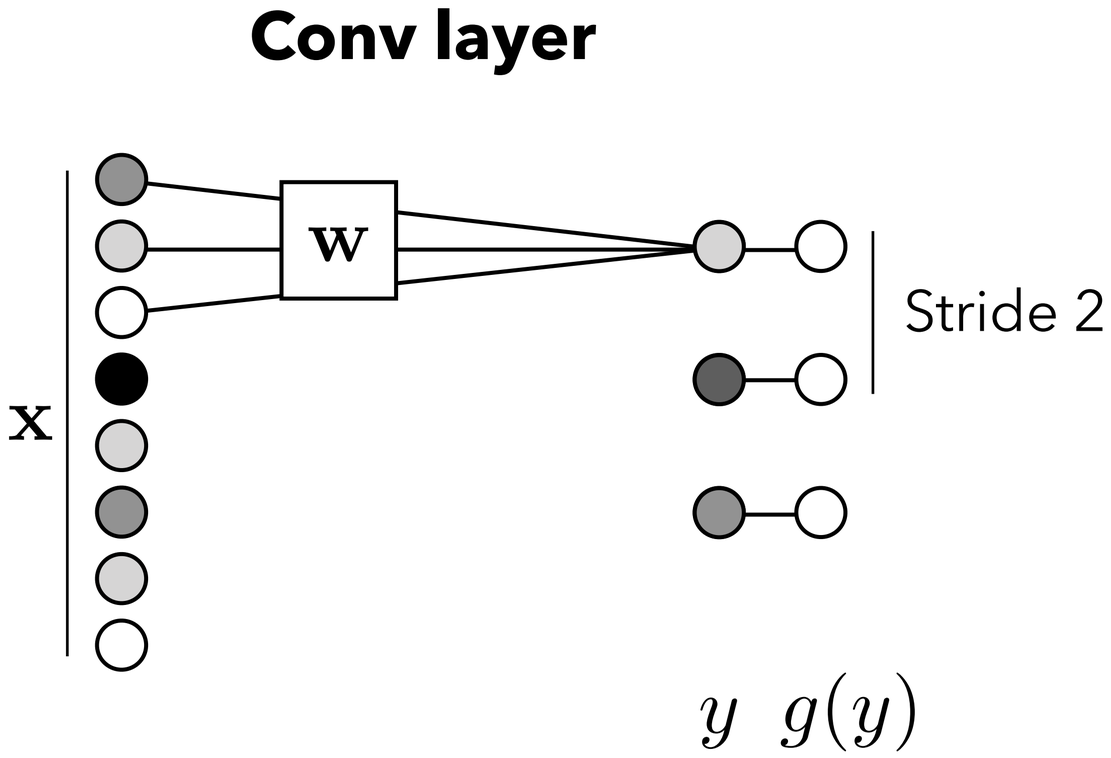
Downsampling



$$\mathbb{R}^{H^{(l)} \times W^{(l)} \times C^{(l)}} \rightarrow \mathbb{R}^{H^{(l+1)} \times W^{(l+1)} \times C^{(l+1)}}$$

Source: Isola, Torralba, Freeman

Strided operations

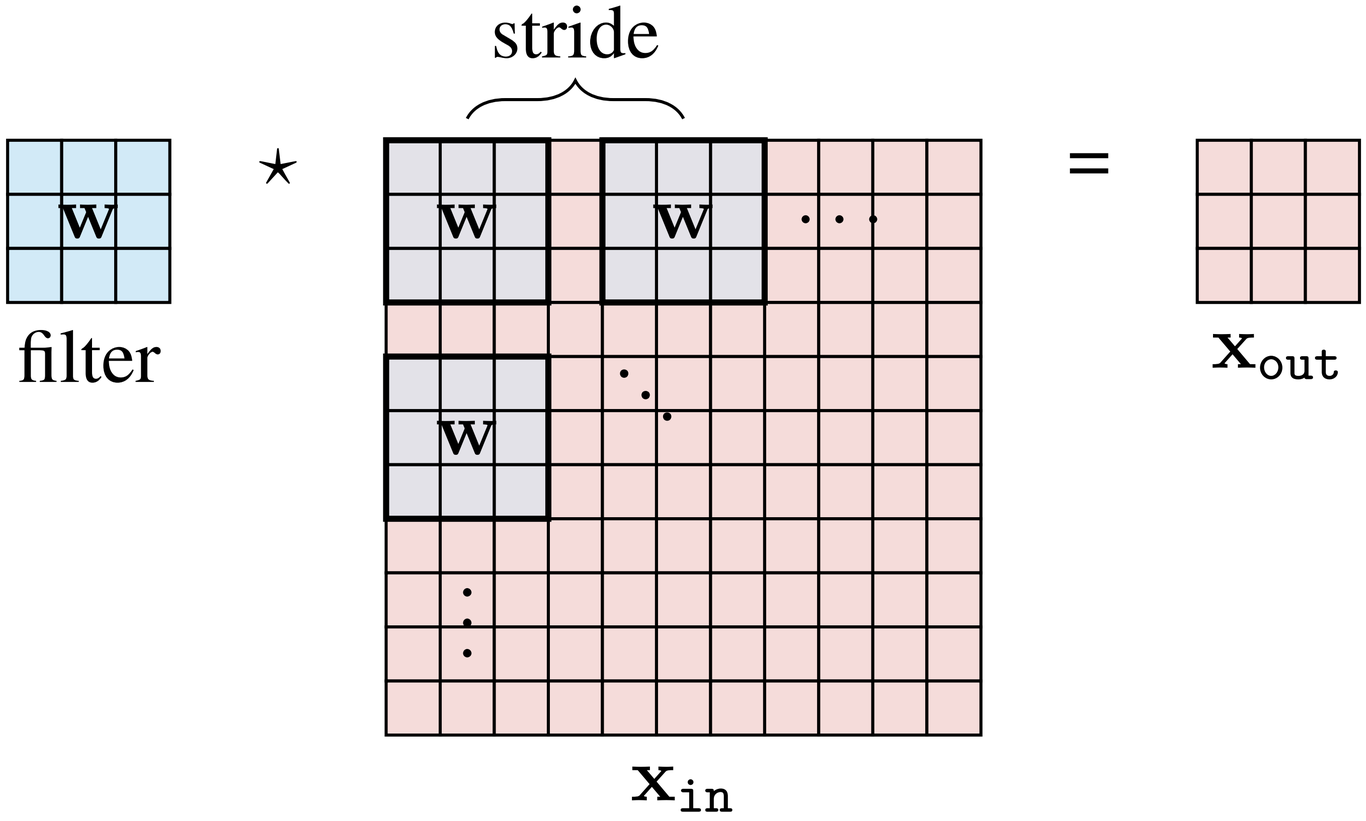


Strided operations combine a given operation (convolution or pooling) and downsampling into a single operation.

Strided convolution is an alternative to pooling layers: just do a strided convolution!

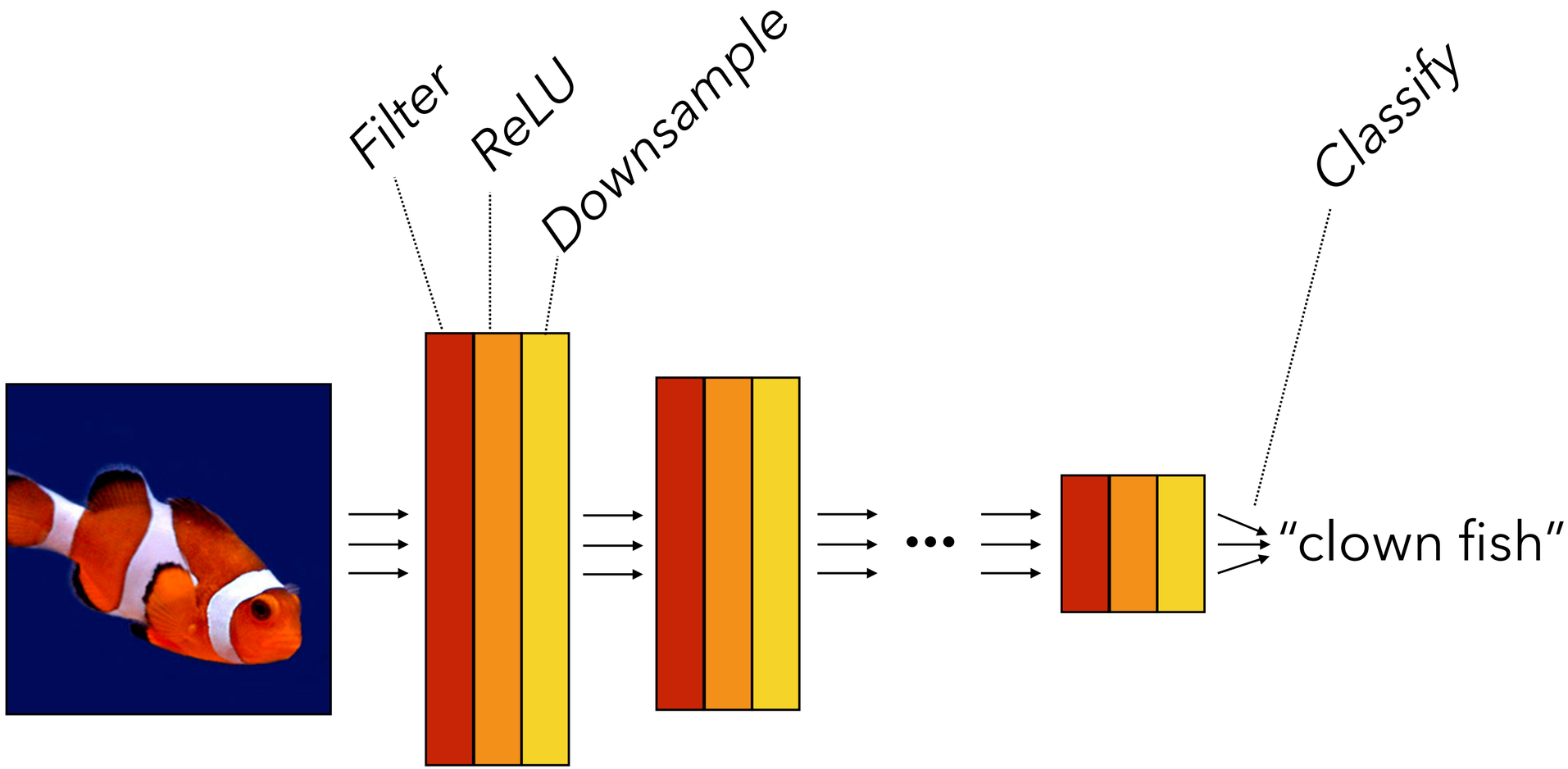
Source: Isola, Torralba, Freeman

Strided operations (2D)



Source: Foundations of Computer Vision. Torralba, Isola, Freeman

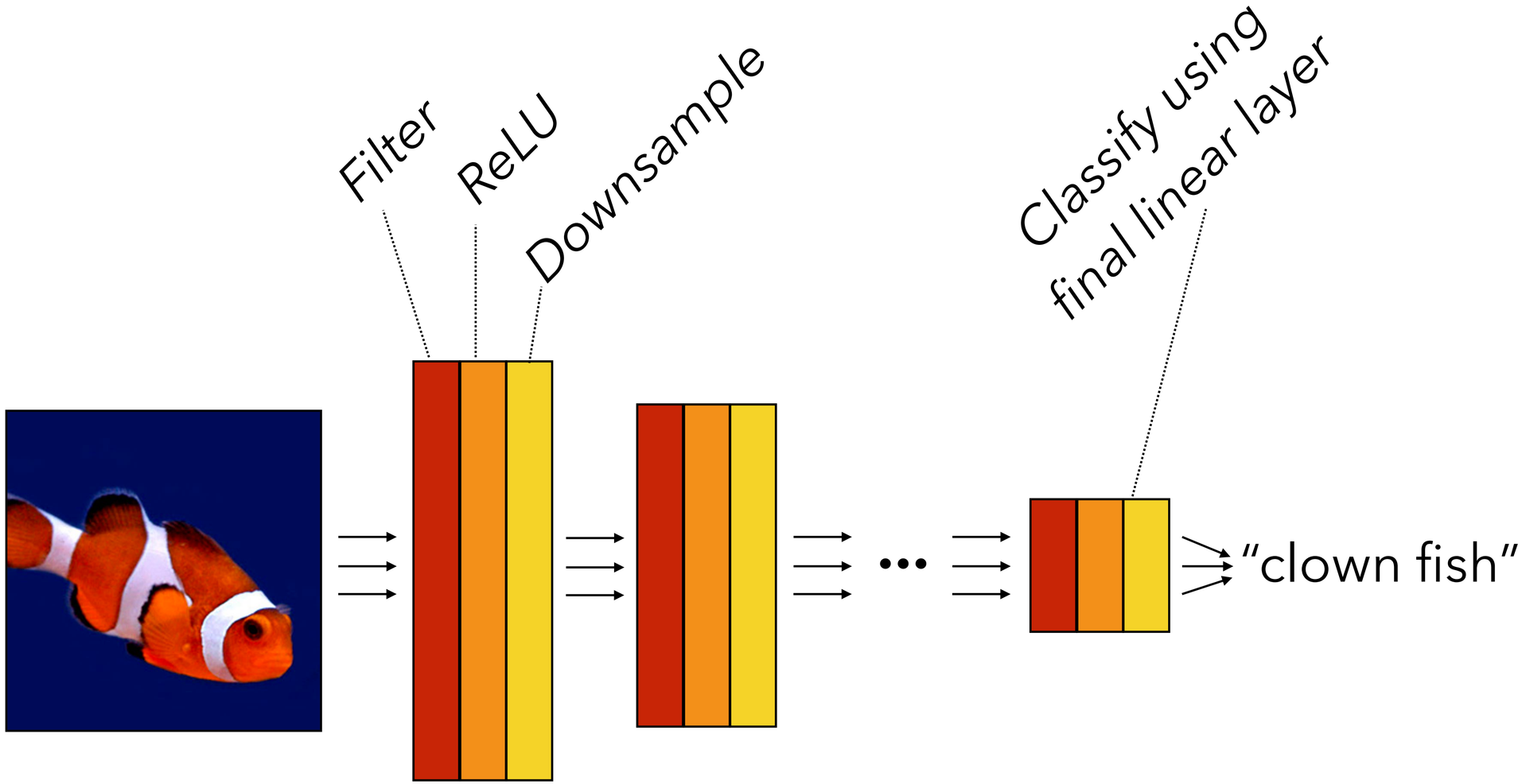
Computation in a neural net



$$f(\mathbf{x}) = f_L(\ldots f_2(f_1(\mathbf{x})))$$

Source: Isola, Torralba, Freeman

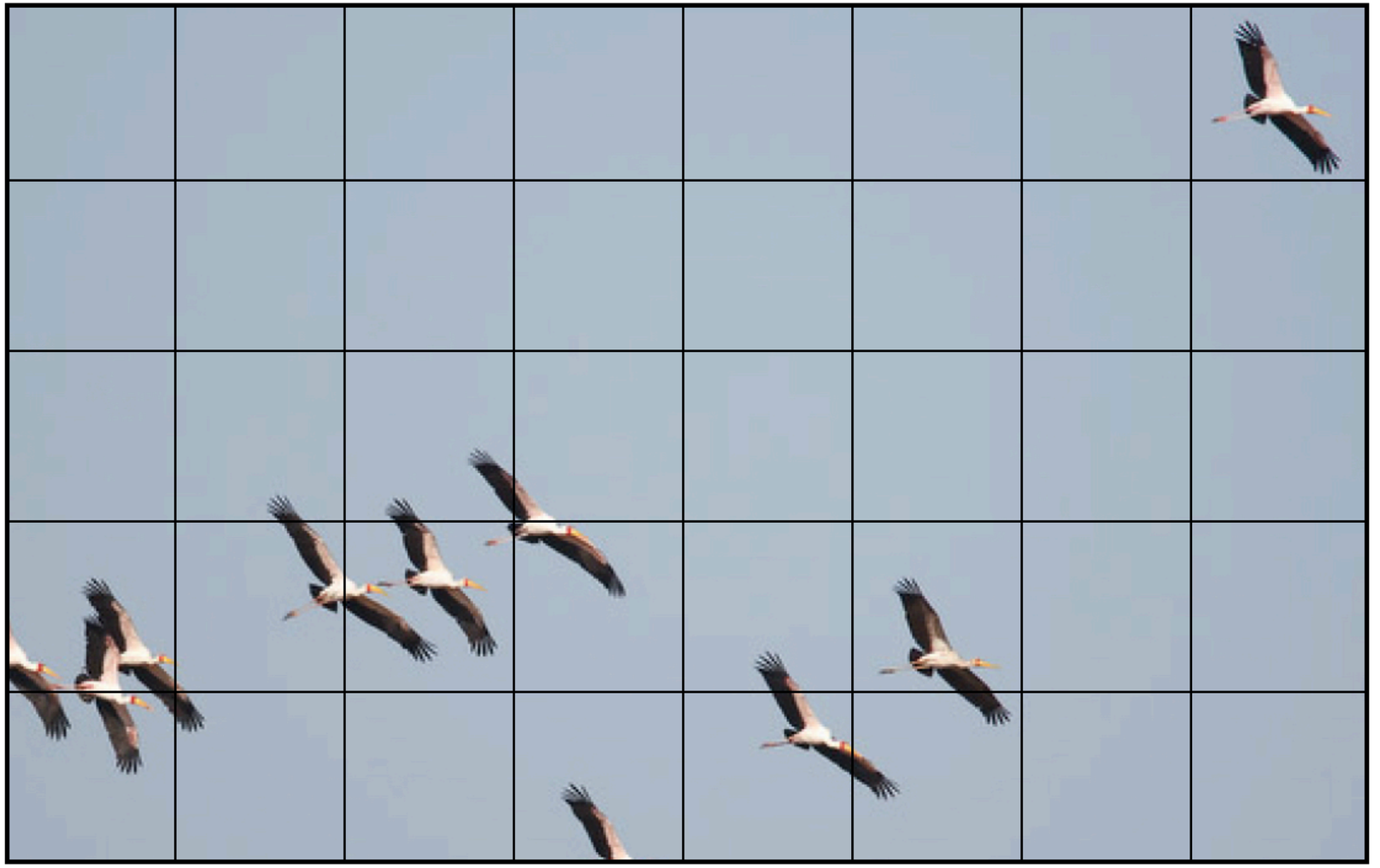
Computation in a neural net



$$f(\mathbf{x}) = f_L(\ldots f_2(f_1(\mathbf{x})))$$

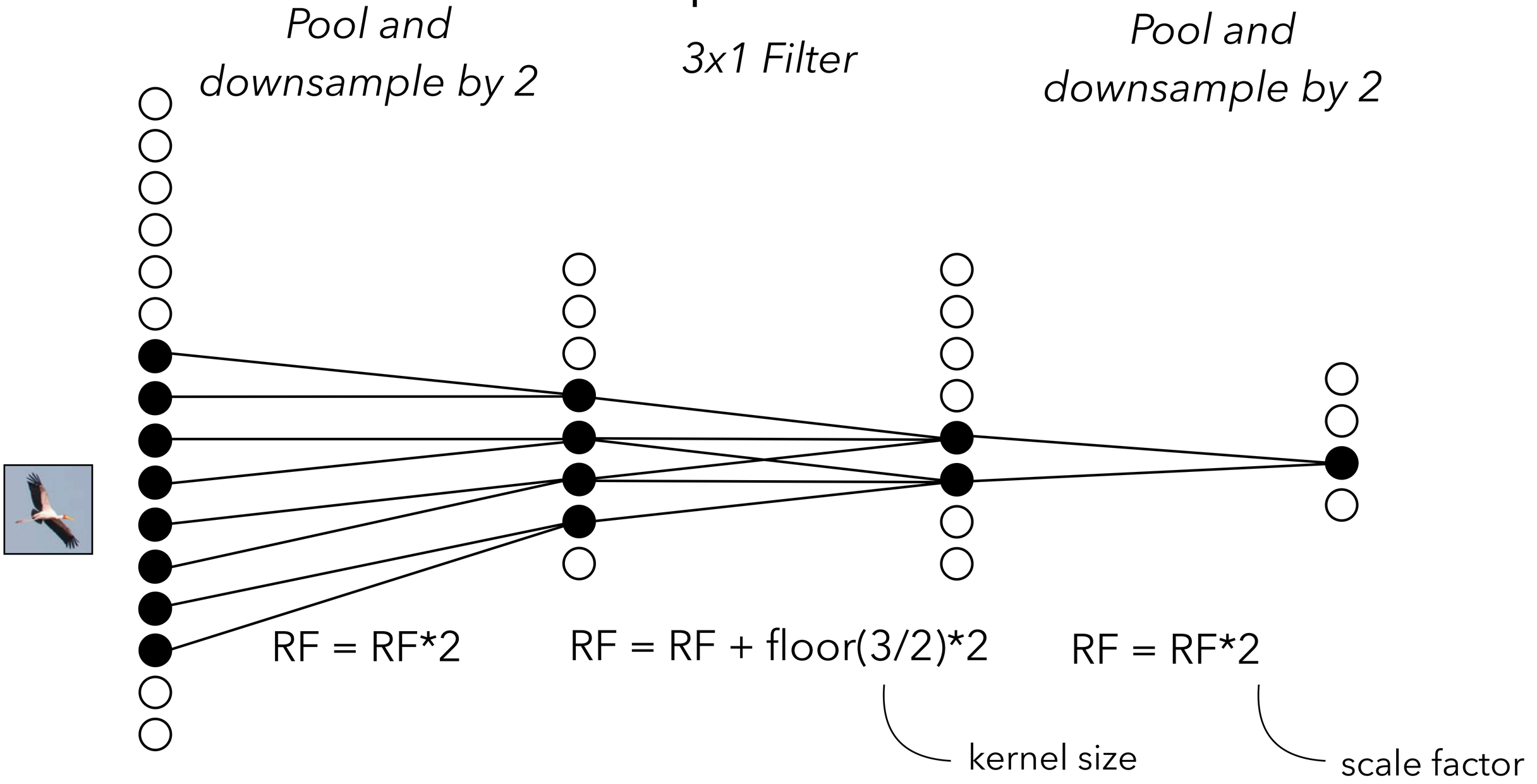
Source: Isola, Torralba, Freeman

Receptive fields



Source: Isola, Torralba, Freeman

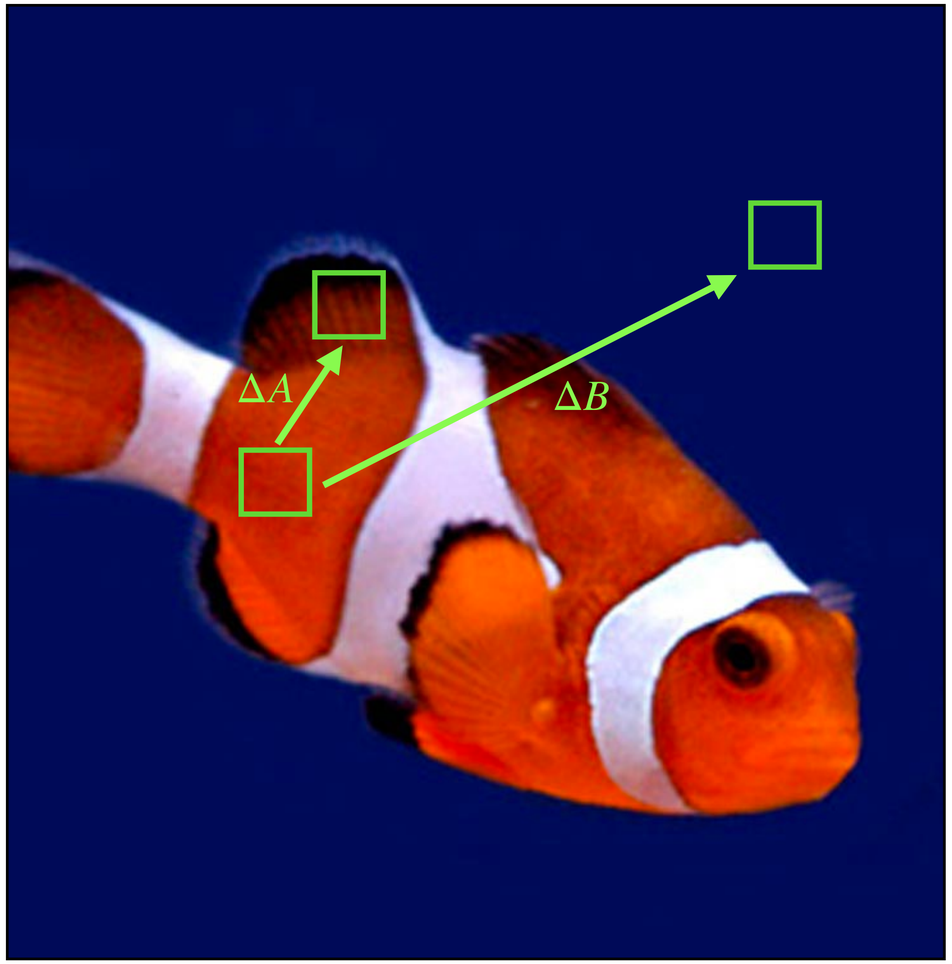
Receptive fields

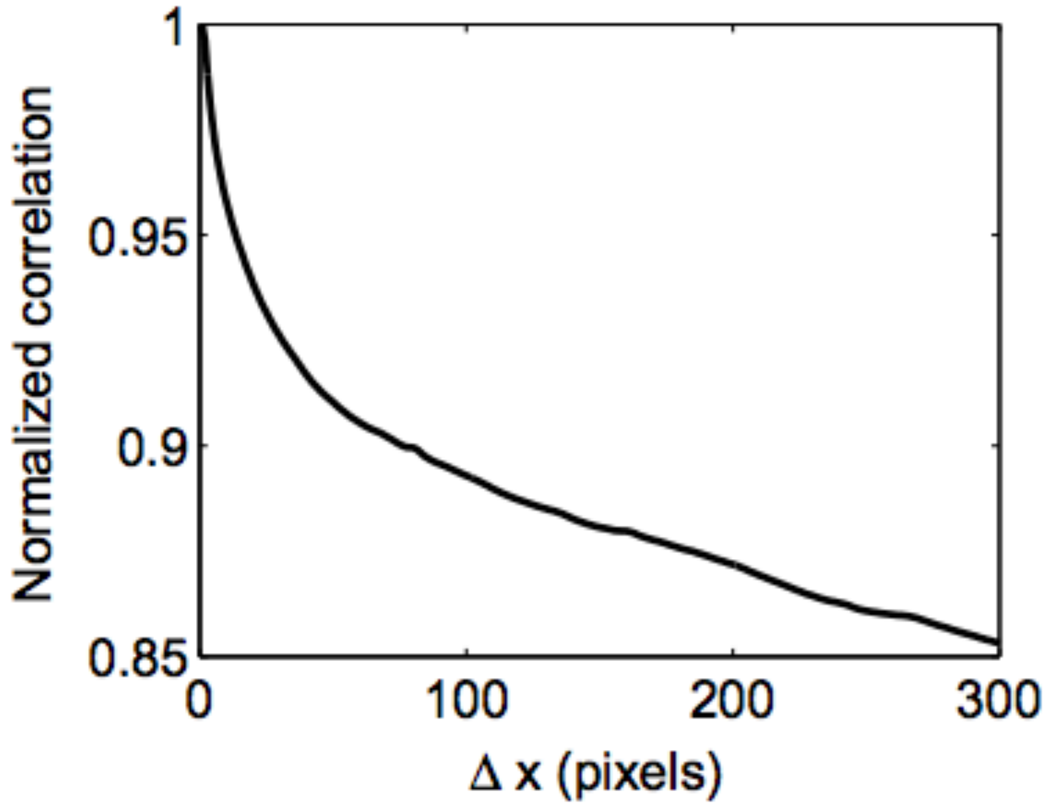


[See also: http://fomoro.com/tools/receptive-fields/index.html]

Source: Isola, Torralba, Freeman

Why have coefficients only for nearby pixels?





[Simoncelli: Statistical Modelling of Photographic Images, 2005]

Source: Isola, Torralba, Freeman

Implementation details

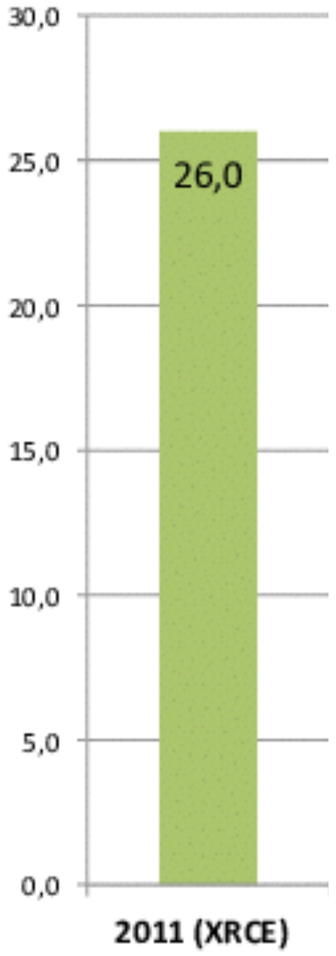
Convolutional layers

Option 1: Just make the giant convolution matrix and use the fully backprop equations for linear layers! Early deep learning frameworks did this.

Option 2: Use a more optimized implementation. There are optimized GPU implementations. For very large filters, these use Fourier Transform.

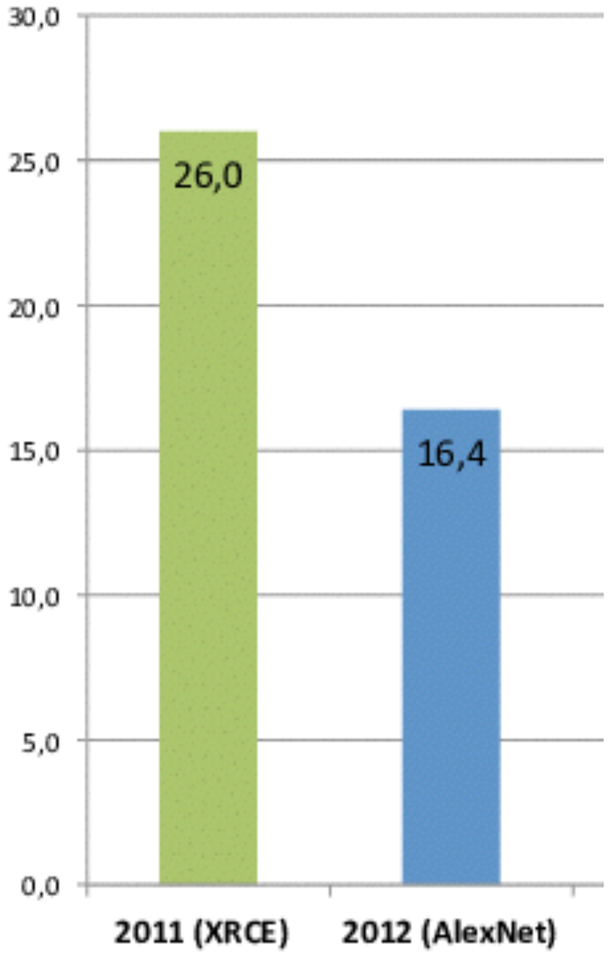
Network designs

ImageNet classification (top 5)

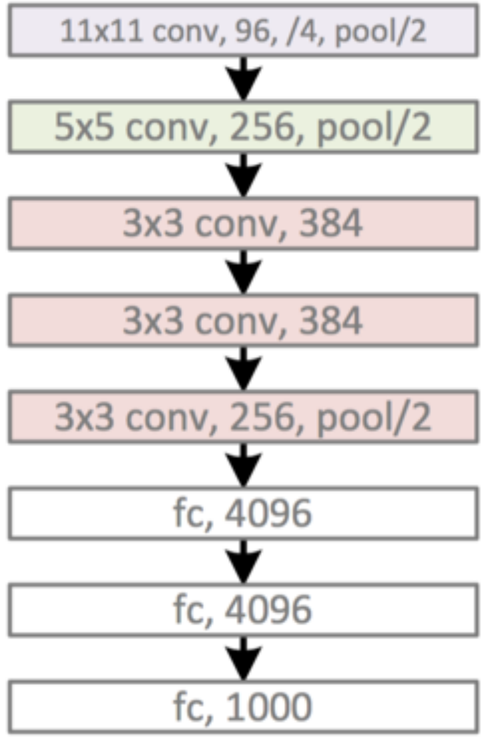


Source: Isola, Torralba, Freeman

ImageNet classification (top 5)



2012: AlexNet
5 conv. layers

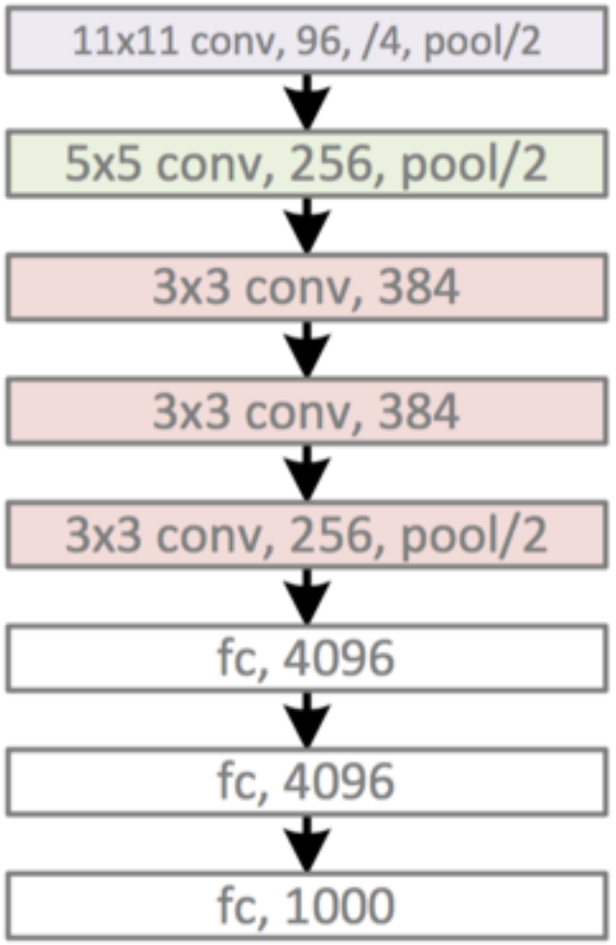


Error: 16.4%

[Krizhevsky et al: ImageNet Classification with Deep Convolutional Neural Networks, NeurIPS 2012]

Source: Isola, Torralba, Freeman

Alexnet – [Krizhevsky et al. NIPS 2012]



[227x227x3] INPUT

[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer

[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer

[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1

[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

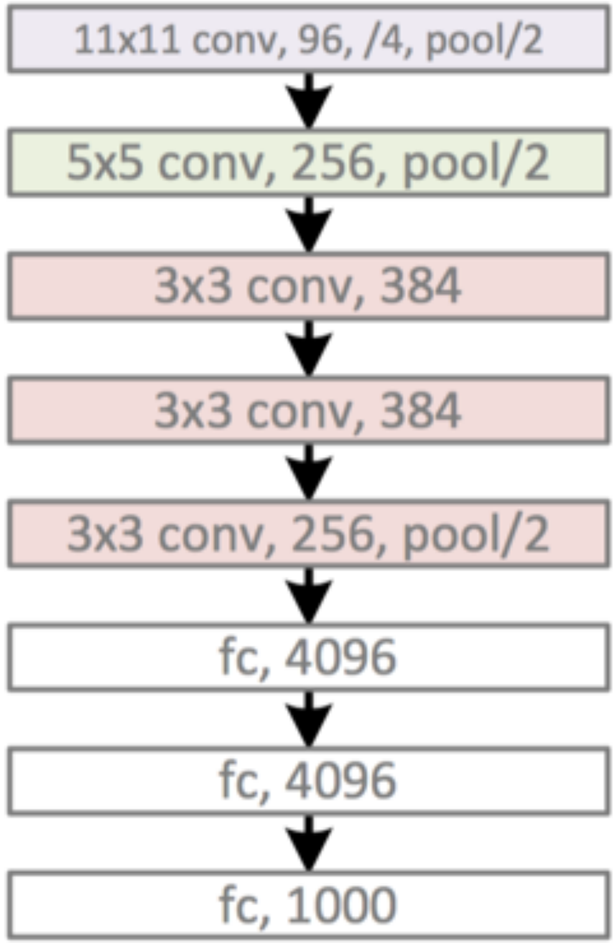
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)

Source: Isola, Torralba, Freeman

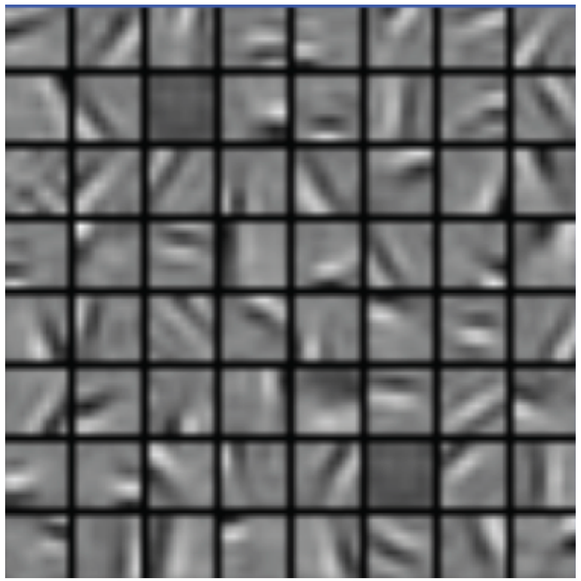


What filters are learned?

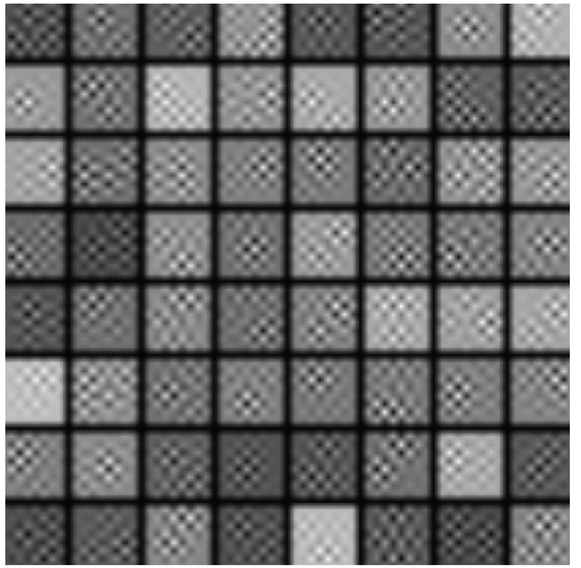
Source: Isola, Torralba, Freeman

What filters are learned?

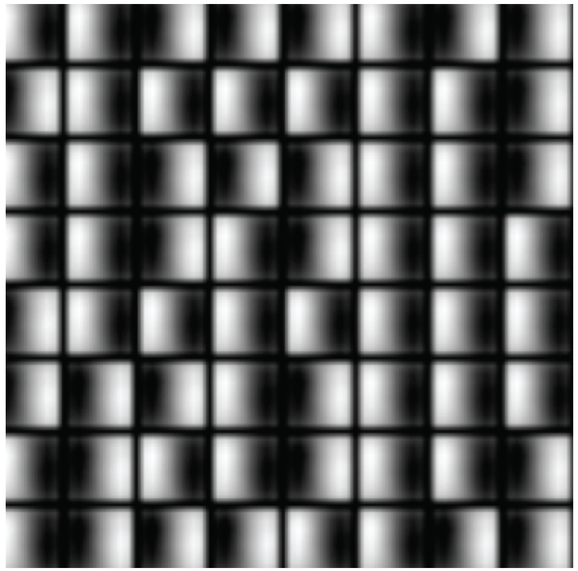
A



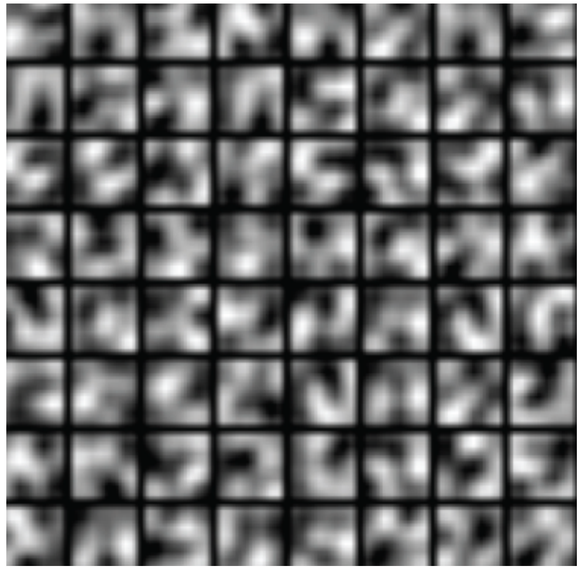
B



C

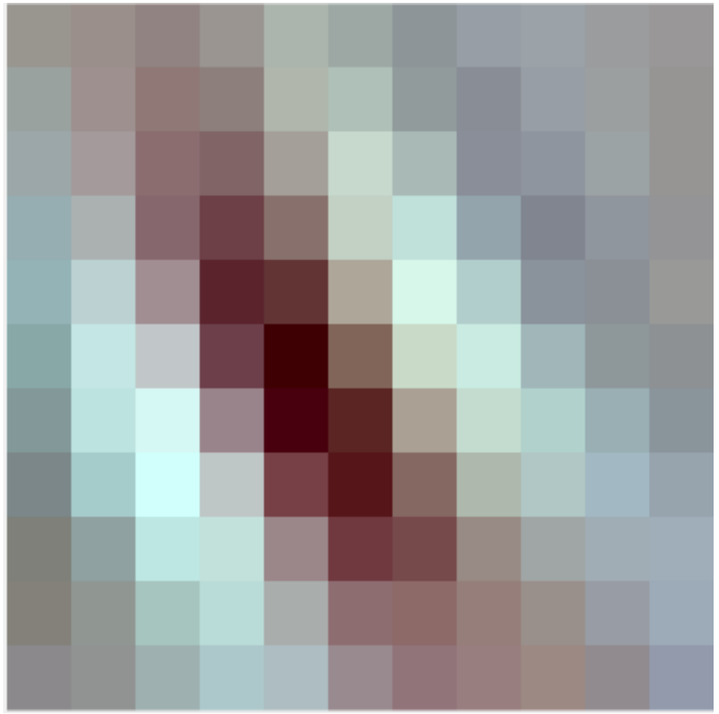


D

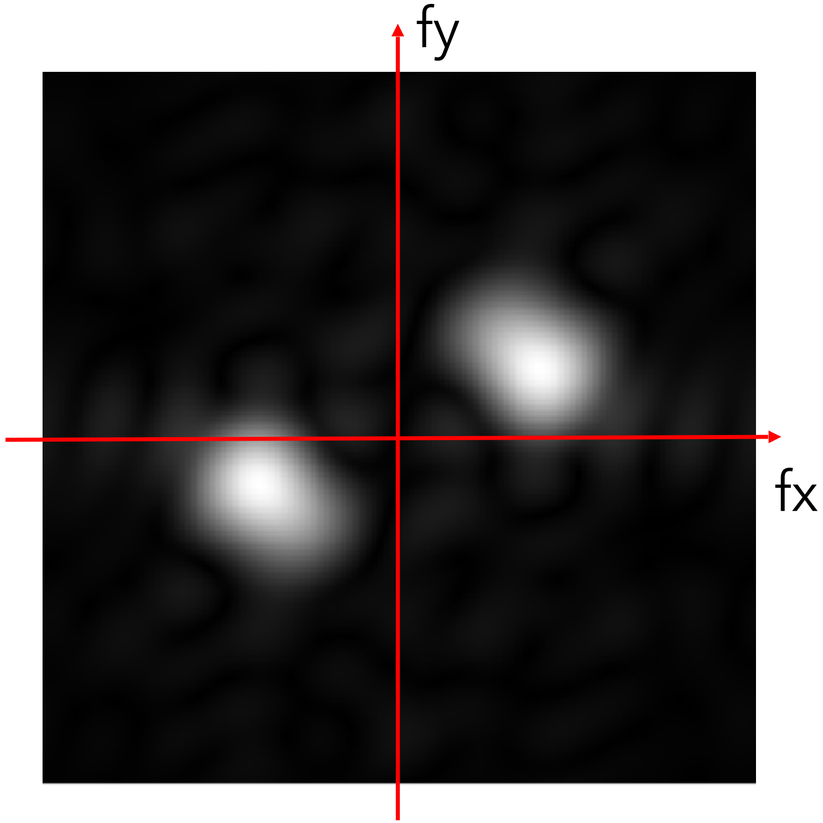


Source: Marc'Aurelio Ranzato & Isola, Torralba, Freeman

Filters in first layer

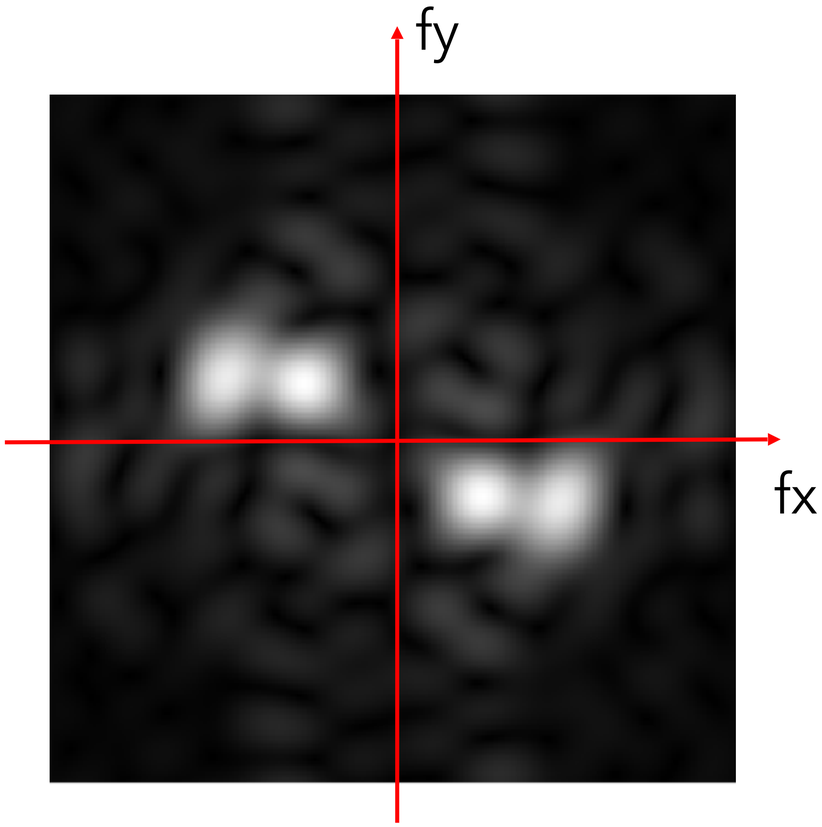


11x11 convolution kernel
(3 color channels)



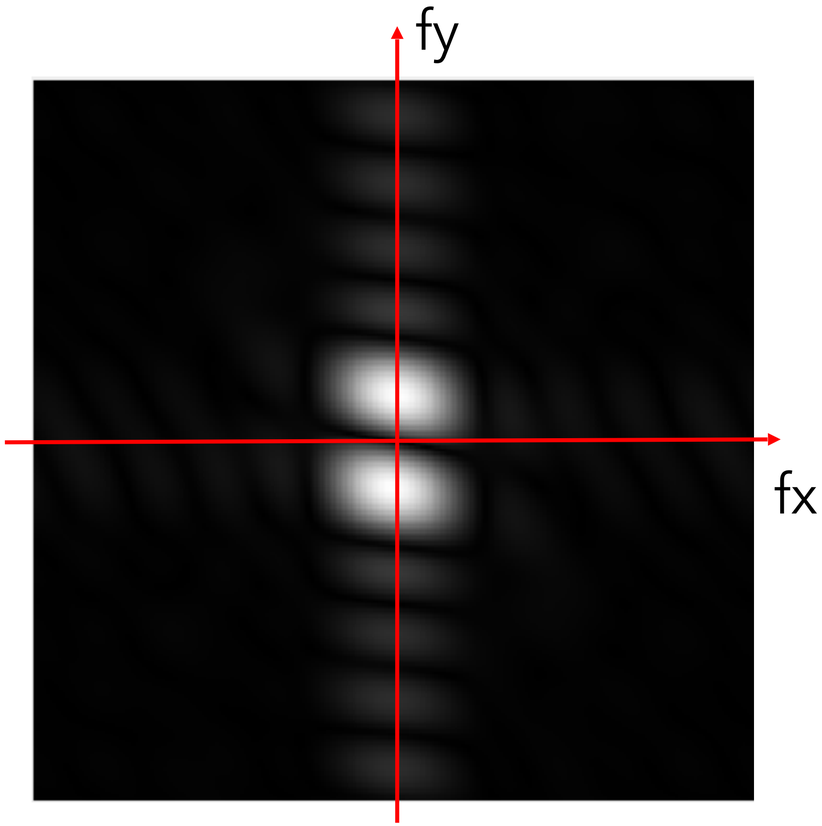
Source: Isola, Torralba, Freeman

Filters in first layer



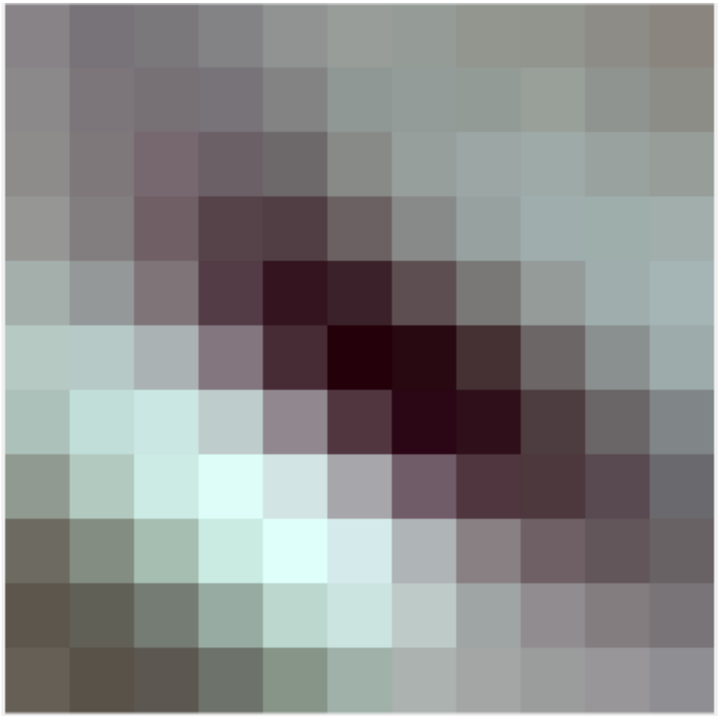
Source: Isola, Torralba, Freeman

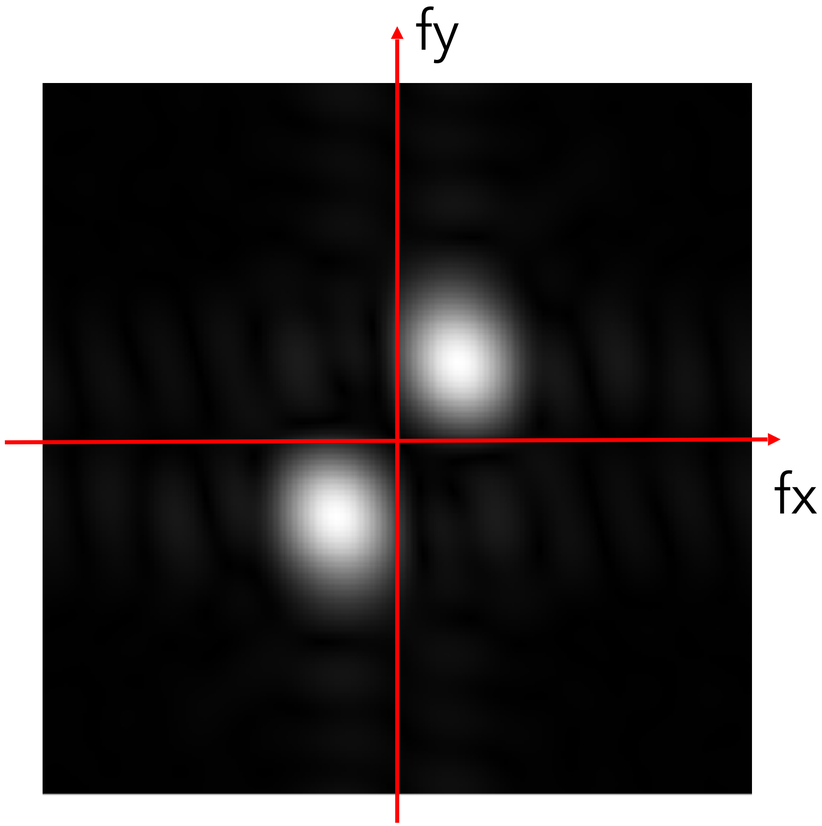
Filters in first layer



Source: Isola, Torralba, Freeman

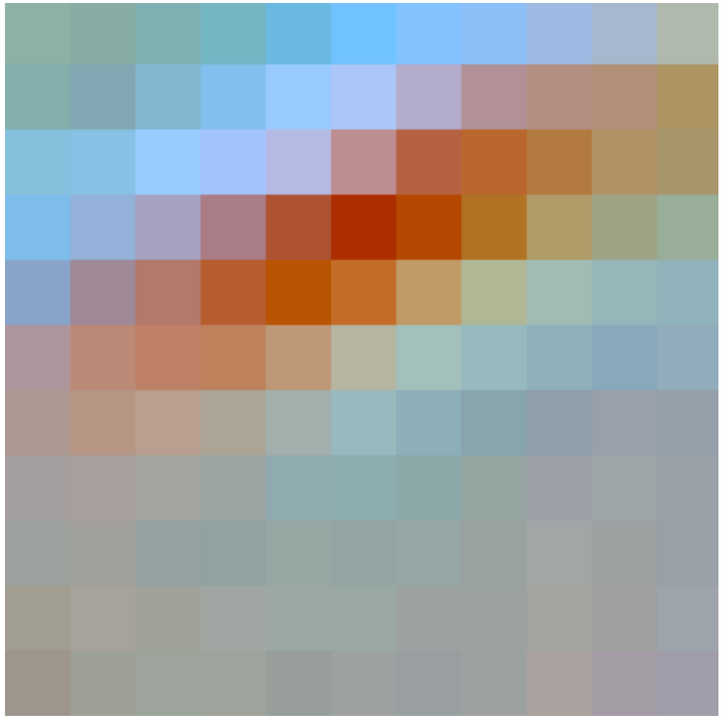
Filters in first layer

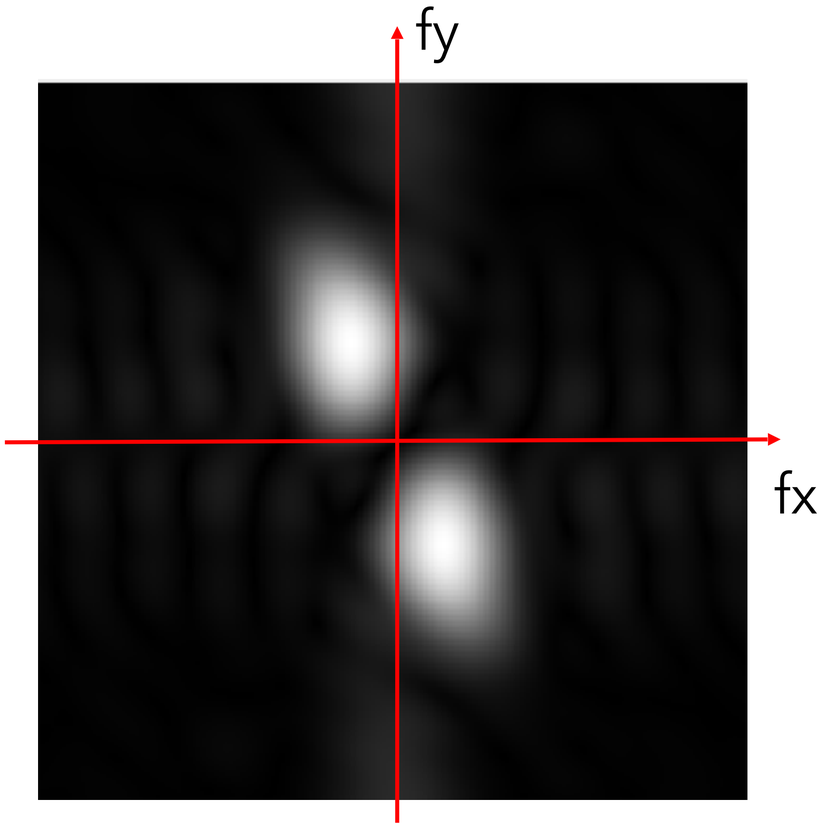




Source: Isola, Torralba, Freeman

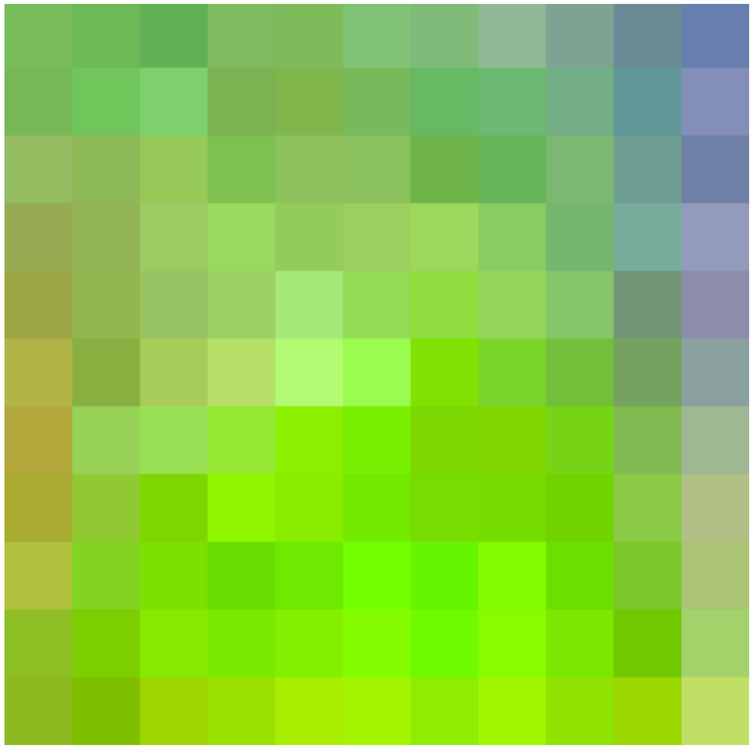
Filters in first layer

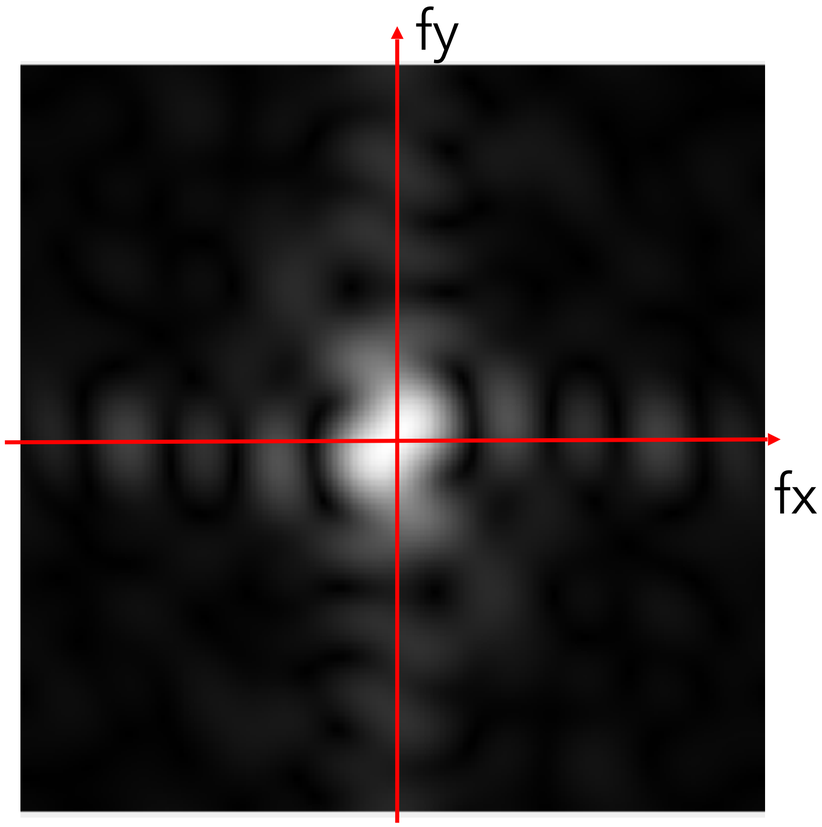




Source: Isola, Torralba, Freeman

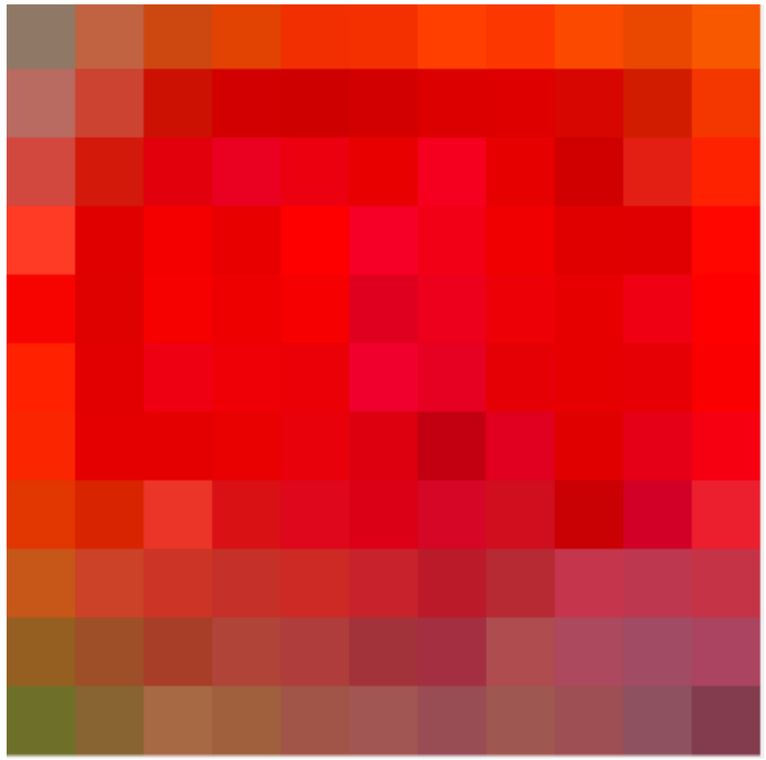
Filters in first layer

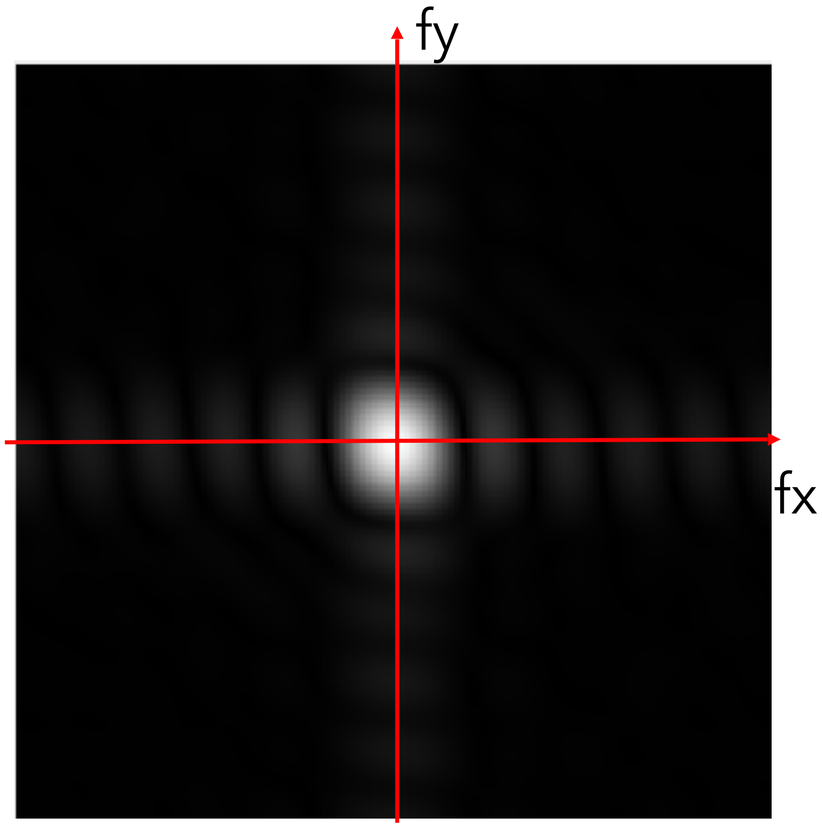




Source: Isola, Torralba, Freeman

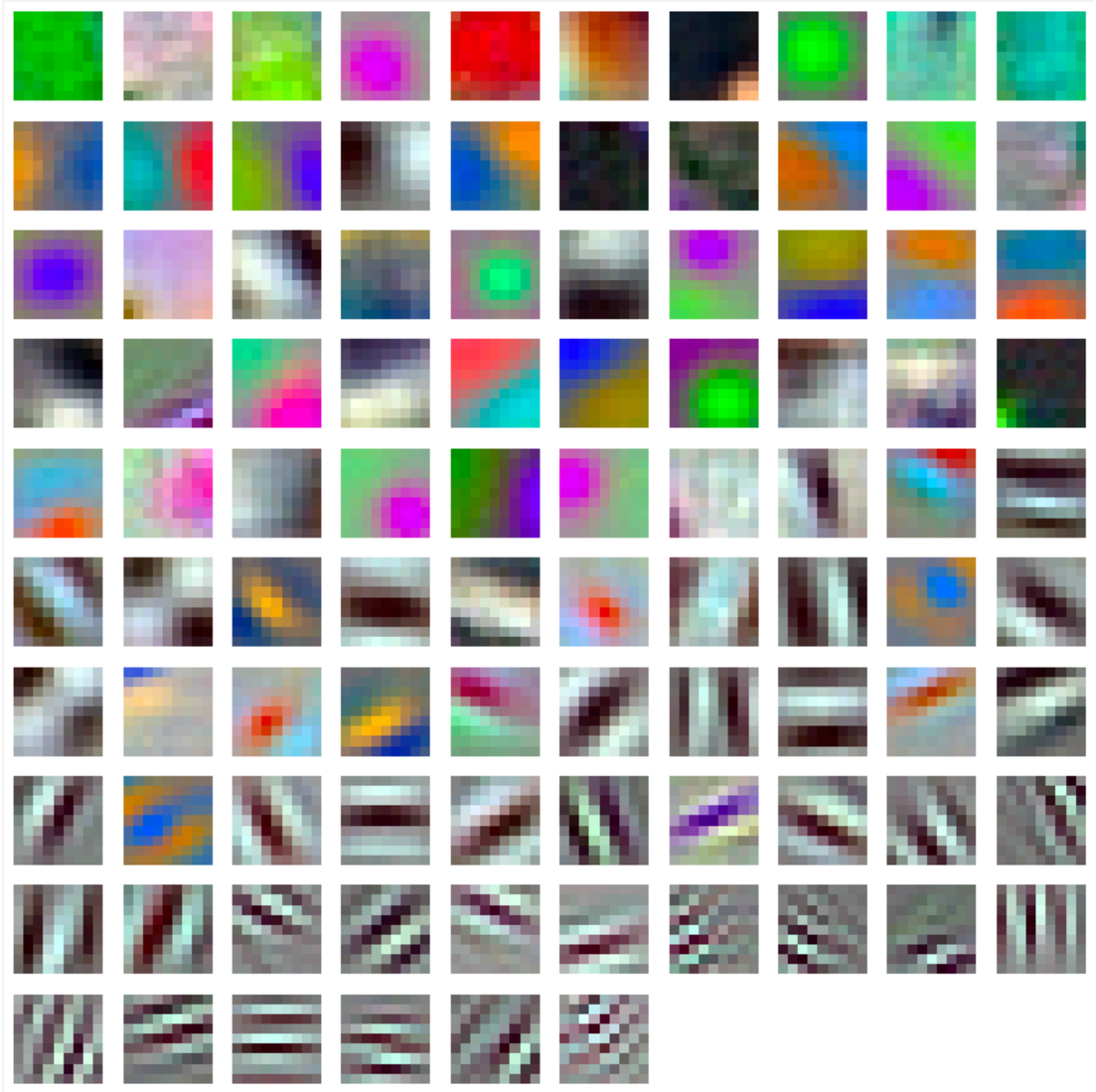
Filters in first layer



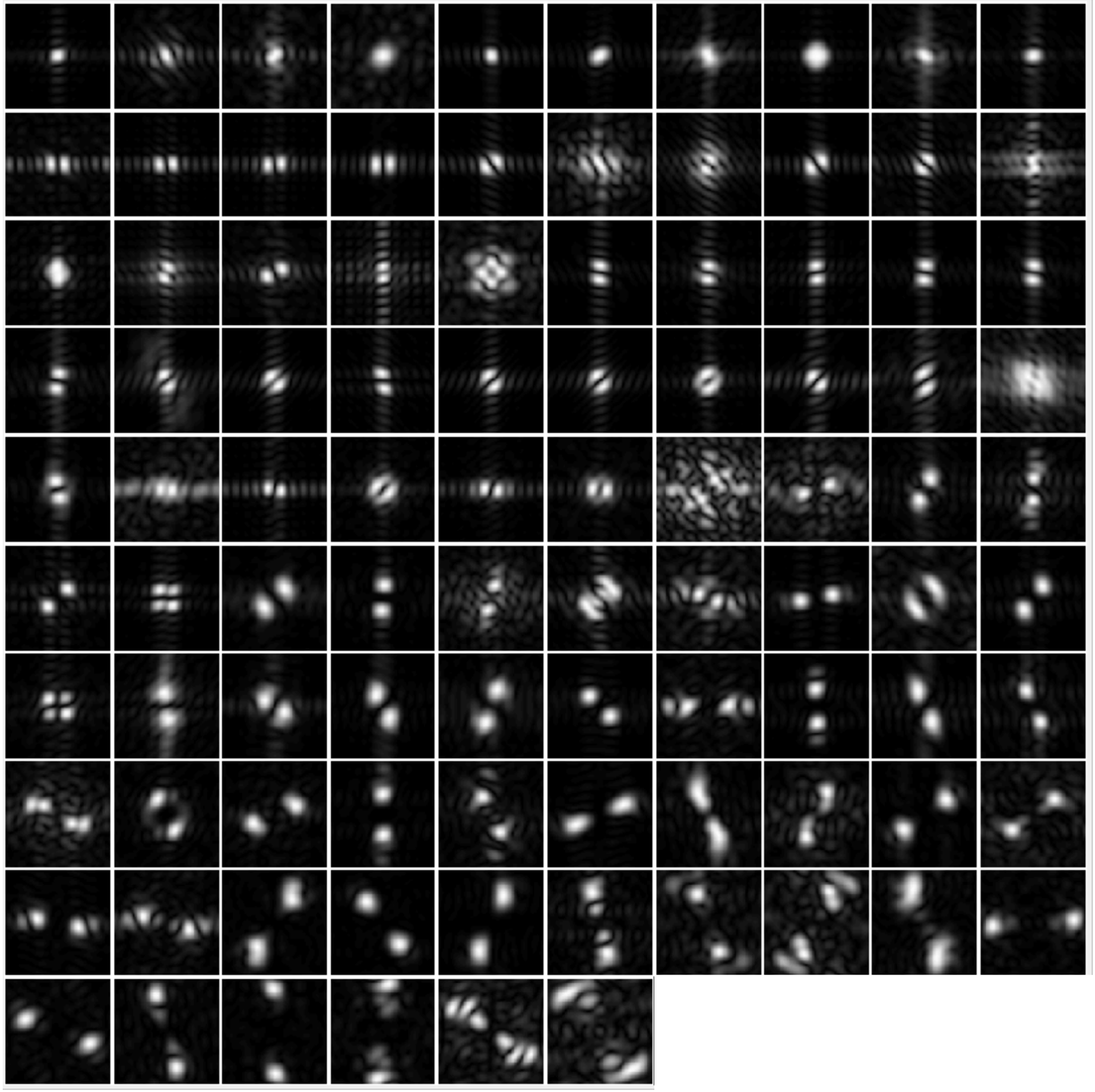


Source: Isola, Torralba, Freeman

Filters in first layer

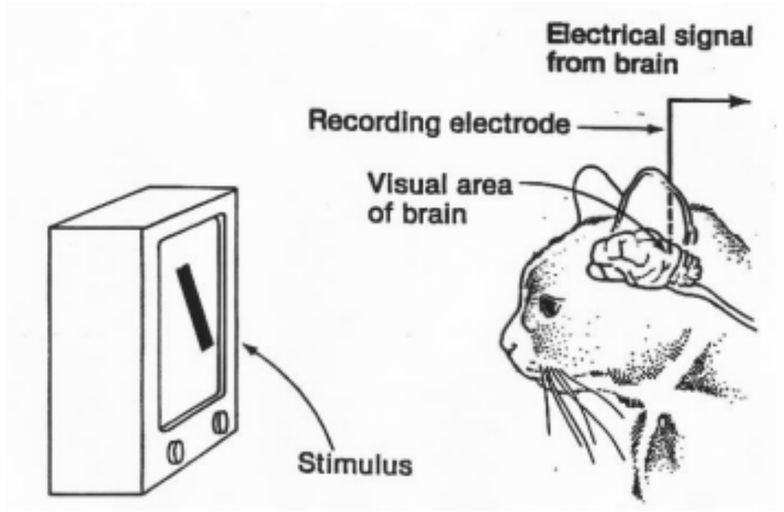


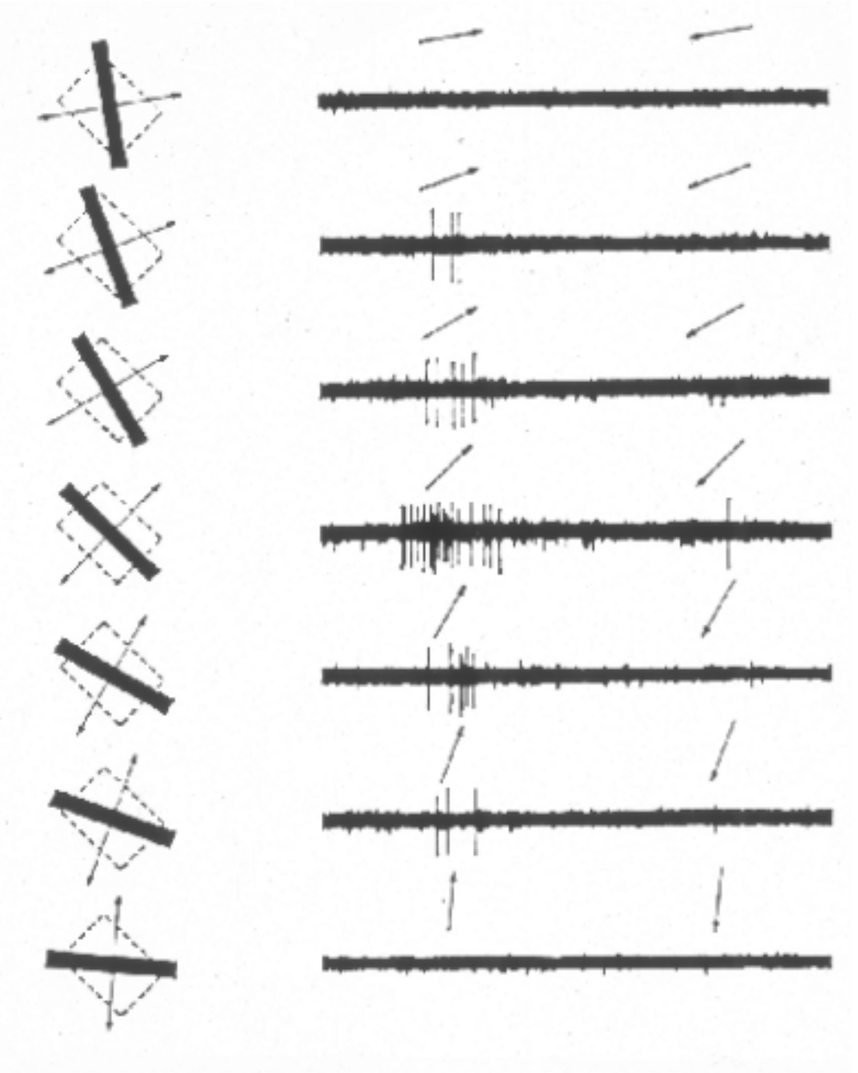
96 Units in conv1



Source: Isola, Torralba, Freeman

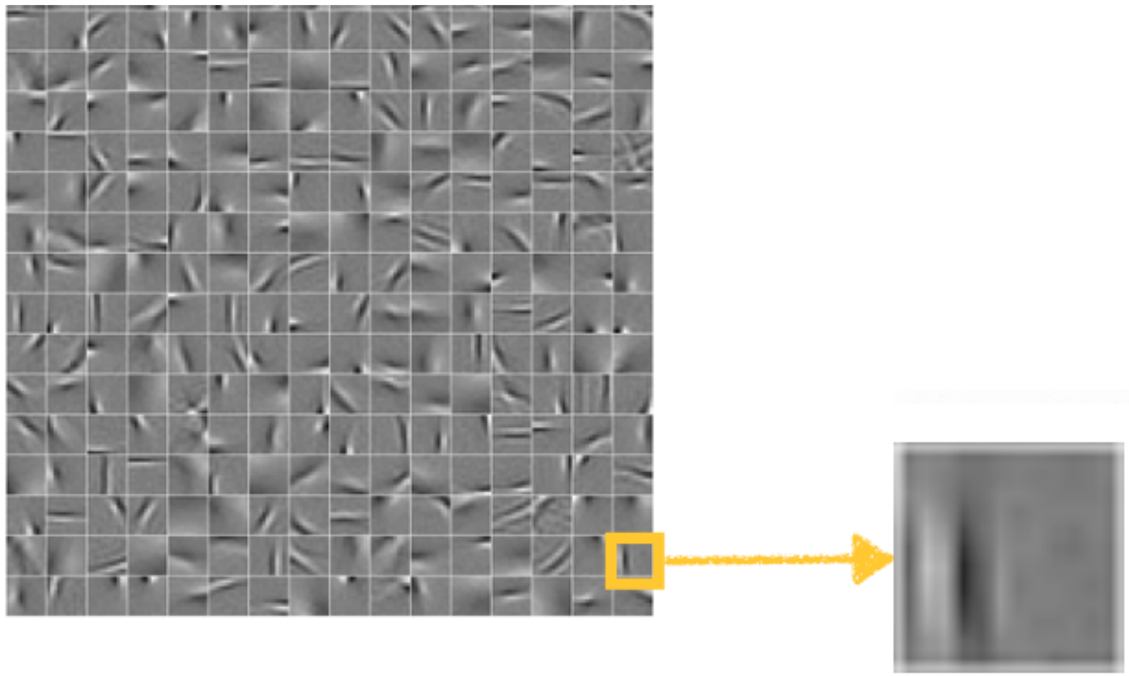
[Hubel and Wiesel 59]



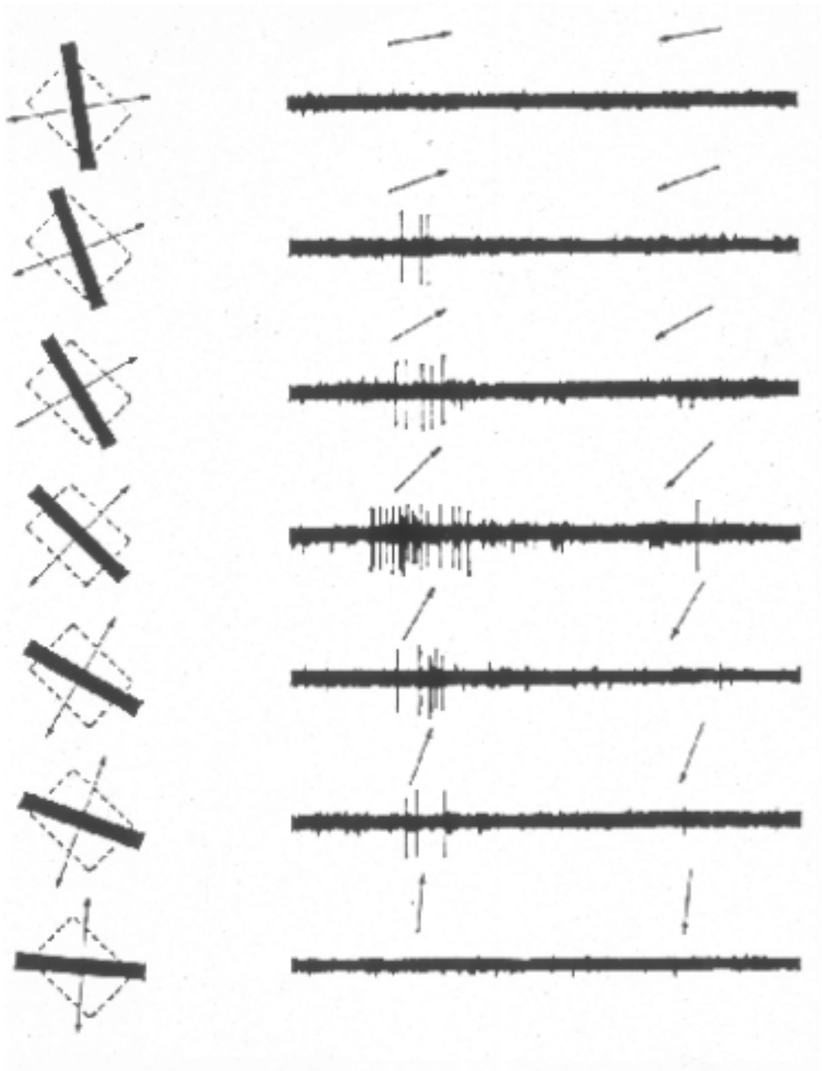


Source: Andrea Vedaldi

A good fit to the experimental results

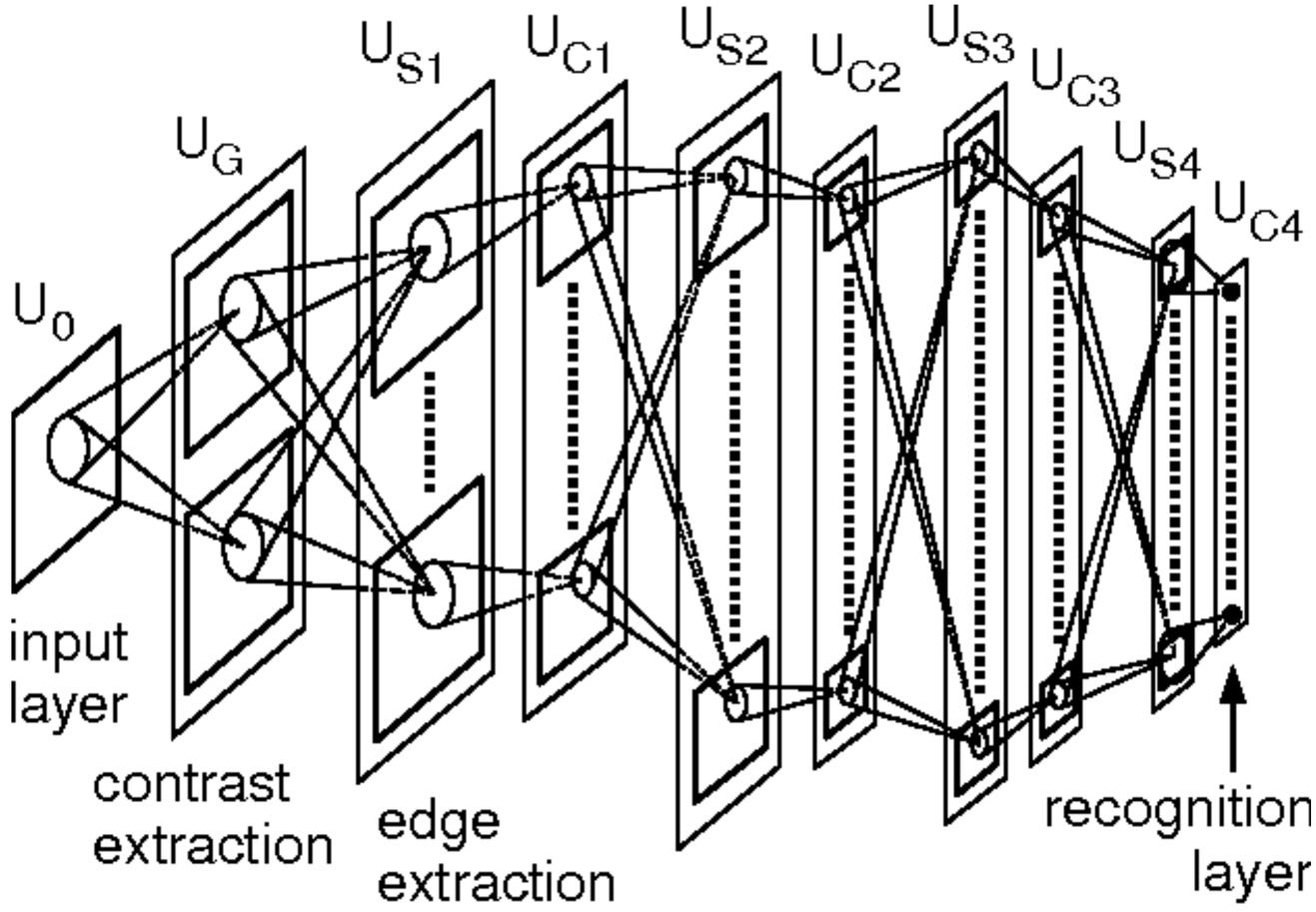


Oriented filters



Source: Andrea Vedaldi

History: Neocognitron

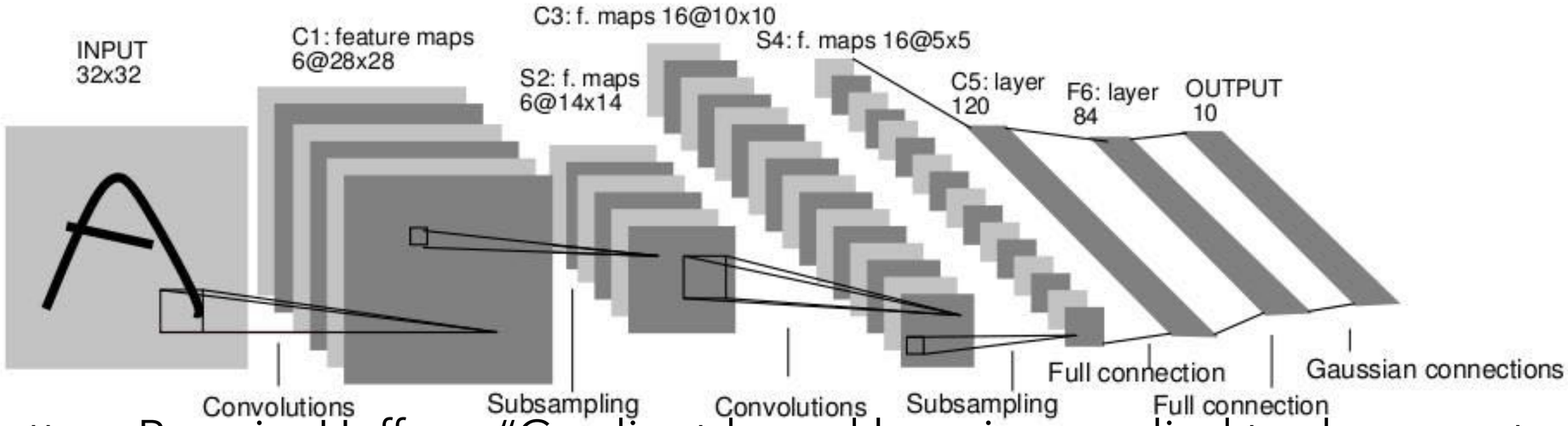


K. Fukushima, 1980s

Figure source: Wikipedia

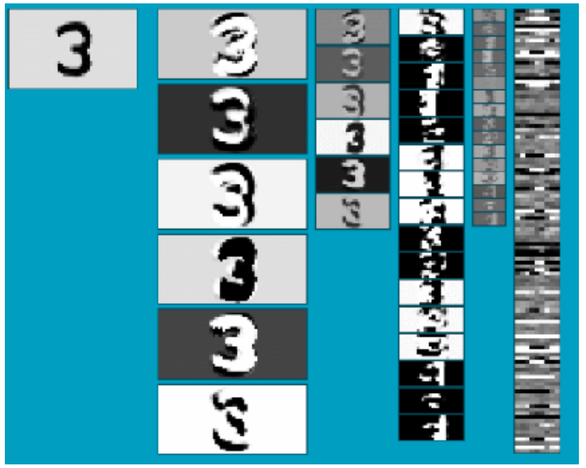
Source: S. Lazebnik

History: LeNet



[LeCun, Bottou, Bengio, Haffner. "Gradient-based learning applied to document recognition", 1998]

- Neocognitron + backpropagation
- Average pooling
- Sigmoid or tanh nonlinearity
- Fully connected layers at the end
- Trained on MNIST digit dataset with 60K training examples



Source: S. Lazebnik

ImageNet Challenge

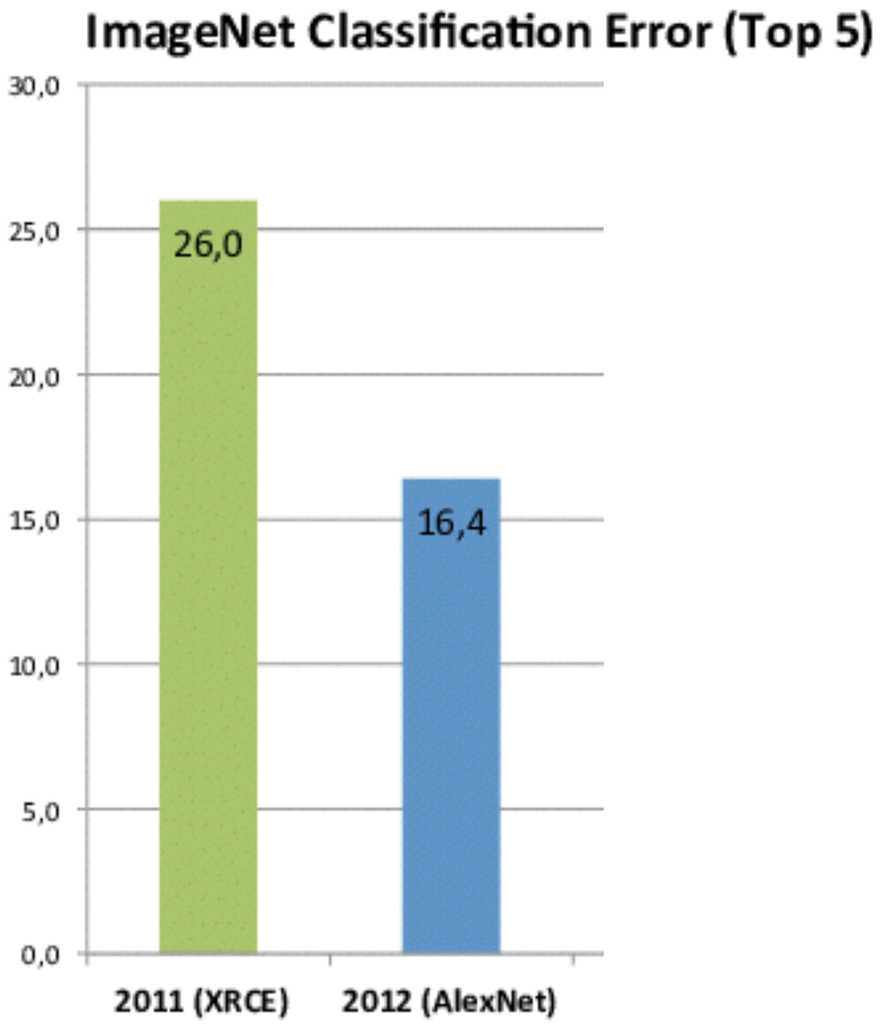
- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- ImageNet Large-Scale Visual Recognition Challenge (ILSVRC):
  1.2 million training images, 1000 classes

[Russakovsky, Deng, Su, Krause, Satheesh, Ma, Huang, Karpathy, Khosla, Bernstein, Berge, Fei-Fei, "ImageNet Large Scale Visual Recognition Challenge", 2015]

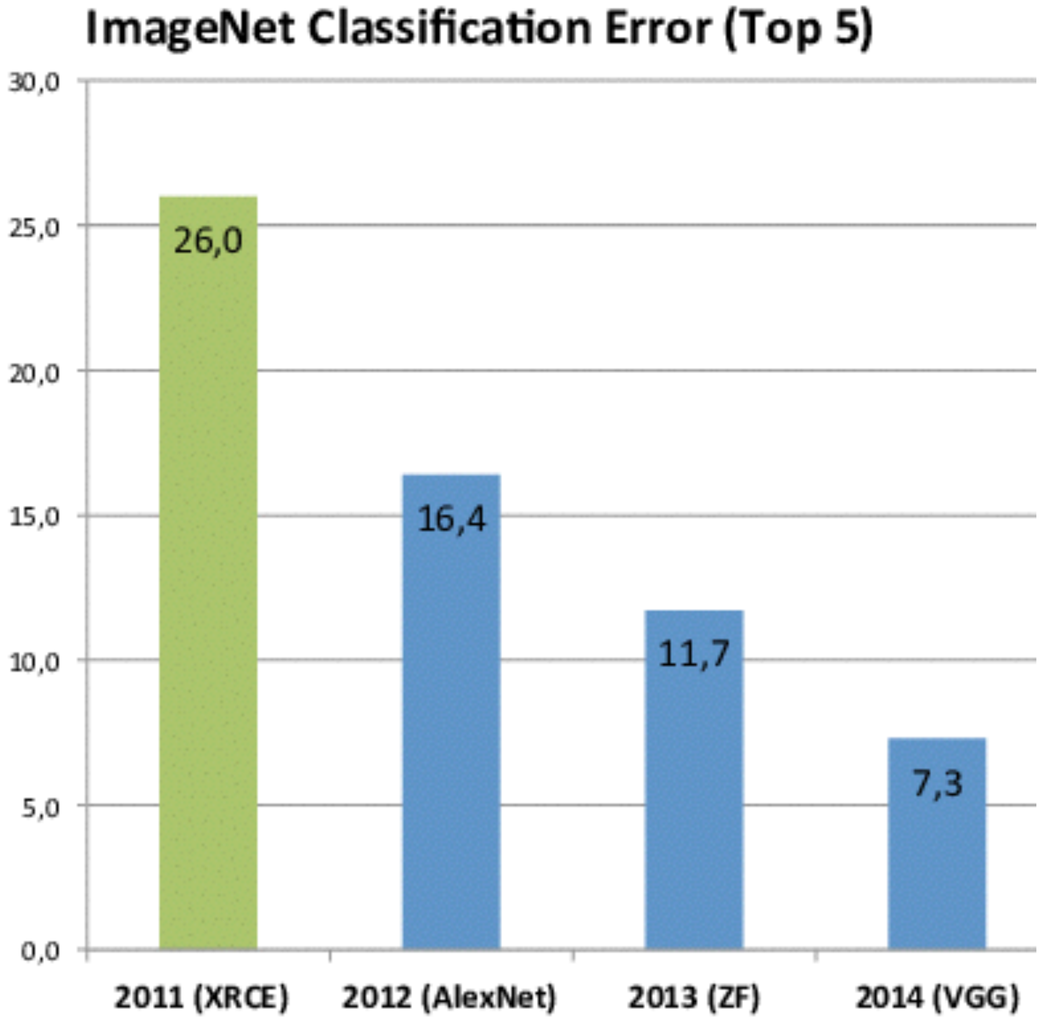
More recent networks

And advances that make them work:

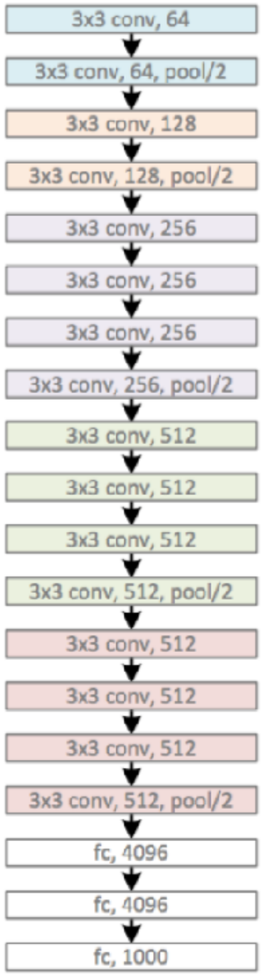
- Chaining small filters
- Residual layers
- Normalization



Source: Isola, Torralba, Freeman



2014: VGG
16 conv. layers



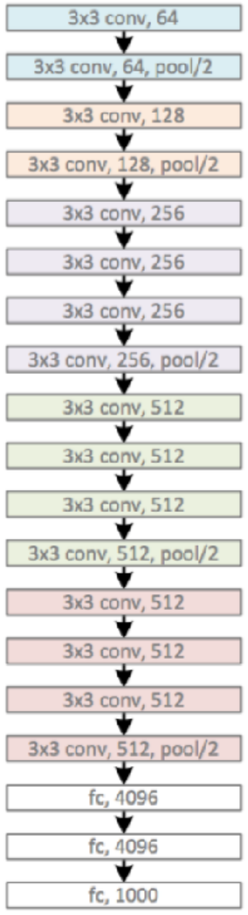
Error: 7.3%

[Simonyan & Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Source: Isola, Torralba, Freeman

VGG-Net [Simonyan & Zisserman, 2015]

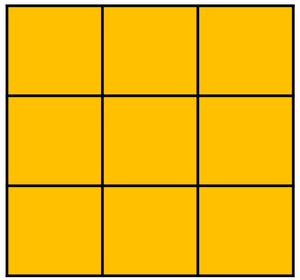
2014: VGG
16 conv. layers



Error: 7.3%

Main developments

- Small convolutional kernels: only 3x3

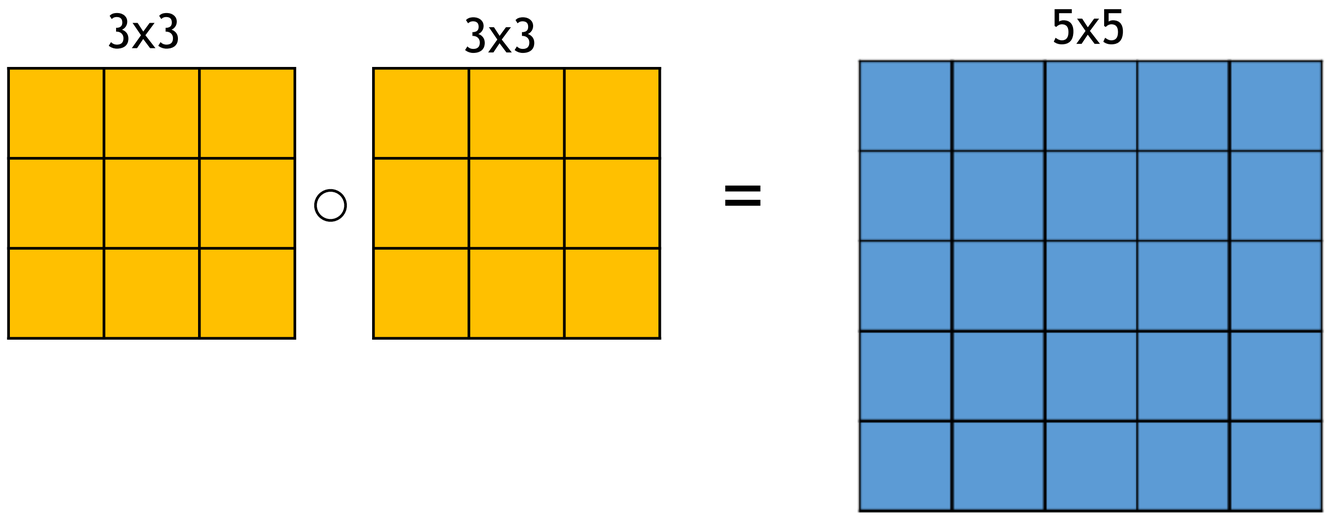


- Increased depth (5 -> 16/19 layers)

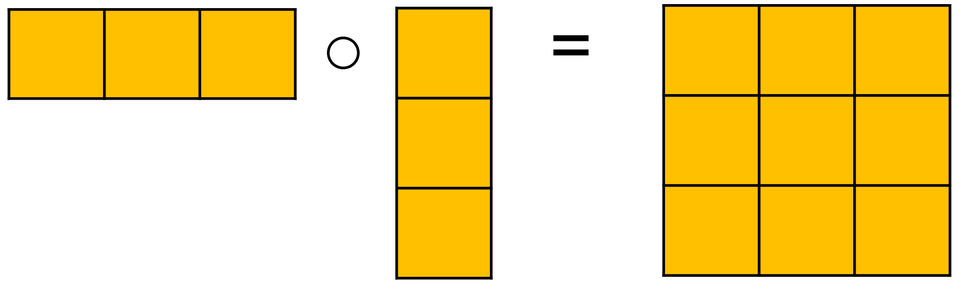
Source: Isola, Torralba, Freeman

Other tricks for designing convolutional nets

Chaining convolutions



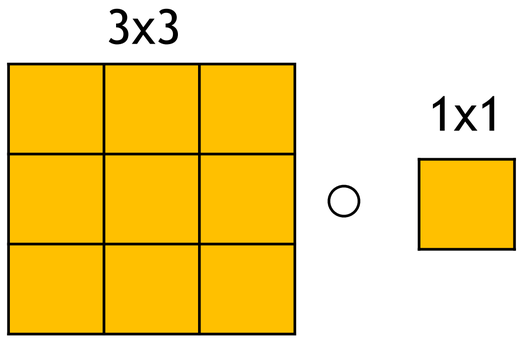
Nonlinearity in between.
25 coefficients, but only
18 degrees of freedom



9 coefficients, but only
6 degrees of freedom.
Less common.

Source: Isola, Torralba, Freeman

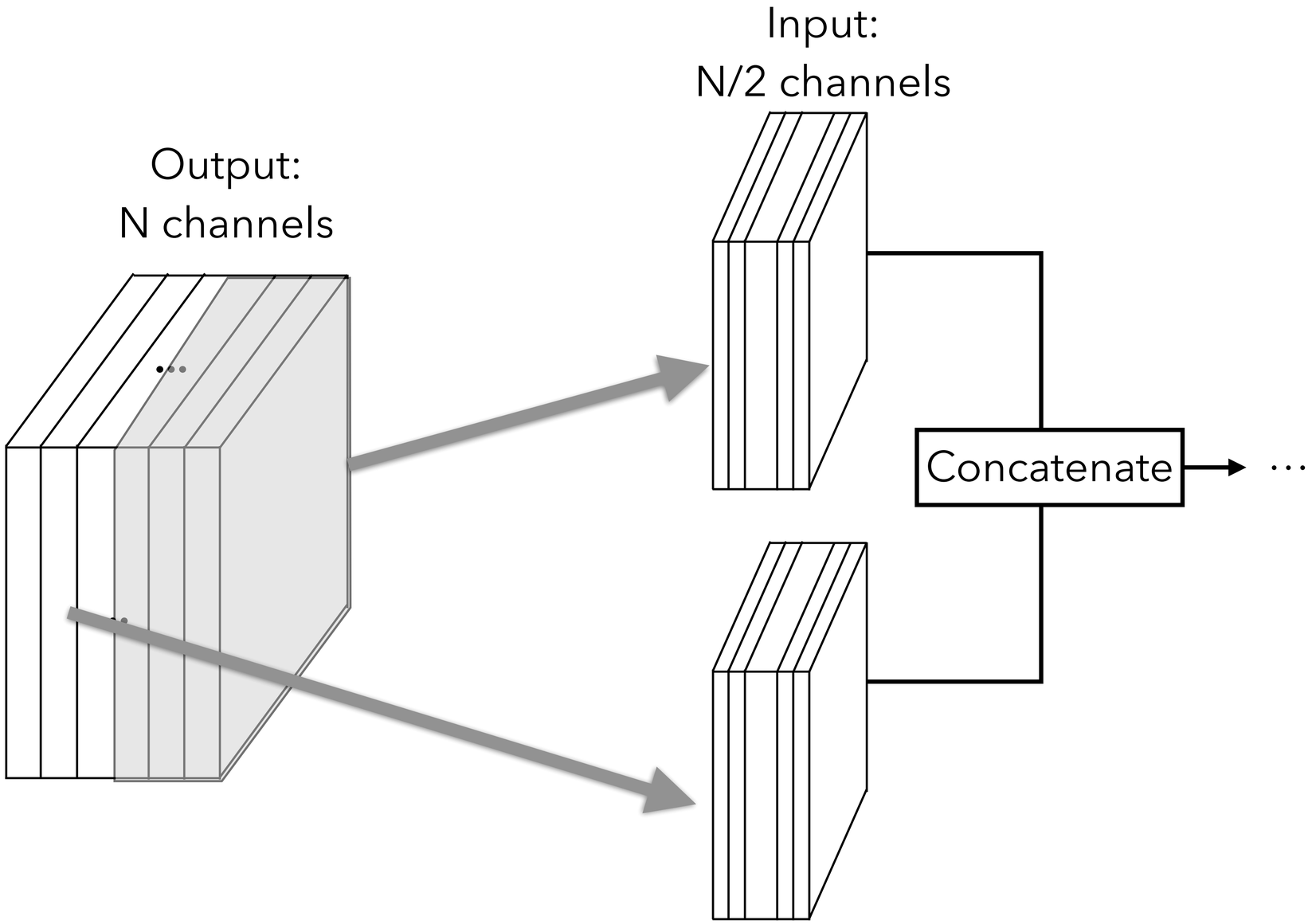
1x1 convolutions



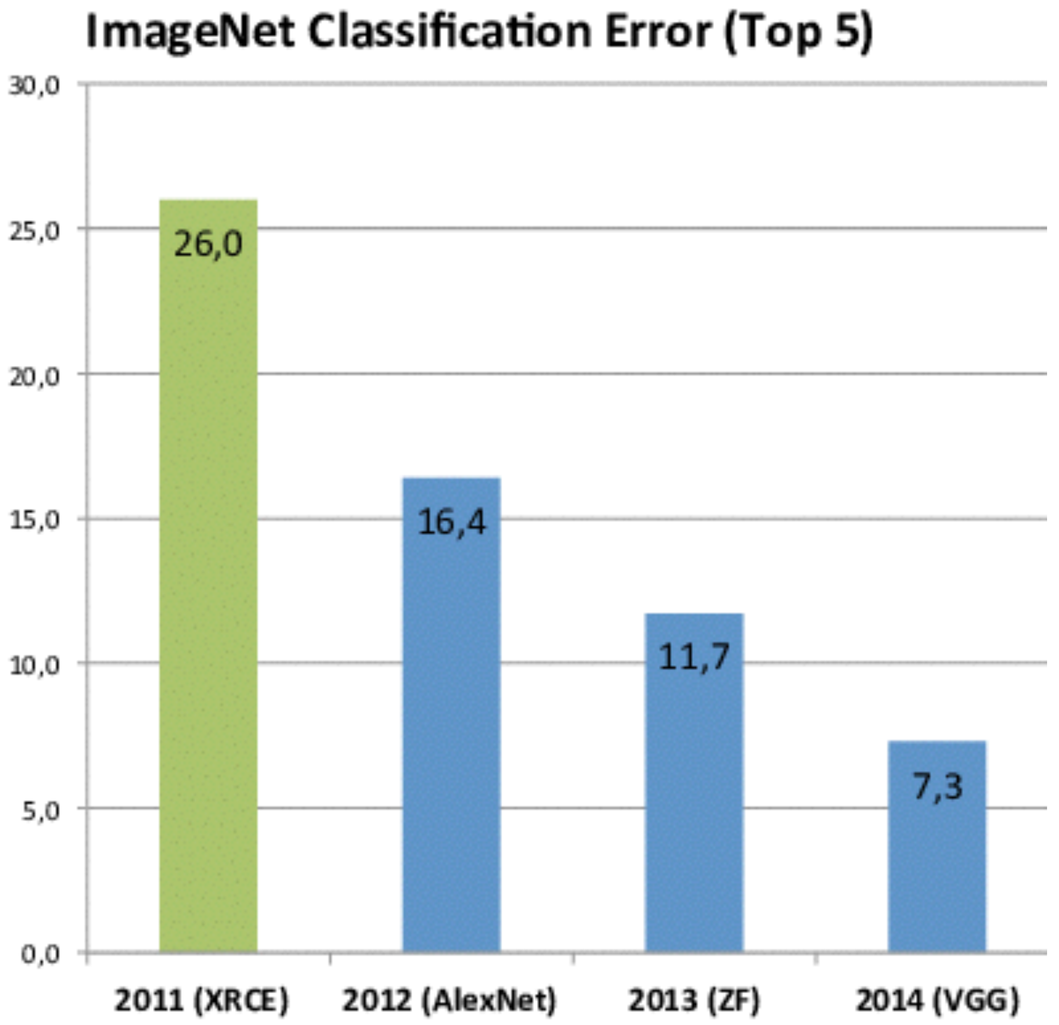
Why do this?

(nonlinearity in between)

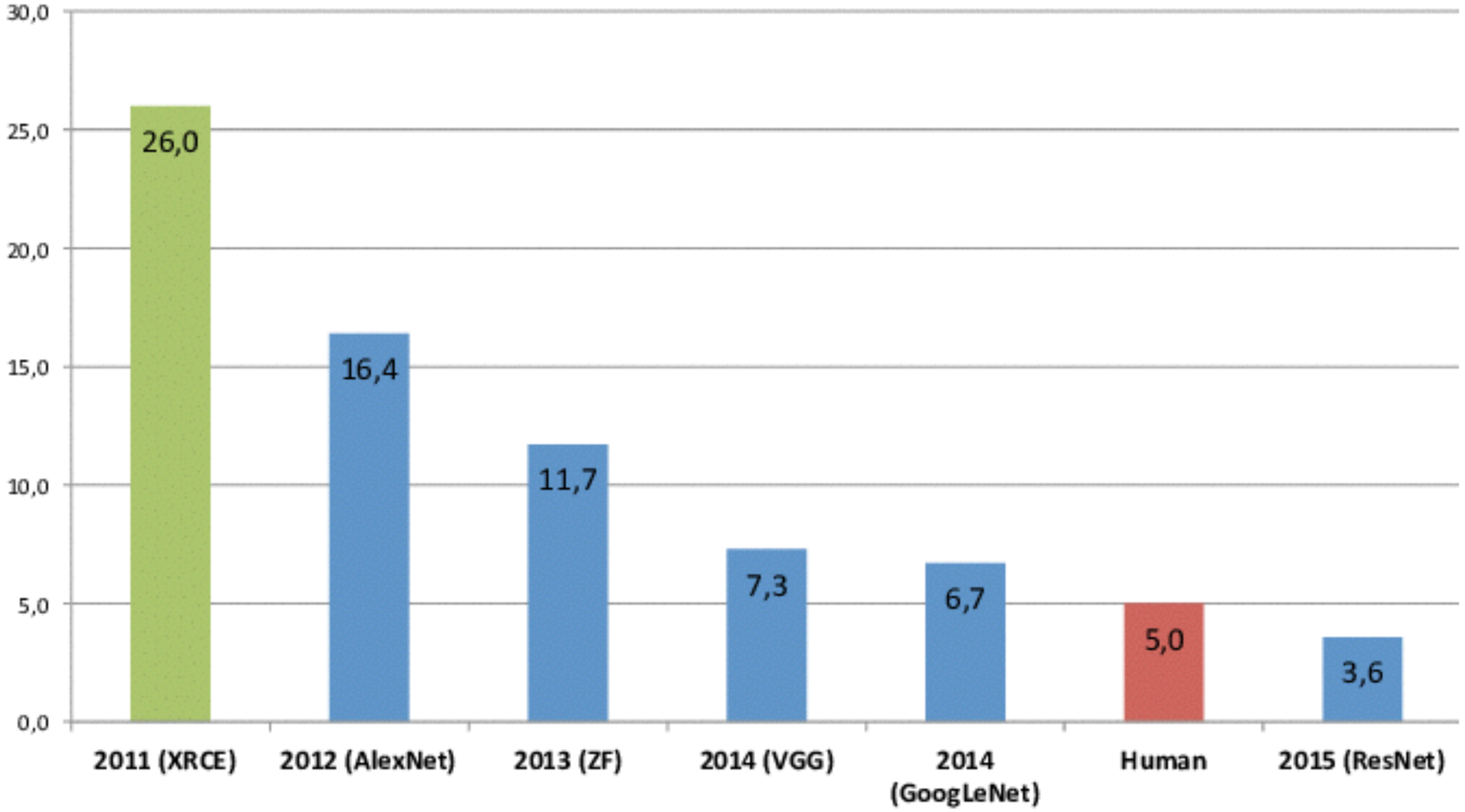
Grouped Convolutions



Split channels into N groups, and process separately with N convolution layers.



Source: Isola, Torralba, Freeman



2016: ResNet
>100 conv. layers

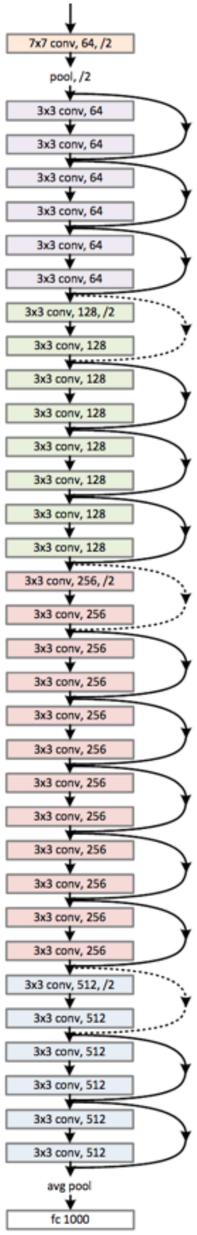
Error: 3.6%

[He et al: Deep Residual Learning for Image Recognition, CVPR 2016]

Source: Isola, Torralba, Freeman

2016: ResNet
>100 conv. layers

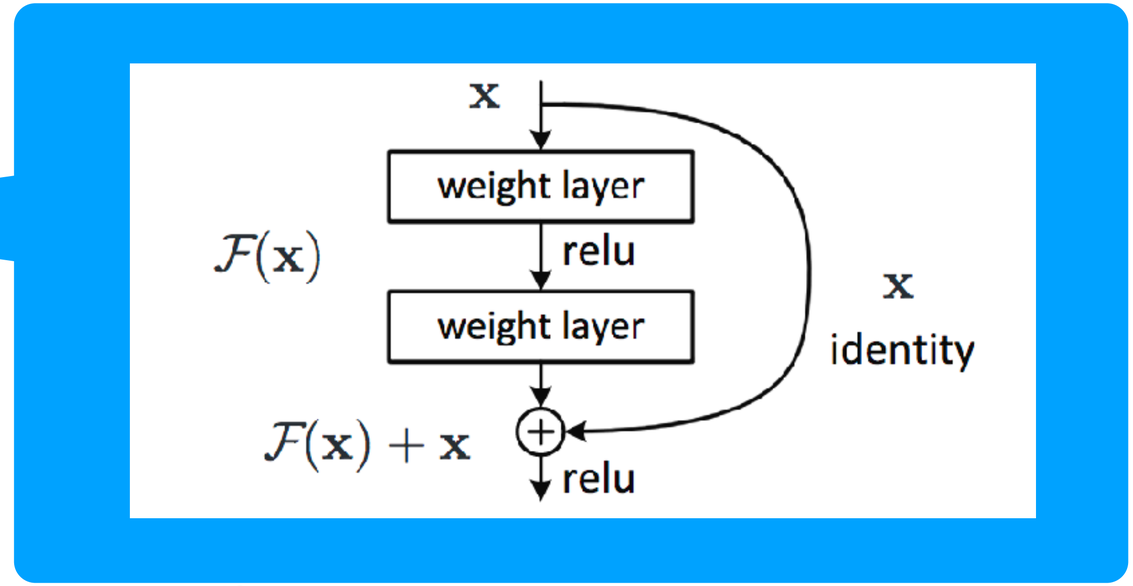
ResNet [He et al, 2016]



Error: 3.6%

Main developments

- Increased depth possible through residual blocks



Source: Isola, Torralba, Freeman

Residual Blocks

Problem: Hard to train very deep nets (50+ layers). This is an optimization issue, not overfitting: shallow models often get higher *training* accuracy than deep ones!

Idea: Make it easy to represent for the network to implement the identity.

Normal convolution + relu:

$$x_{i+1} = \text{relu}(x_i \circ f)$$

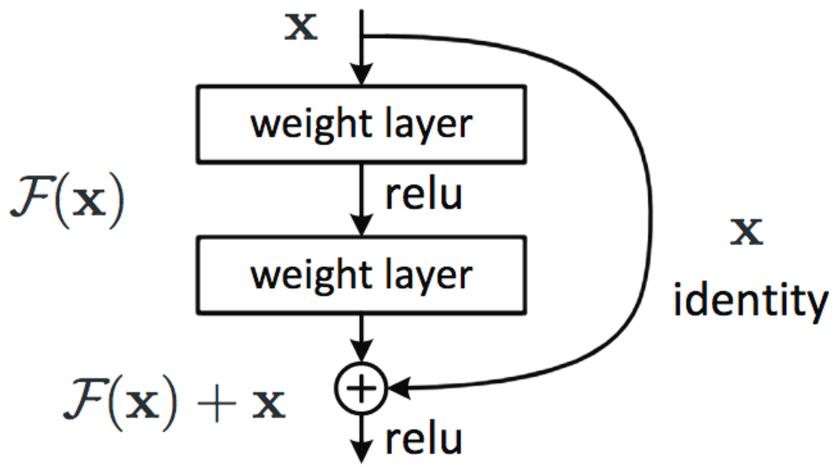
Residual connection

$$x_{i+1} = \text{relu}((x_i \circ f) + x_i)$$

More generally: do multiple convolutions (with nonlinearities) before summing:

$$x_{i+1} = \text{relu}(\mathcal{F}(x_i) + x_i)$$

Residual Blocks



Why do they work?

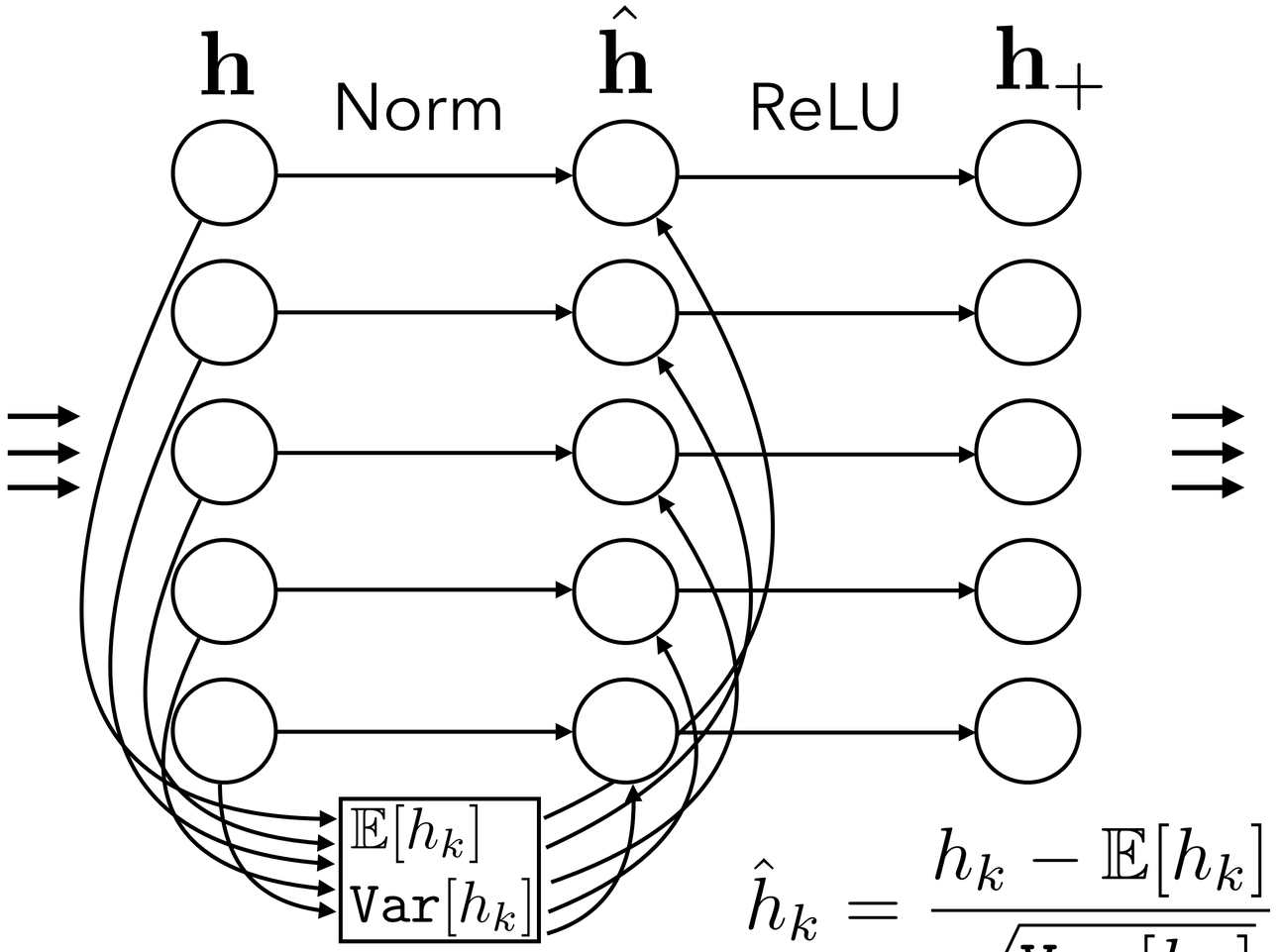
- Gradients can propagate faster (via the identity mapping)
- Within each block, only small residuals have to be learned

Source: Isola, Torralba, Freeman

Normalization layers

- Standardize activations by subtracting mean and dividing by standard deviation (averaged over all spatial locations).
- This provides a constant “interface” for later layers of the networks. Ensures that the previous layer will have unit variance and zero mean.
- Obtains invariance to mean and variance.
- Can allow you to train with larger learning rate and significantly speed up training!

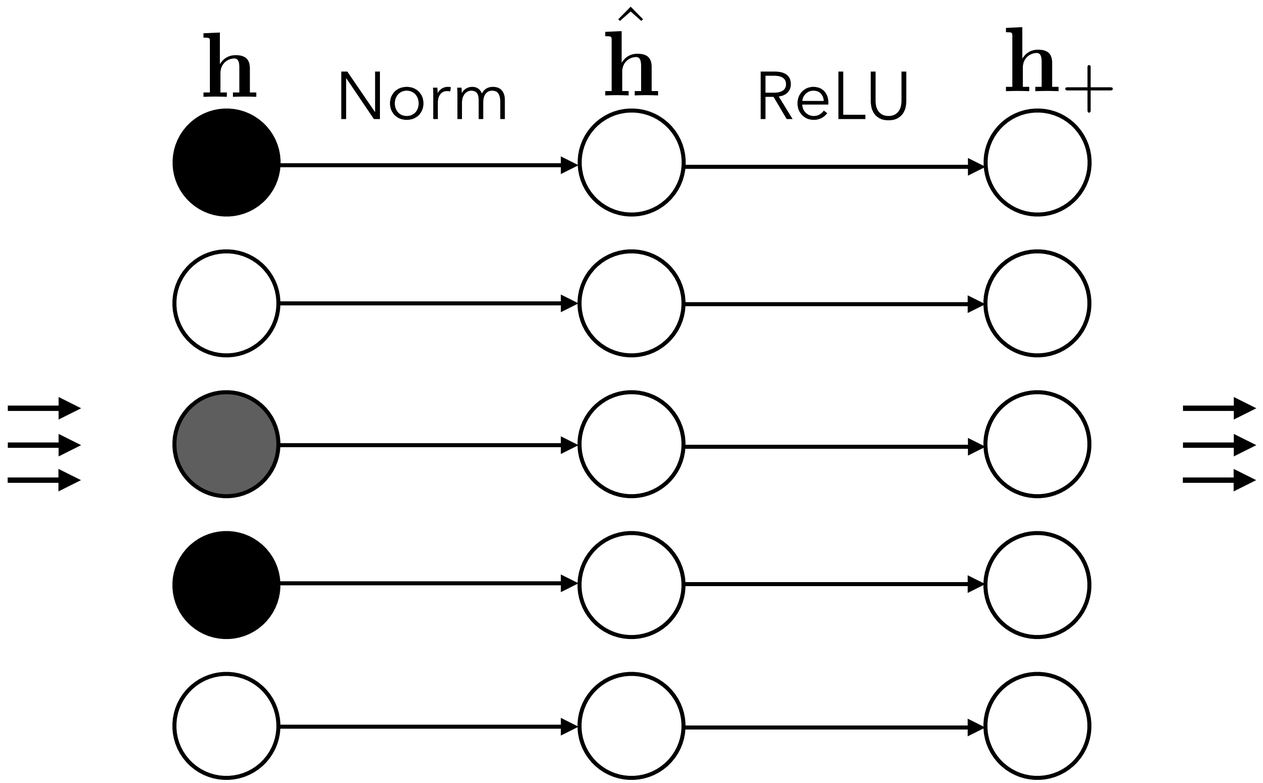
Normalization layers



$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Source: Isola, Torralba, Freeman

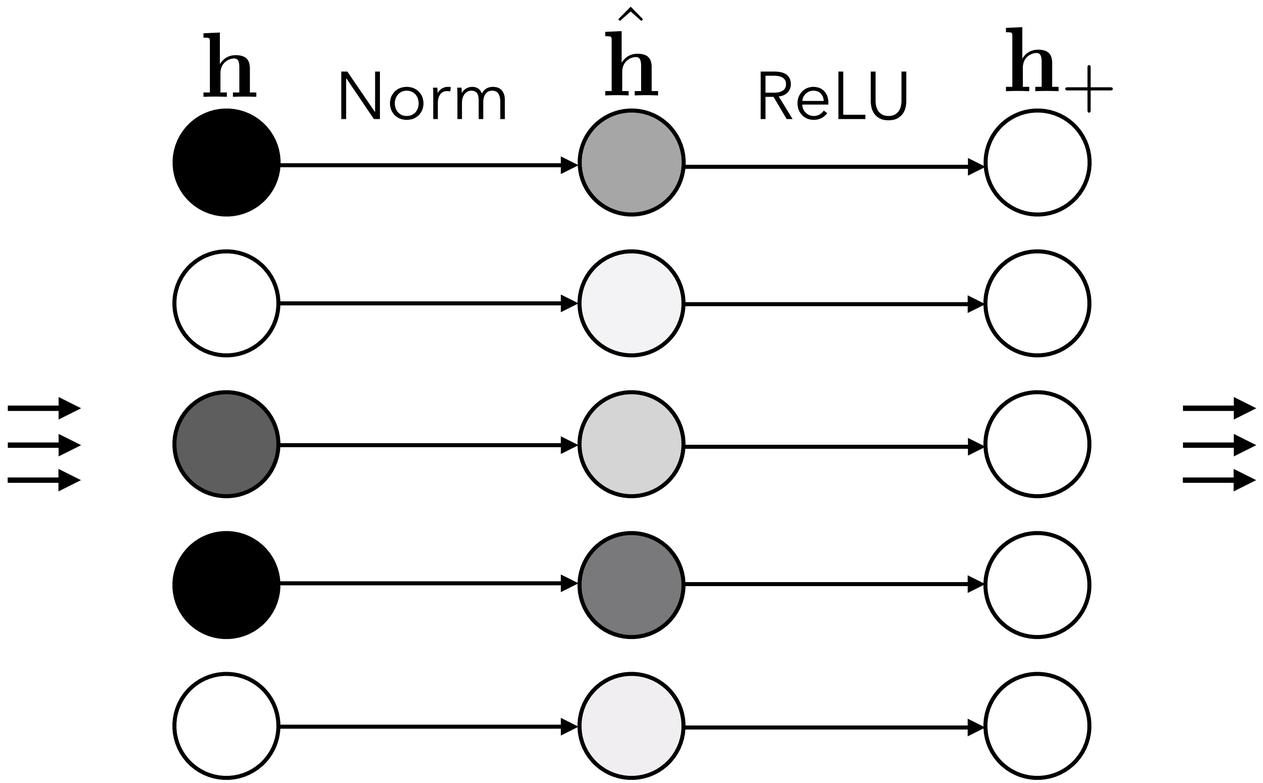
Normalization layers



$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\texttt{Var}[h_k]}}$$

Source: Isola, Torralba, Freeman

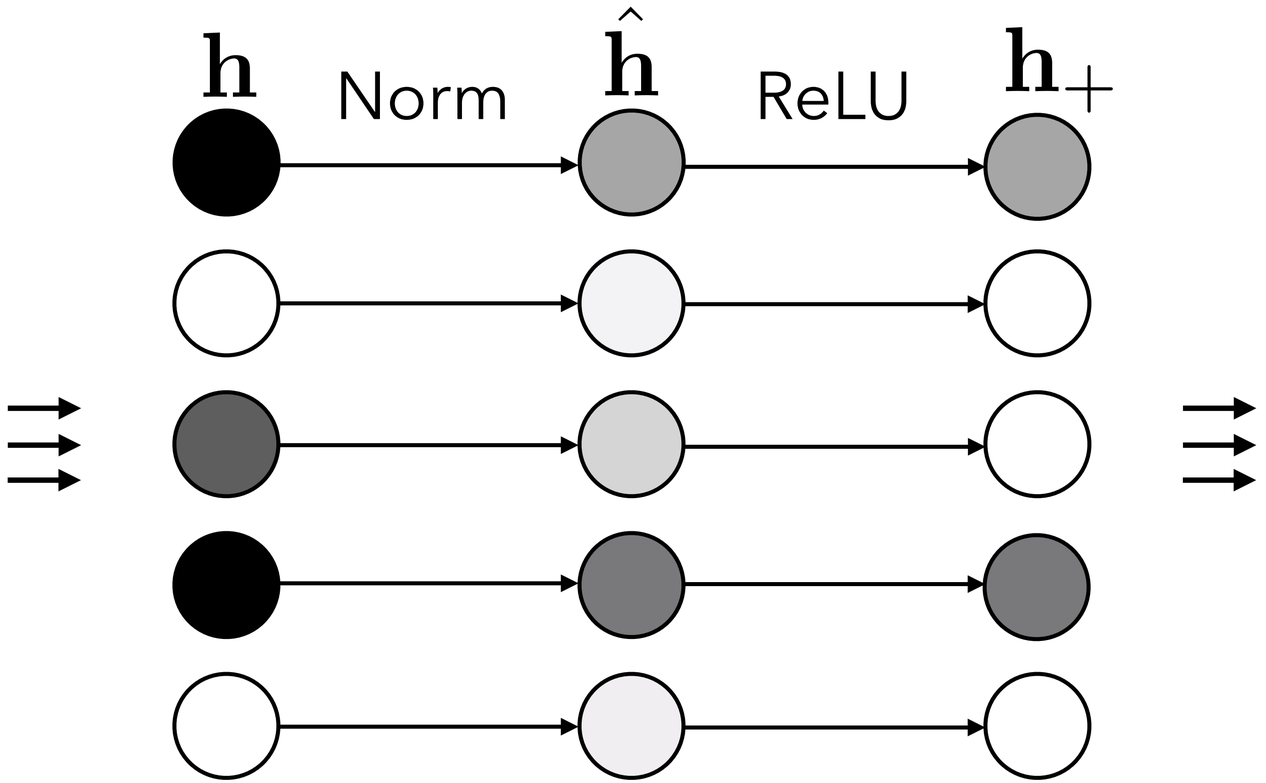
Normalization layers



$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\texttt{Var}[h_k]}}$$

Source: Isola, Torralba, Freeman

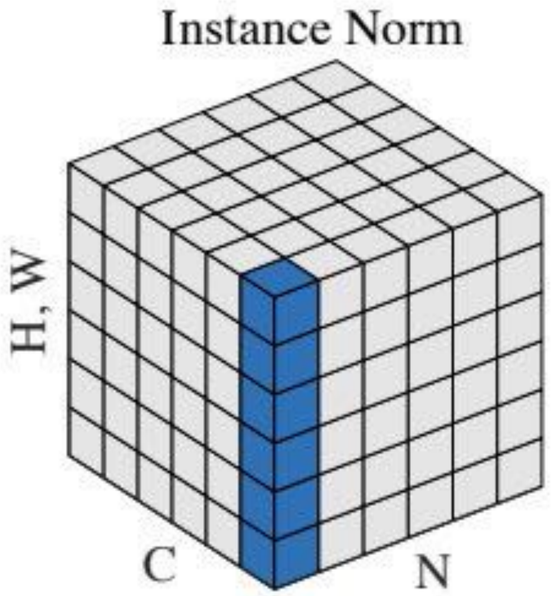
Normalization layers



$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\texttt{Var}[h_k]}}$$

Source: Isola, Torralba, Freeman

Instance normalization



Filter value in a CNN layer

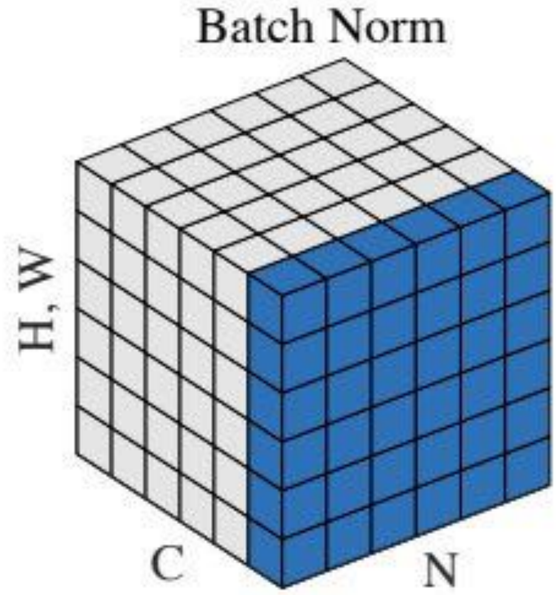
Average and standard deviation each filter response, estimated over **instance**.

$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\texttt{Var}[h_k]}}$$

Normalize a single hidden unit's activations to be mean 0, standard deviation 1.

[Figure from Wu & He, 2018][Ulyanov et al., 2015]

Batch normalization



Filter value in a CNN layer

Average and standard deviation each filter response, estimated over **whole batch**.

$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\texttt{Var}[h_k]}}$$

Normalize a single hidden unit's activations to be mean 0, standard deviation 1.

At test time, remember the mean and standard deviation seen during training.

[Figure from Wu & He, 2018; Ioffe & Szegedy, 2015]

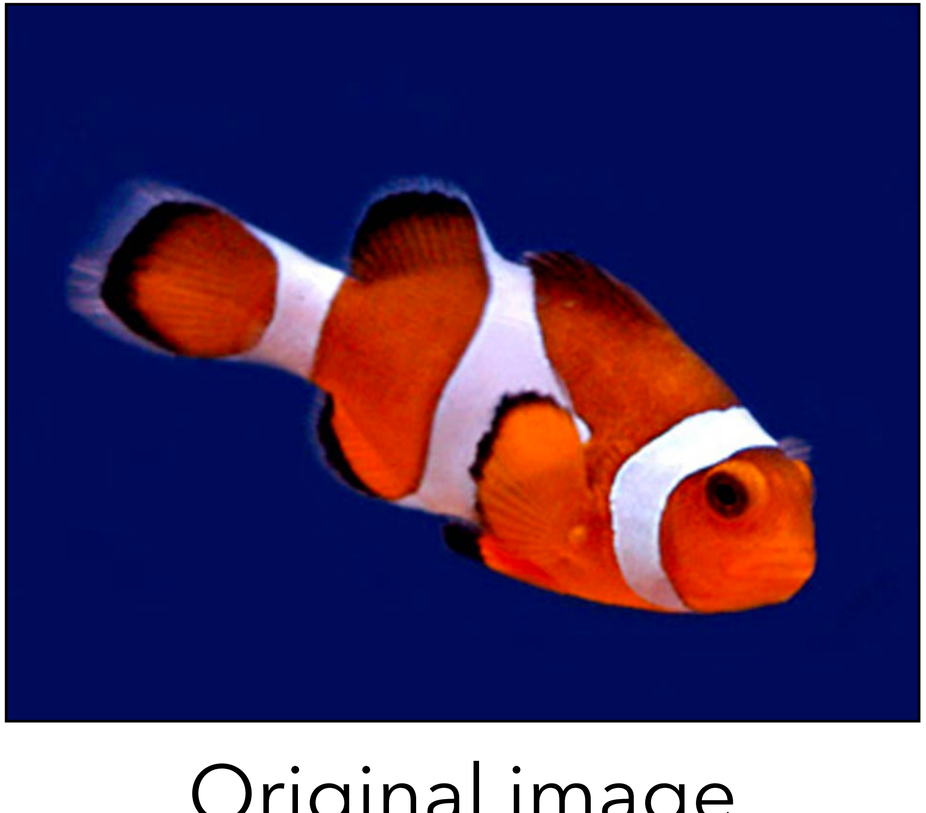
A few practical issues

Dealing with rectangular images

Rectangular images

Resize, then take square crop from center

Training with data augmentation



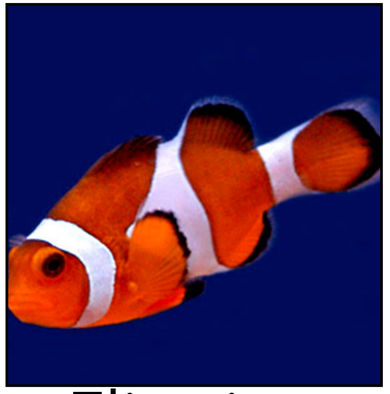
Original image

Flipping

- Less susceptible to overfitting.
- Improves performance by simulating example

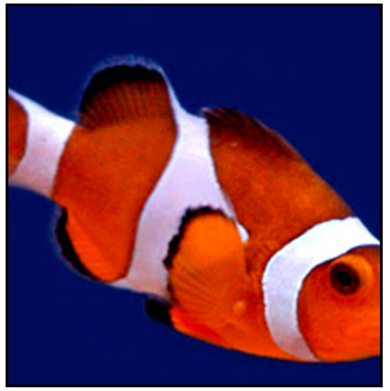
Training with data augmentation

Original image

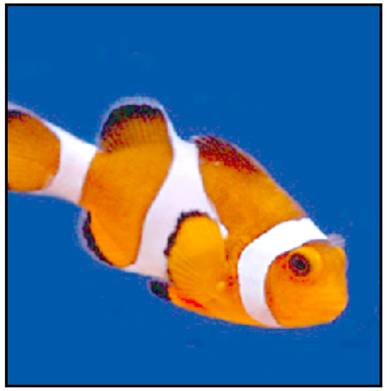


Flipping

Cropping



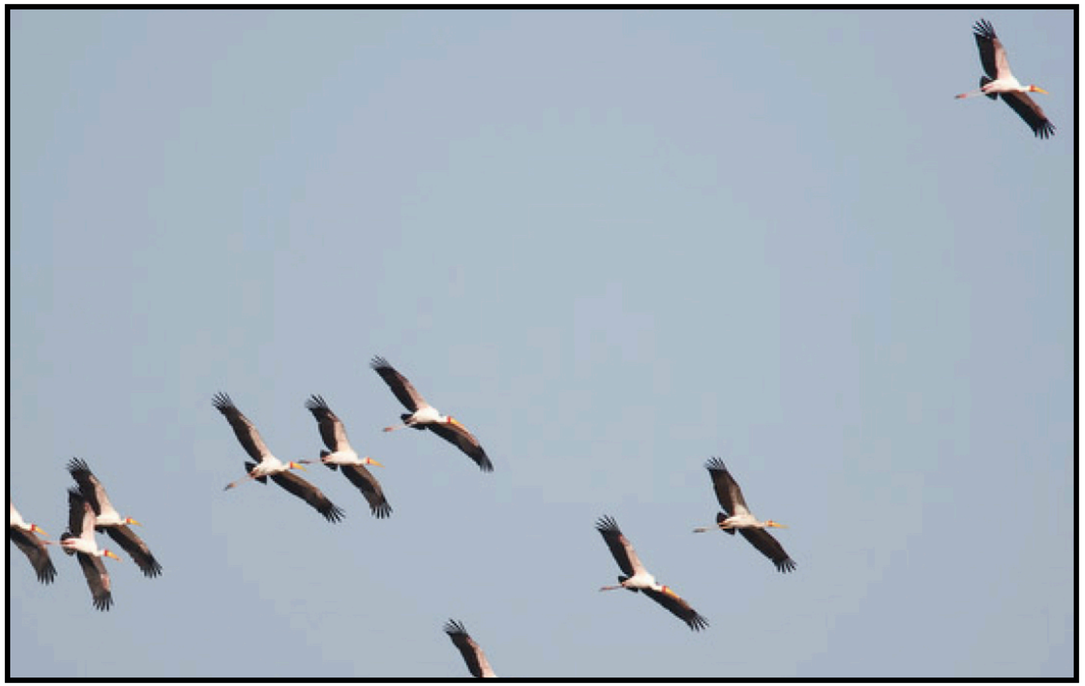
Scaling



Color jittering

Beyond image labeling

Object recognition: what objects are in the image?

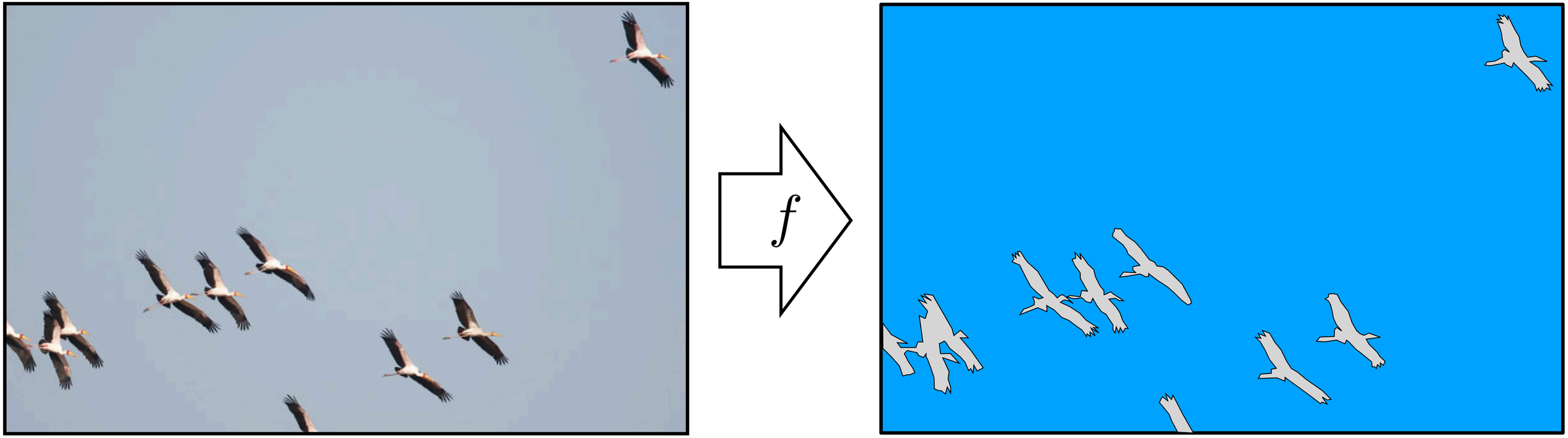


f

"Birds"

Source: Torralba, Freeman, Isola

Semantic segmentation

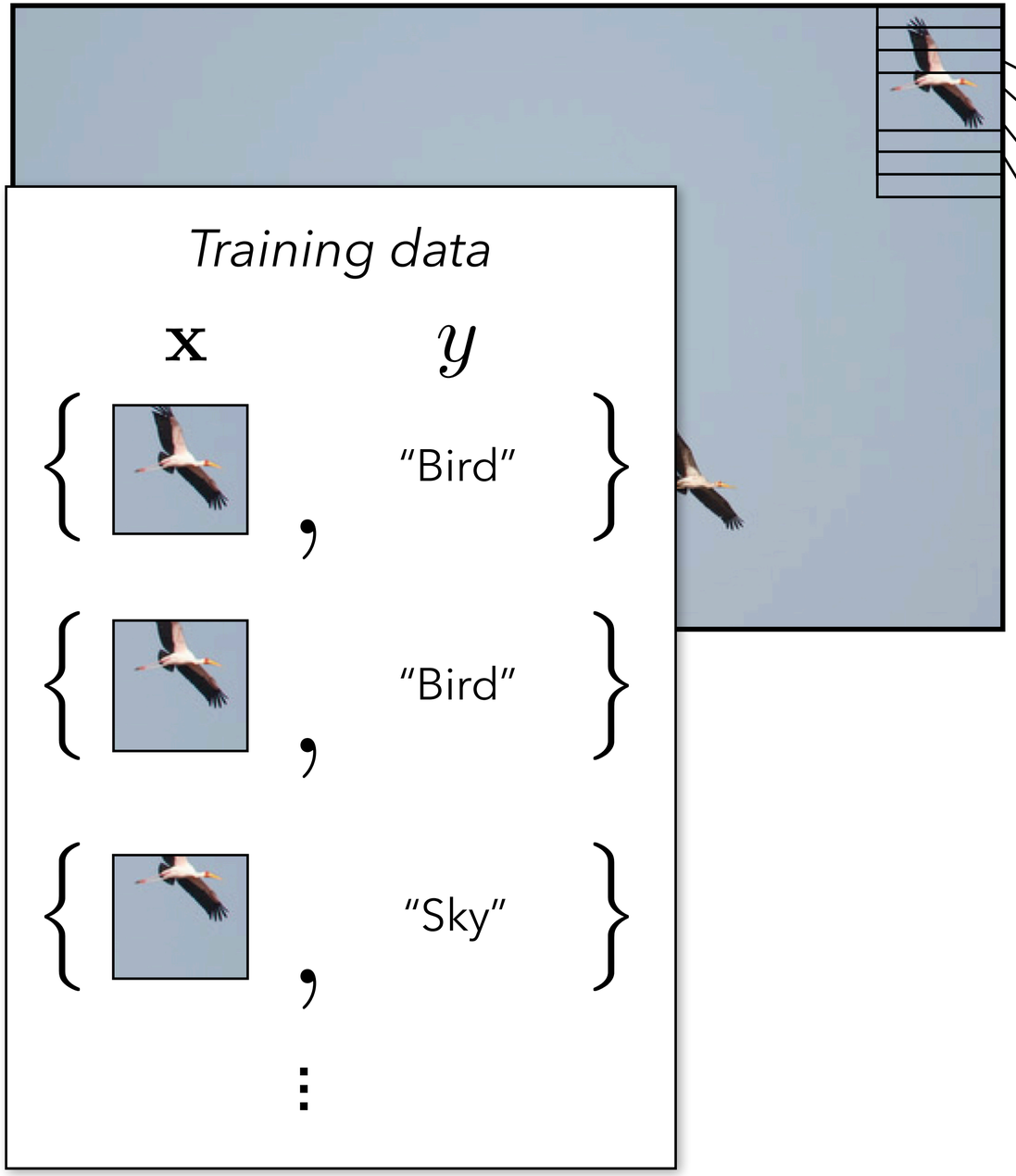


(Colors represent categories)

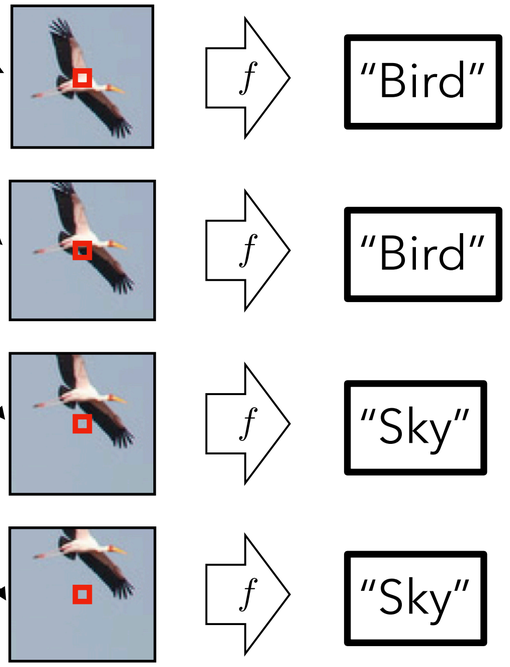
General technique: predict something at every pixel!

Source: Torralba, Freeman, Isola

Idea #1: Independently classify windows



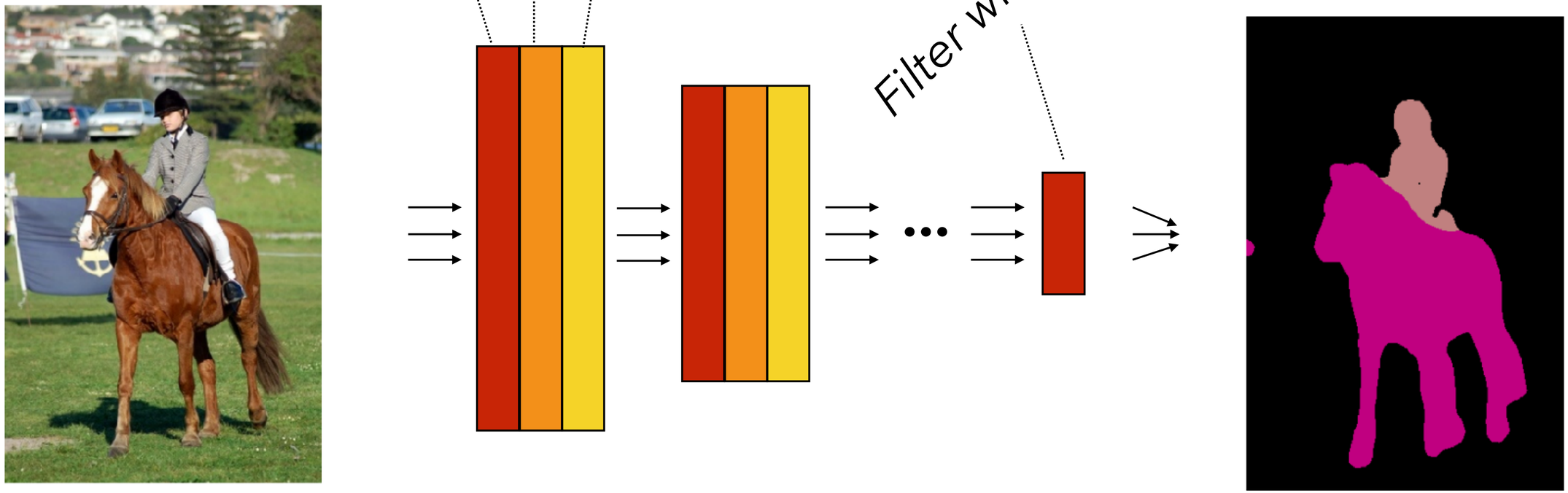
What's the object class of the center pixel?



Source: Torralba, Freeman, Isola

Idea #2: Fully convolutional networks

Fully convolutional network



Classification problem with K classes

Idea #3: Dilated convolutions

Dilated convolutions

3x3

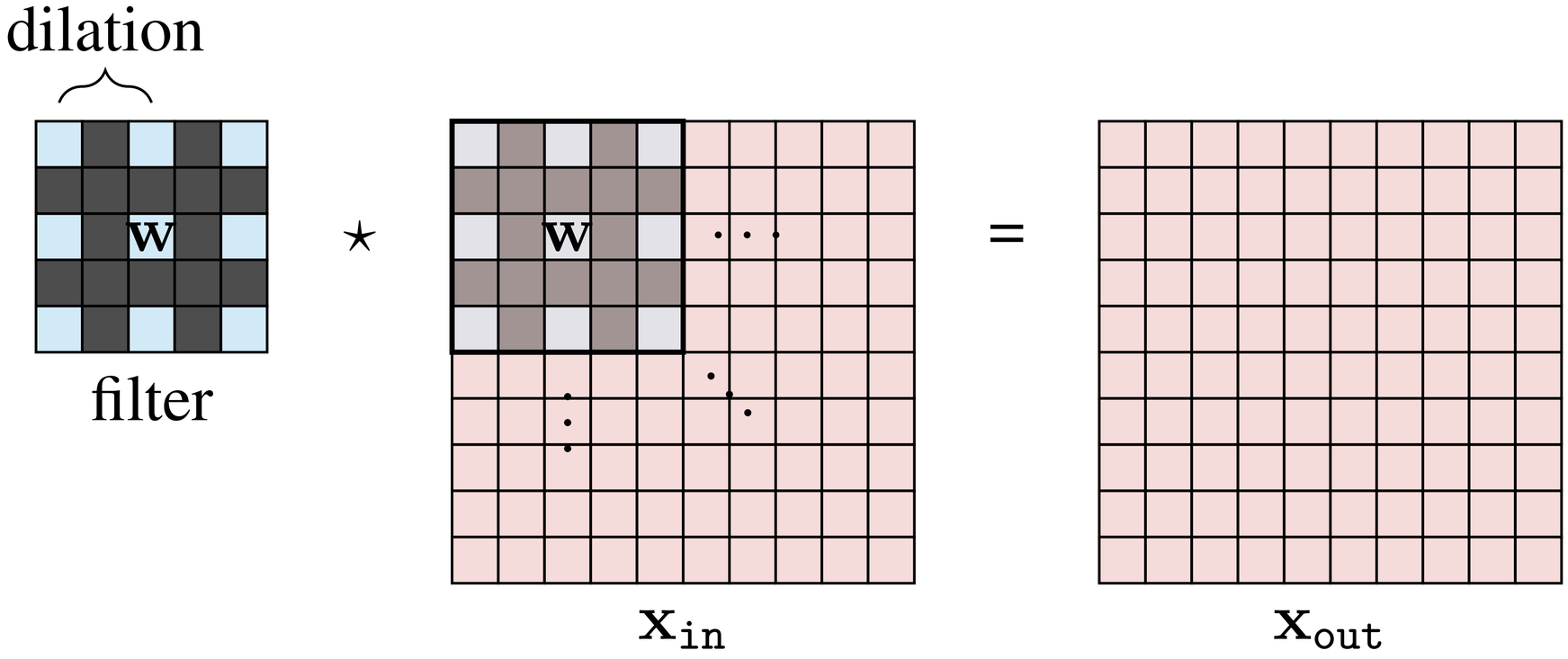
a	**b**	**c**
d	**e**	**f**
g	**h**	**i**

5x5

a	0	**b**	0	**c**
0	0	0	0	0
d	0	**e**	0	**f**
0	0	0	0	0
g	0	**h**	0	**i**

- Alternative to pooling that preserves input size
- 9 degrees of freedom
- 5x5 receptive field

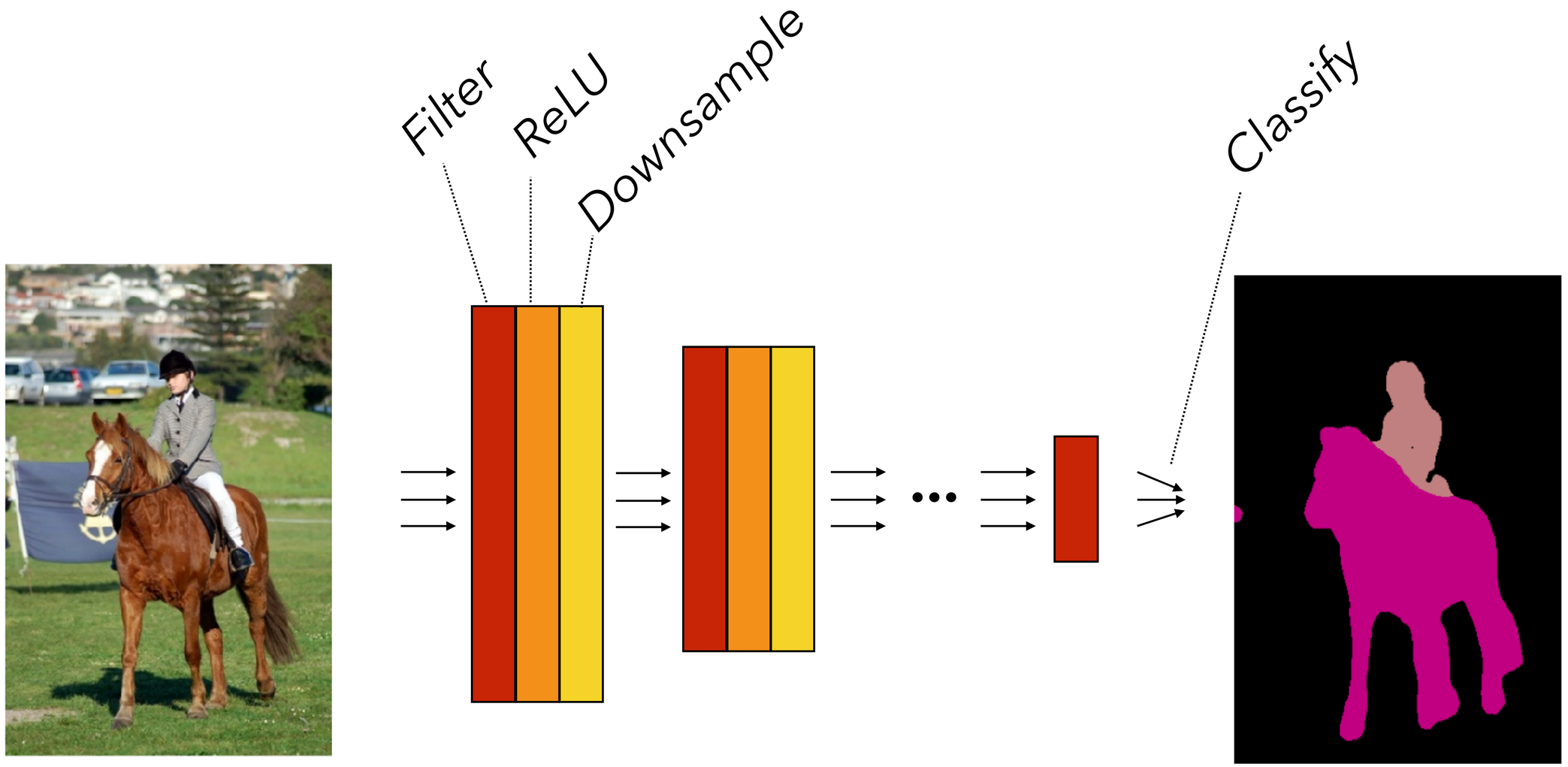
Dilated filter



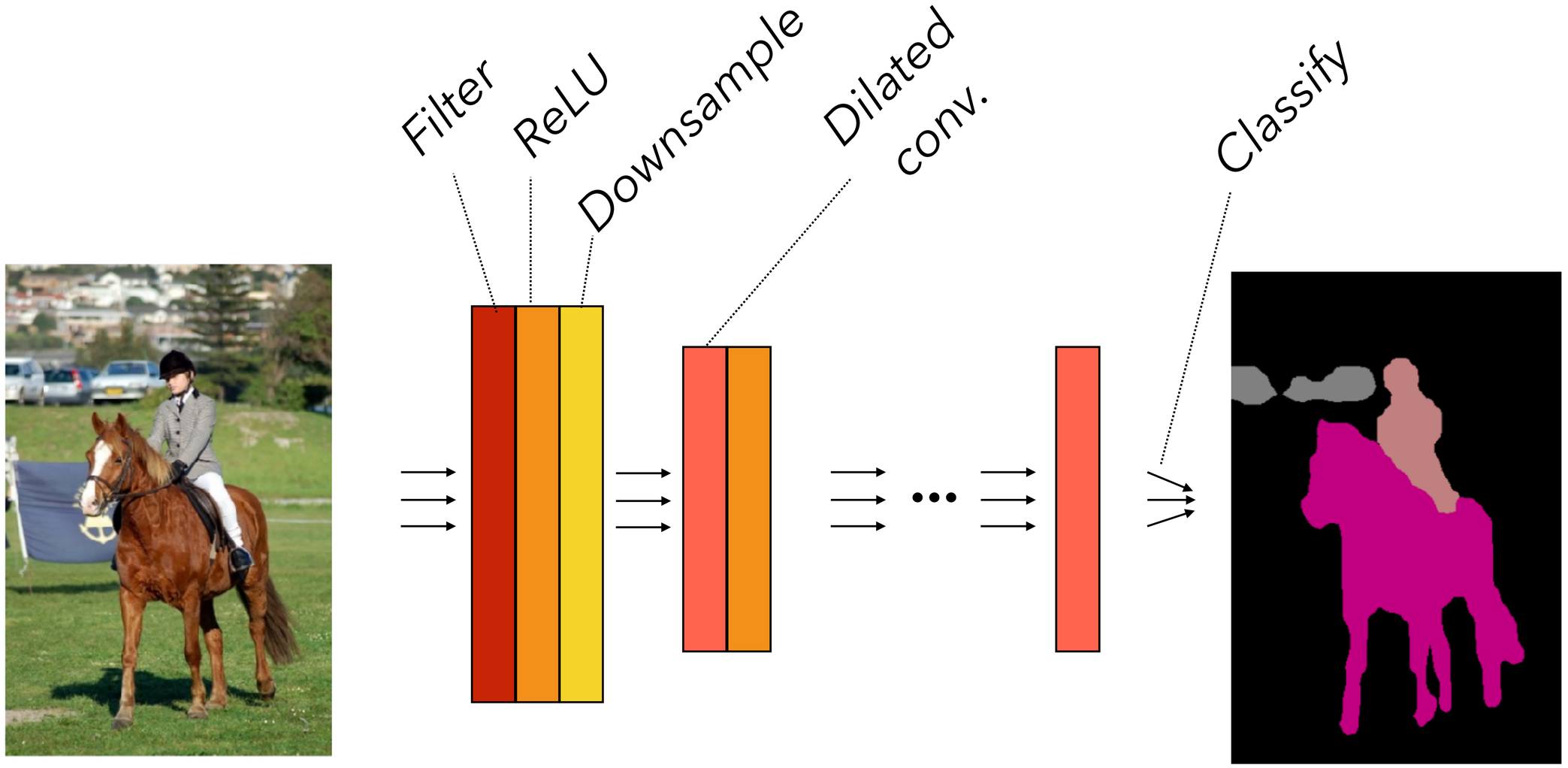
Covers a large receptive field with fewer parameters.

Source: Foundations of Computer Vision. Torralba, Isola, Freeman

CNN without dilated convolutions



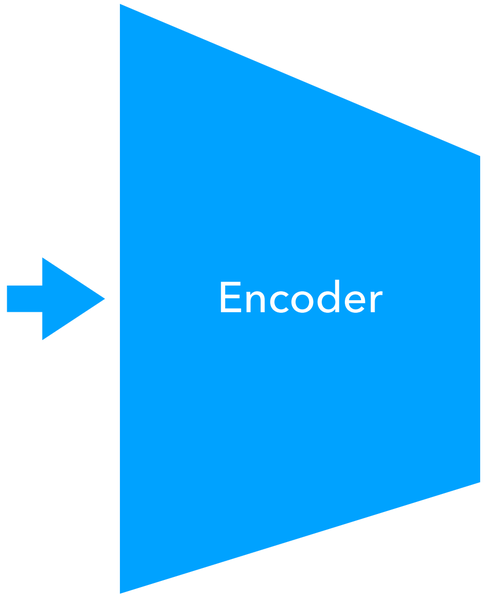
CNN with dilated convolutions



Even with dilated convolutions, still not full resolution

Idea #4: Encoder-decoder models

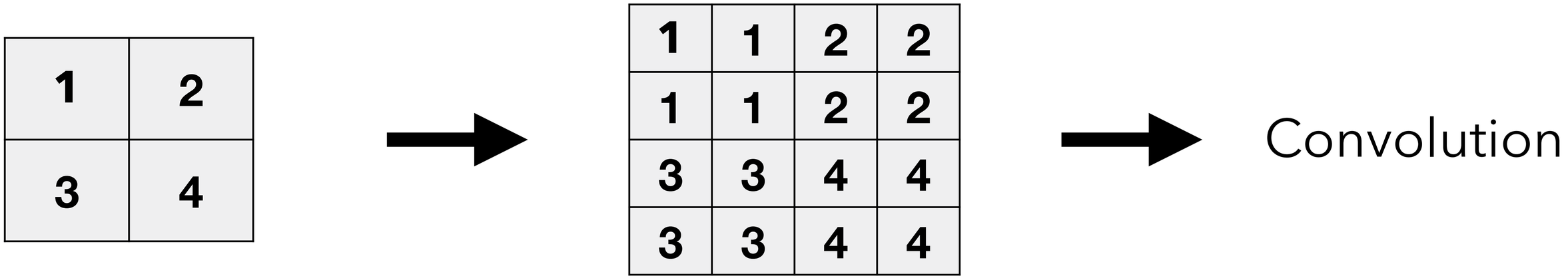
Encoder-decoder architectures



Convolutions **Deconvolutions**

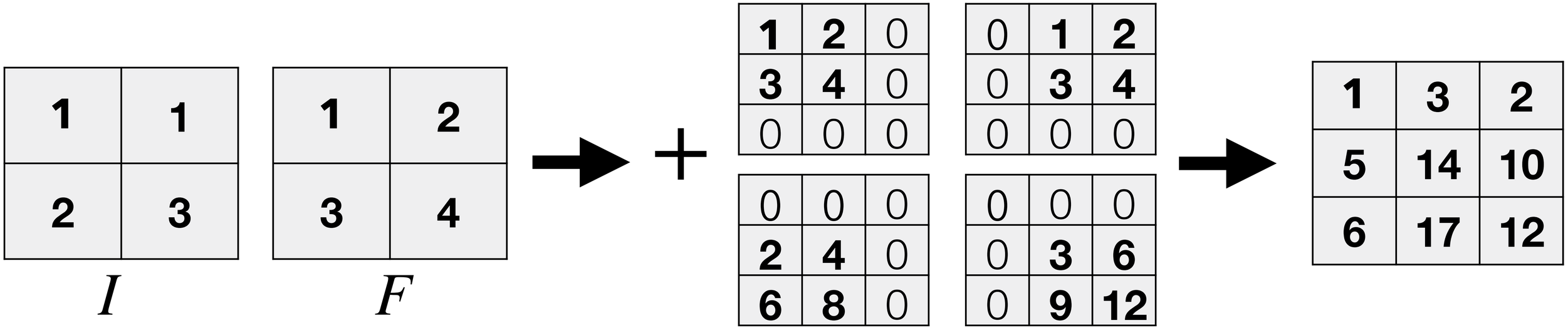
Source: Torralba, Freeman, Isola

Upsampling



- Often using nearest-neighbor upsampling
- Can also use interpolation.
- Produces fewer “checkerboard” artifacts

Transposed convolution



- Weight the filter by the image coefficient and sum.
- Also sometimes called “upconvolution” or “deconvolution”.

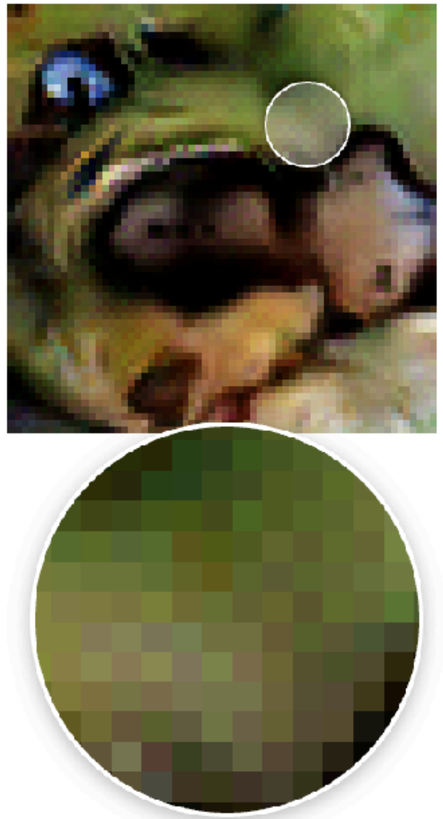
Transposed convolution

1	1
2	3

I

1	2
3	4

F

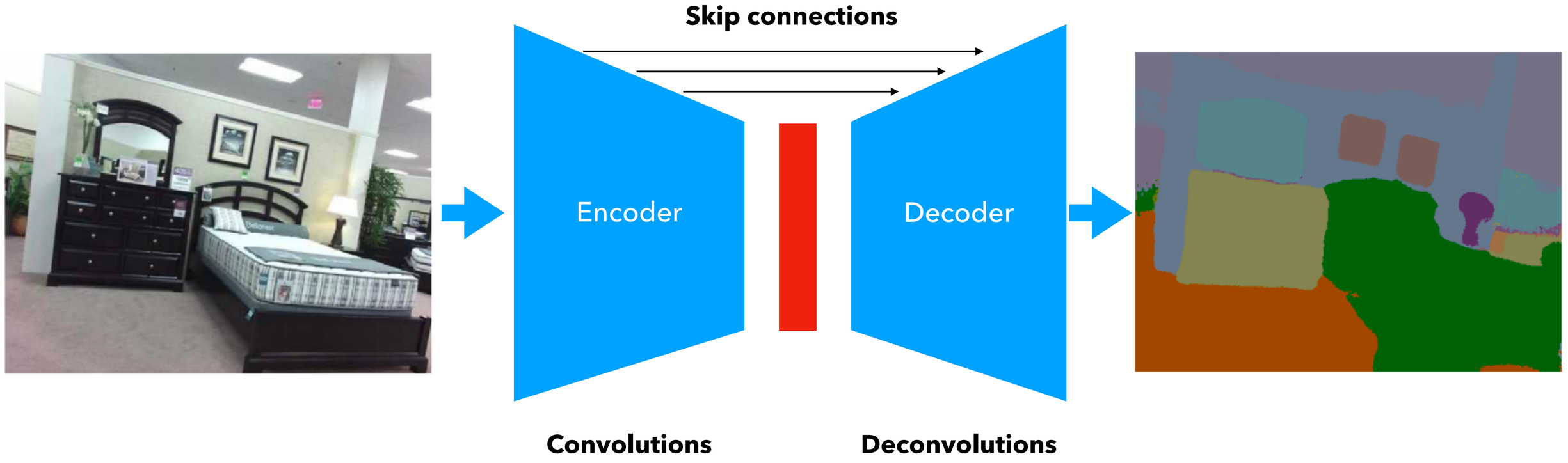


Donahue, et al., 2016 [3]

Can lead to “checkerboard” artifacts.

[Odena et al. Distill article]

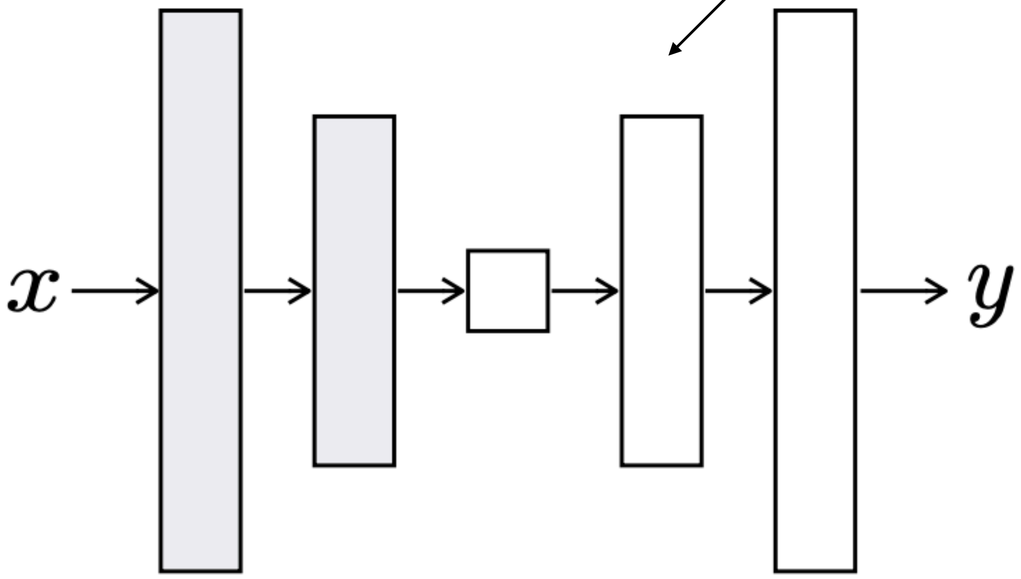
Encoder-decoder architectures



Source: Torralba, Freeman, Isola

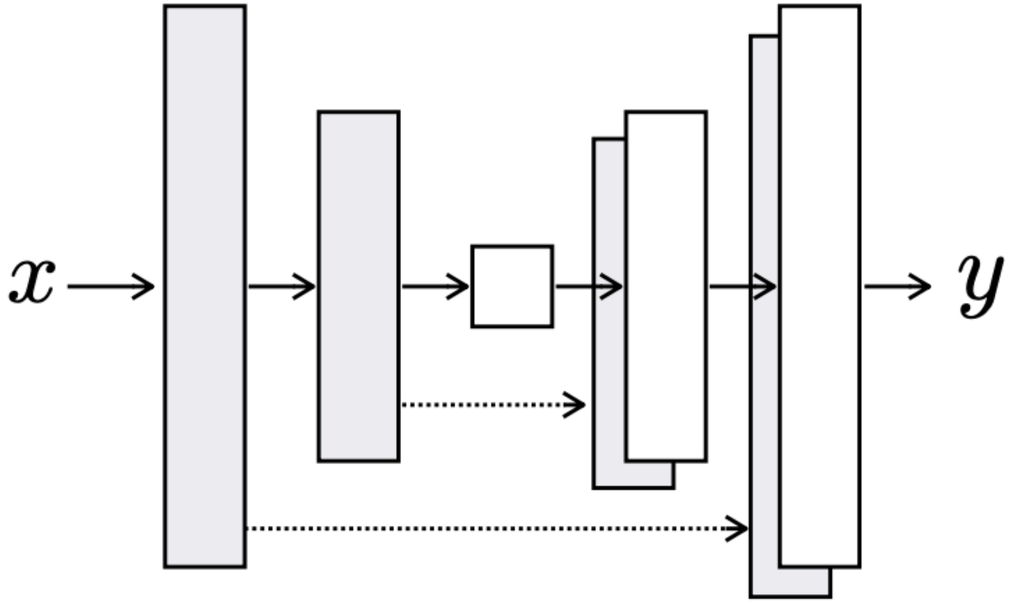
Encoder-decoder architectures

Transposed convolution



"Vanilla" encoder-decoder architecture

Early layers and late layers have same shape. Concatenate channel-wise!



U-Net

Figures from [Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks",

U-net

$W \times H$

concat

$\frac{W}{2} \times \frac{H}{2}$

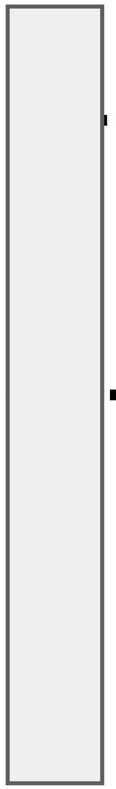
$\cdots$

$\frac{W}{2} \times \frac{H}{2}$

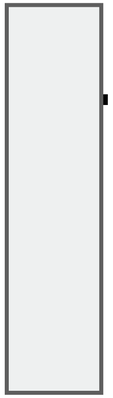
$W \times H$

U-net

$W \times H$



$\frac{W}{2} \times \frac{H}{2}$

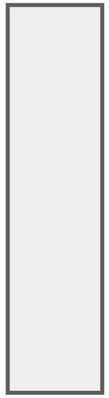


$\frac{W}{4} \times \frac{H}{4}$

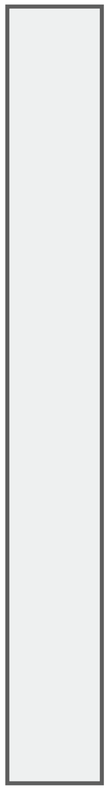
concat

concat

• • •



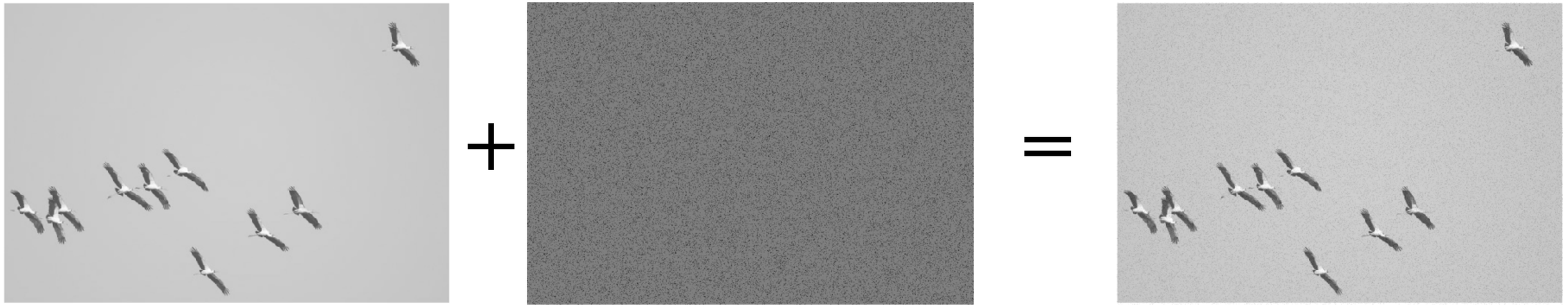
$\frac{W}{4} \times \frac{H}{4}$



$\frac{W}{2} \times \frac{H}{2}$

$W \times H$

Other uses for U-nets



Goal: recover the original image

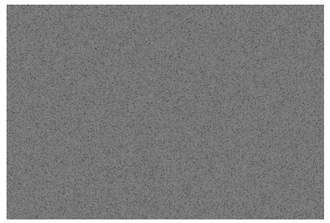
Recall: denoising problem

Denoising

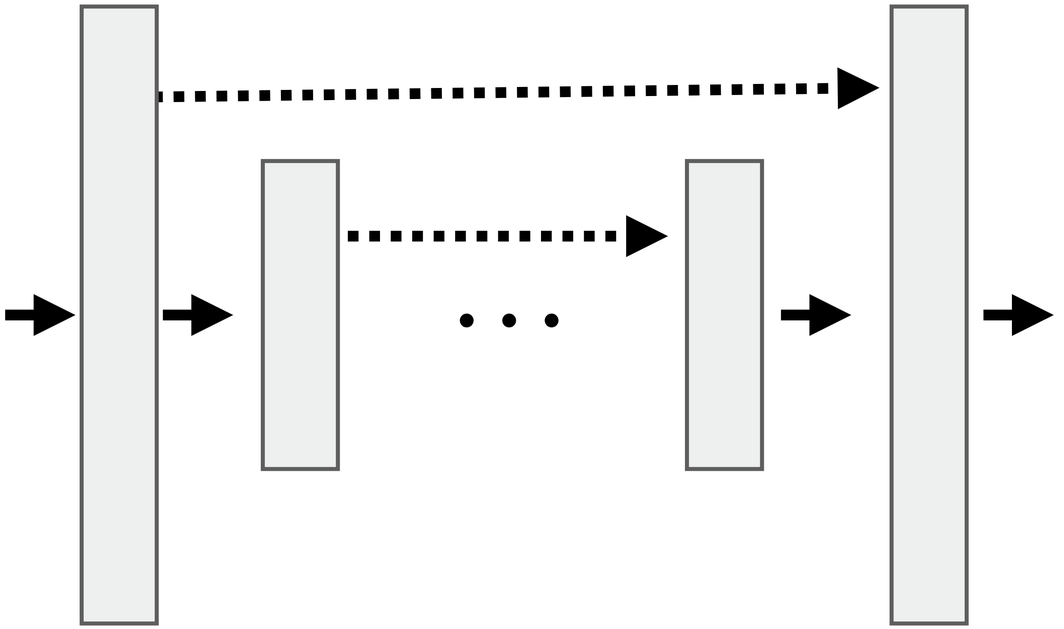
=

$\mathbf{x}_{\text{clean}}$

+



random noise



$\hat{\mathbf{x}}$

Loss: $\|\mathbf{x}_{\text{clean}} - \hat{\mathbf{x}}\|^2$

Next class: vision and language