Announcements

Releases today:

- HW3
- Project descriptions!

Project Format 1/3

- There are **3 project directions** (more next slide) set up by the course team.
- Each team must pick one of these directions.
- For each direction, a document will be up later today, explaining the problem and “**common minimum**” components that each team must execute. This will involve **both data collection and model design**.
  - Specification of the task and its performance metrics
  - Starter data (very small) to guide your data collection and model design
  - Starter ML model code to guide your data collection and model design
- Beyond the common minimum components, each team will craft their own “**further investigation**” questions grounded in that direction and report their progress on answering it.
- On Dec 16, each team will submit their collected data, their trained model(s), and a project report (~5 pages, format TBA soon).

Project Format 2/3: Common Minimum Components

- For the common minimum components, the course team will, besides the starter data and code, set up a leaderboard for teams to have a sense of how other teams are performing.
- Project grade will be based on your project report (more next slide) and not your position on the leaderboard, but:
  - Each team must submit at least one entry to the leaderboard
  - Some fraction of the project grade (e.g. 15%) will be based on surpassing a minimum level of performance on the problem.
  - If you did well on the leaderboard test data AND your report does a good job explaining how you achieved this, we may grant you bonus points.

Project Format 3/3: Further Investigation Components

- Your report, besides explaining your approach to the common minimum components, will also include a report of your “further investigations” (at least 2). For each “investigation”, you will describe:
  - Your question and its motivation E.g. “does random hyperparameter sampling perform better than grid search?”
  - Your research on prior work or course material related to the question, and what you expect to be the answer before conducting your investigation. E.g. search on google scholar
  - Methods for investigation.
  - Results of your investigation, and your updated beliefs about the answer.
  - Limitations of your study / what you would have done with more time or other resources.

CIS 4190/5190: Lec 14 Wed Oct 23, 2024

Convolutional Neural Networks Wrap-Up

Convolutional Layer Summary

- Local connectivity
- Weight sharing
- Handling multiple input/output channels
- Retains location associations

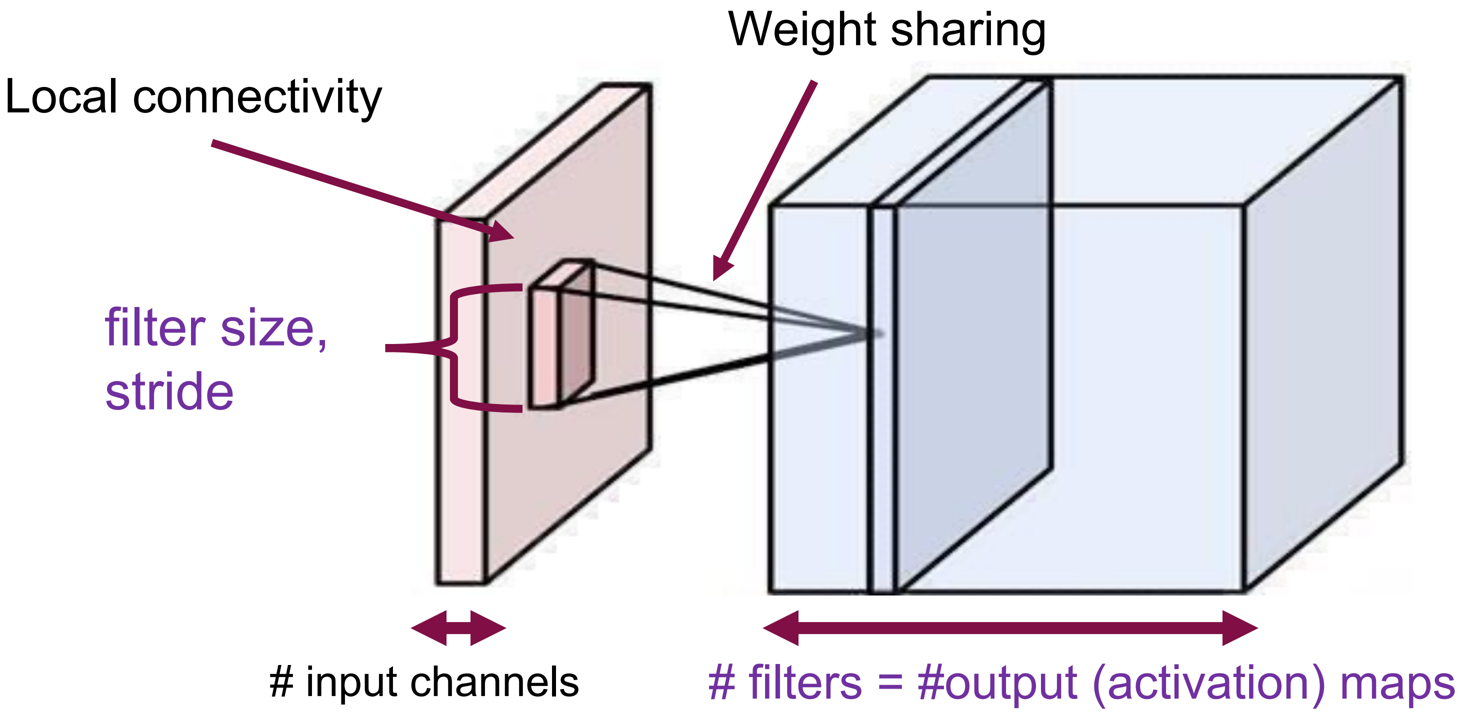
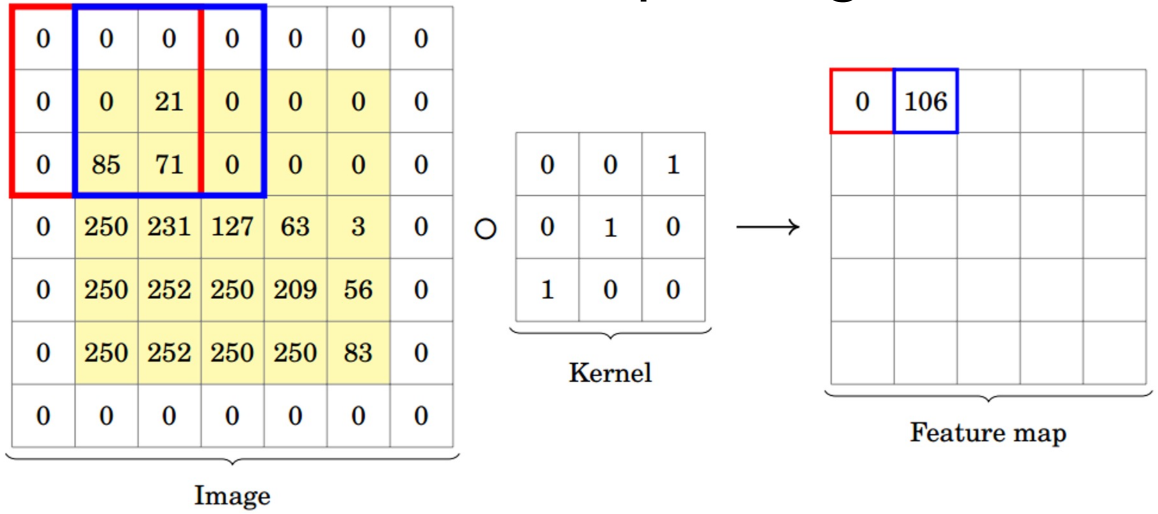


Image credit: A. Karpathy

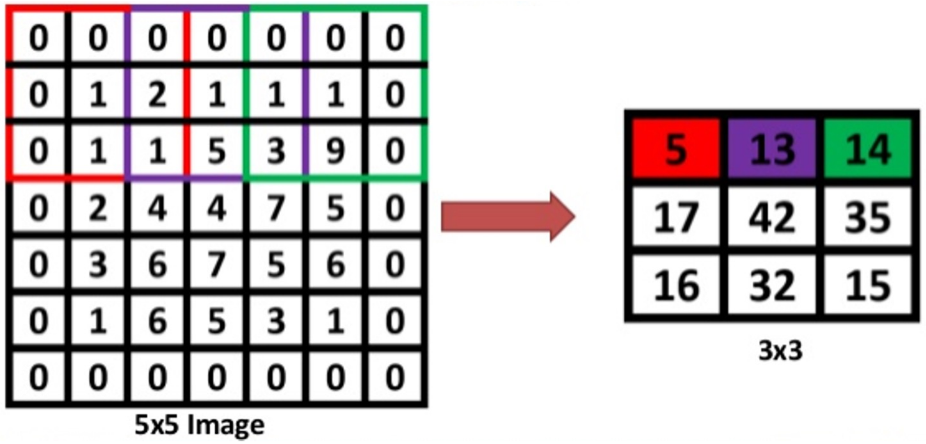
Slide credit: Jia-Bin Huang

Zero-Padding

stride = 1, zero-padding = 1



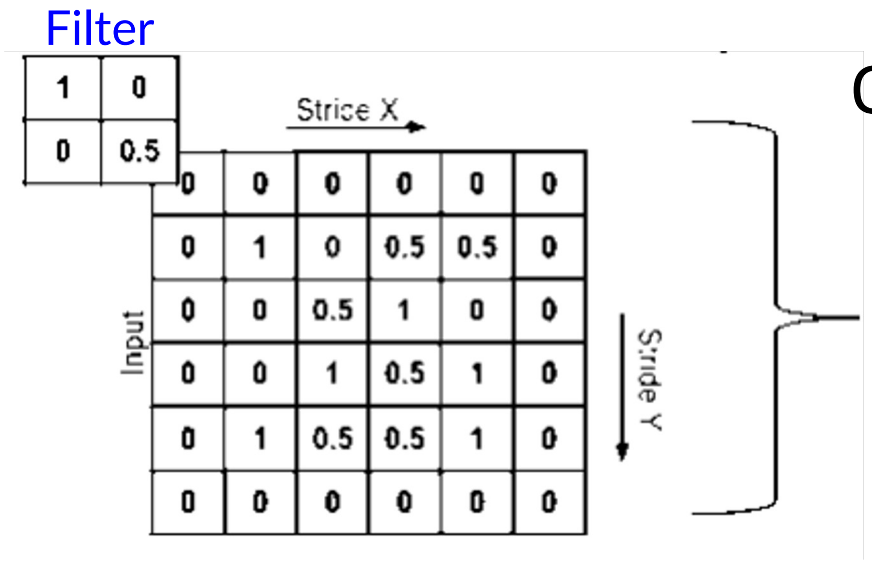
stride = 2, zero-padding = 1



Q: What if you had a different-sized kernel? E.g. 5x5? 4x4?

https://medium.com/@ayeshmanthaperera/what-is-padding-in-cnns-71b21fb0dd7

Stride



Output with stride 1

0.5	0	0.25	0.25	0
0	1.25	0.5	0.5	0.5
0	0.5	0.75	1.5	0
0.5	0.25	1.25	1	1
0.	1	0.5	0.5	1

Output with stride 2

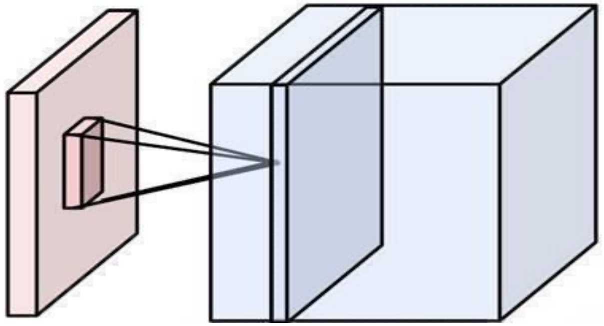
0.50	0.25	0.00
0.00	0.75	0.00
0.00	0.50	1.00

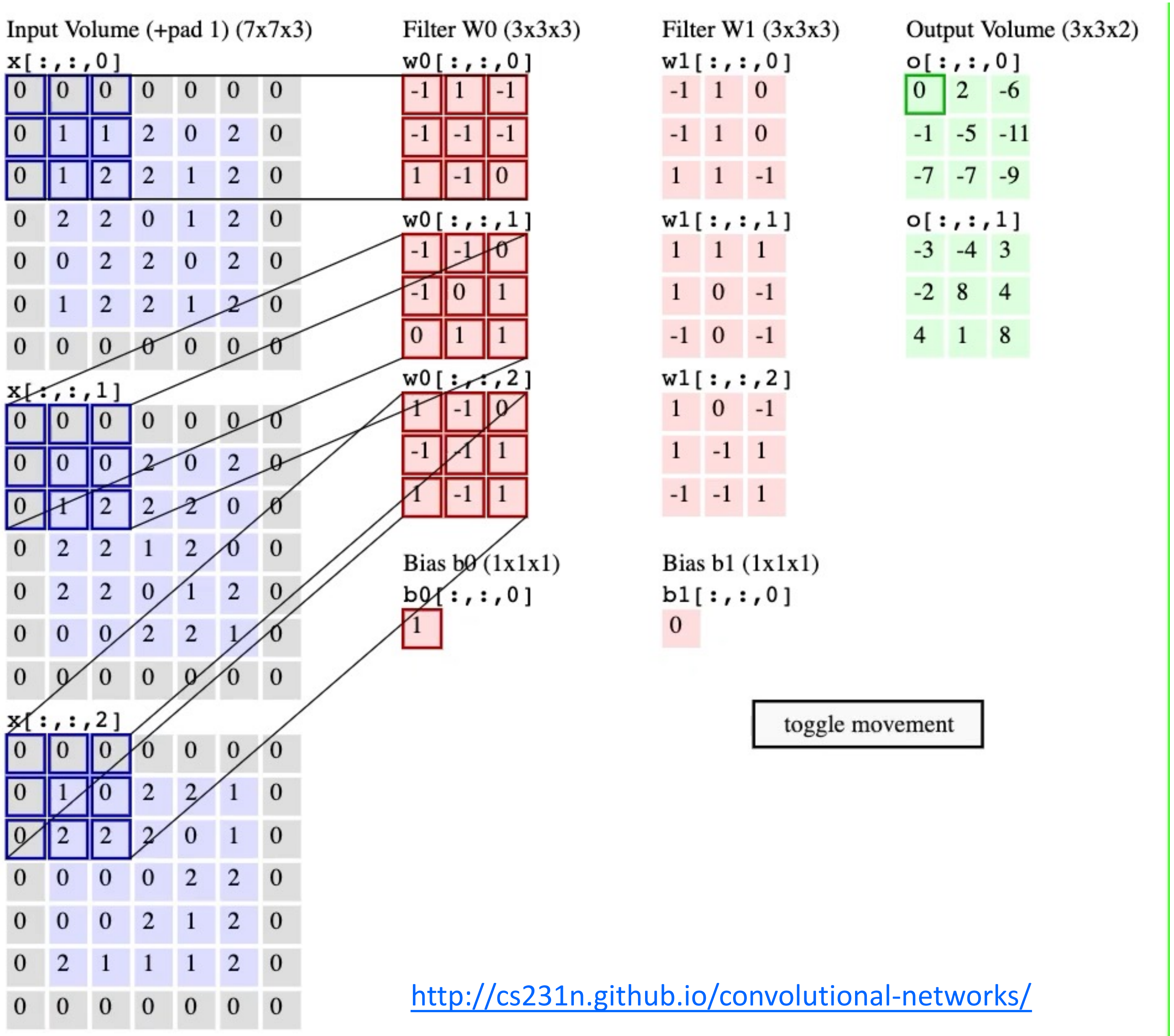
Can you spot the relationship between these 2 outputs?

The kernel size, amount of zero-padding, and stride, together determine the output spatial dimensions

https://medium.com/@ayeshmanthaperera/what-is-padding-in-cnns-71b21fb0dd7

Convolution Filter Bank Demo



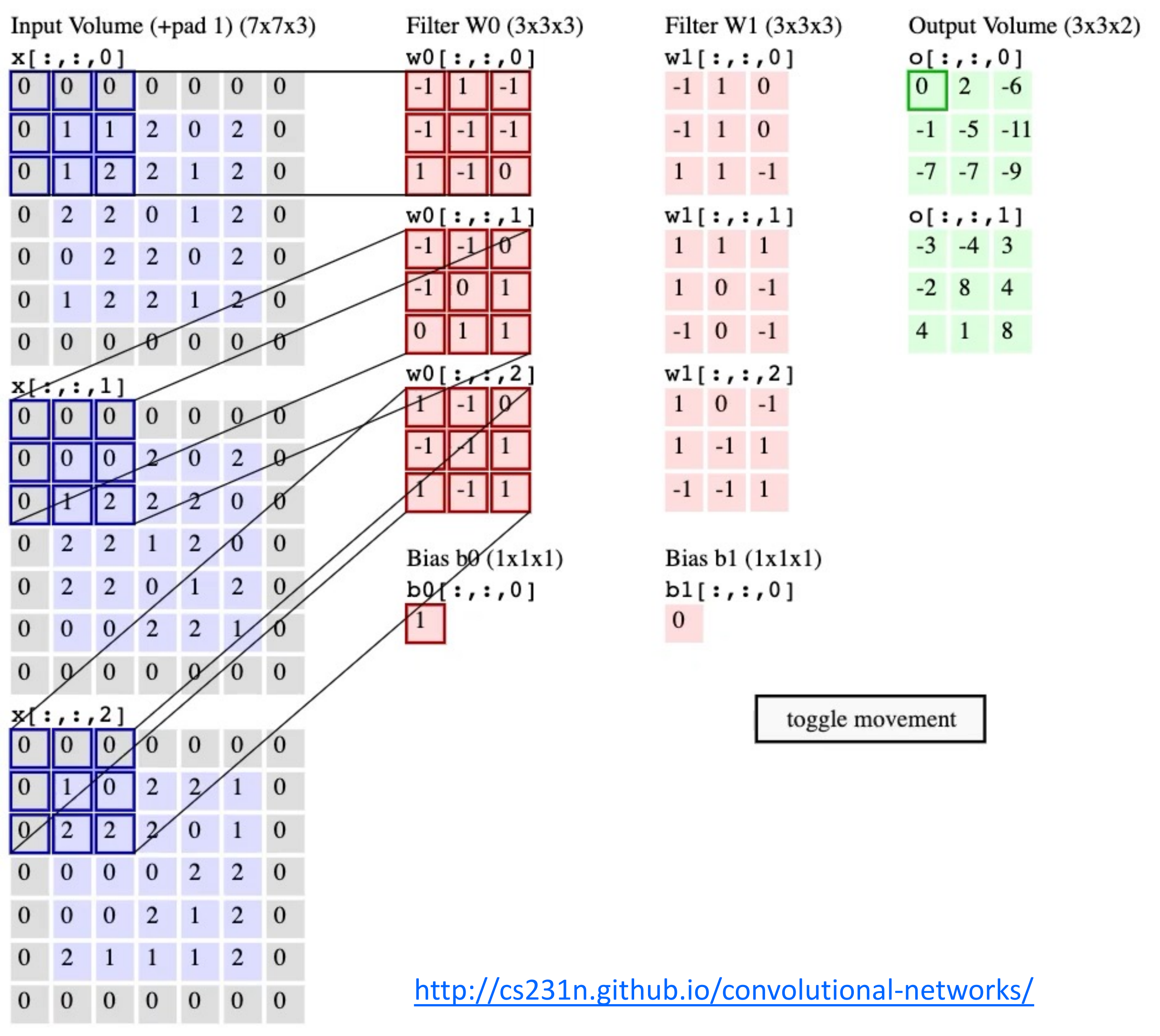


http://cs231n.github.io/convolutional-networks/

Convolution Filter Bank Demo

- Notes:
  - Multiple (3) input channels
    - Hence kernels with 3 channels
  - 2 kernels, hence 2 output channels
  - One bias parameter for each kernel
  - Stride 2, zero-padding 1
  - Kernel size 3x3

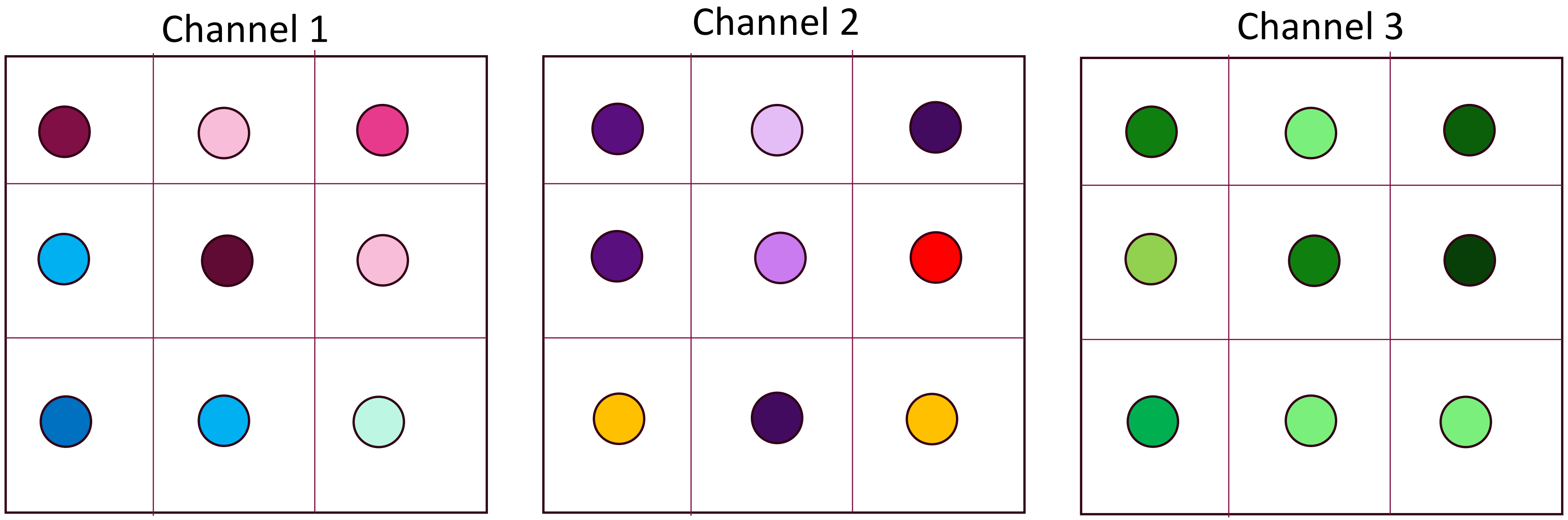
- Net #parameters in the bank:
  - $(3 \times 3 \times 3 + 1) \times 2 \; = \; 56$



http://cs231n.github.io/convolutional-networks/

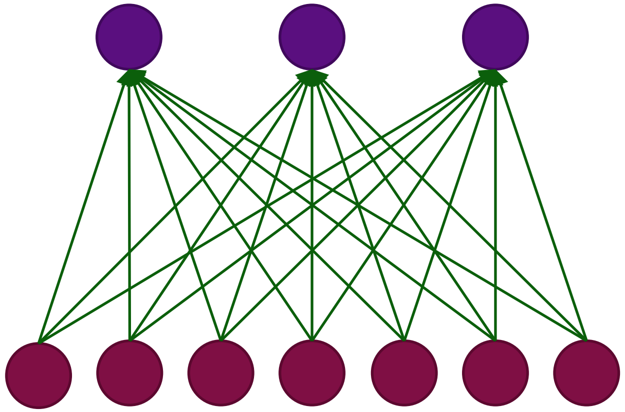
Channels as features in a position

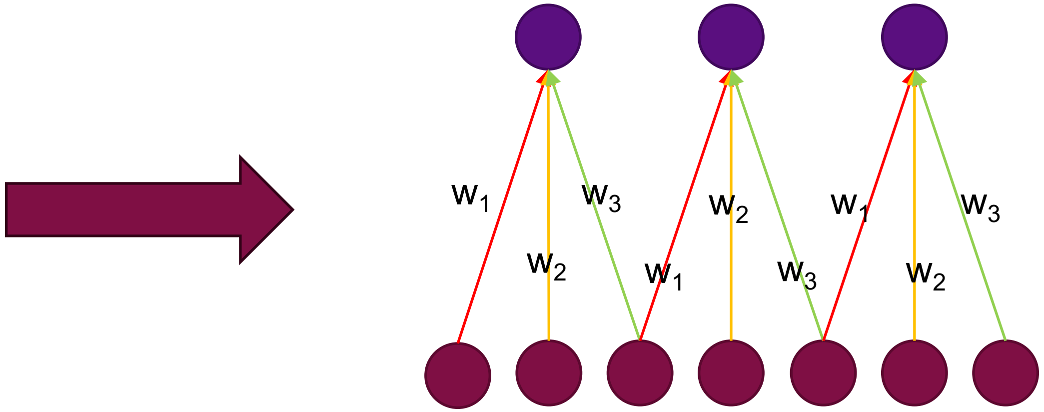
- Filter responses at position form a vector representing a region
- Successive filter responses can be though of mapping positions from input channel dimensional space to output channel dimensional space.



Is Convolution a Linear Operation?

- Recall





"Linear" or "fully connected layer"

$$Y = WX$$

Convolution

Convolution is just a linear layer with some weights set to 0, and some other weights "shared". So, yes, still linear!

Can we back-propagate through a convolution?

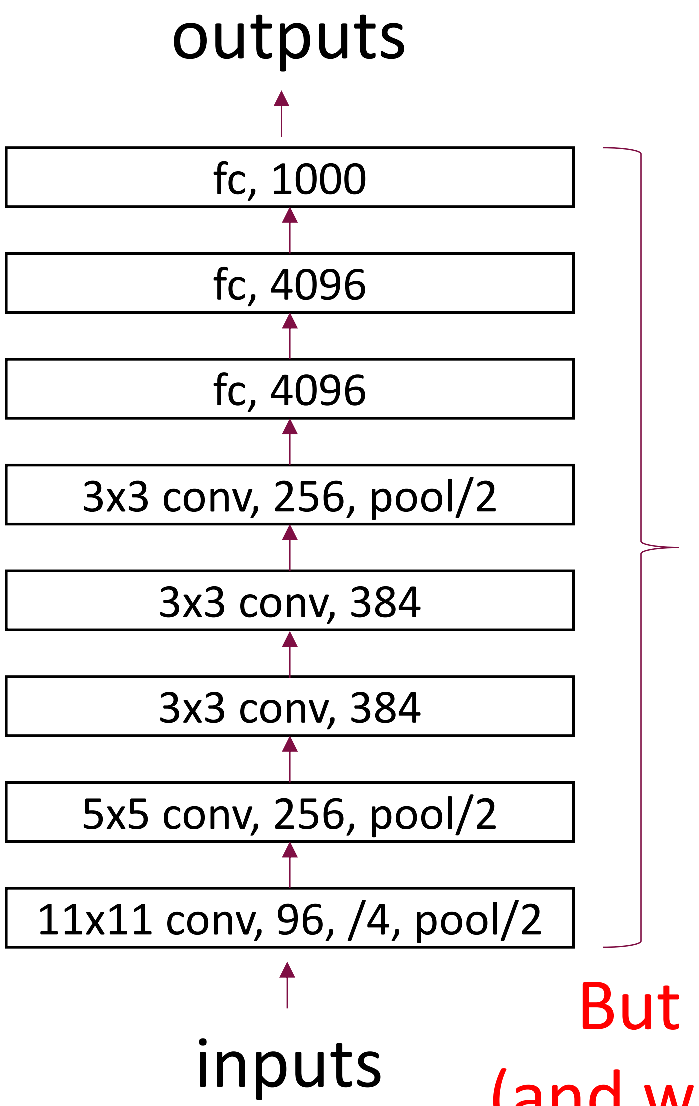
- Yes!
- A convolution is after all a special case of a linear operation $Y = WX$, with local connections and shared weights.
- Differentiable w.r.t. its inputs, as well as w.r.t. its weights.

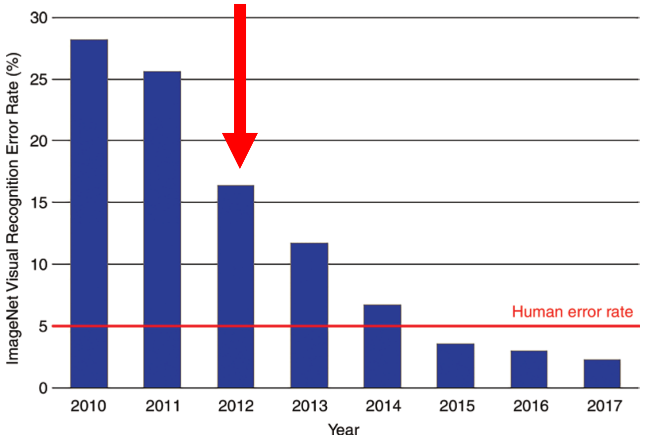
Typical accompaniments to convolutions inside CNNs

Pooling, Normalization, Activation Functions …

Convolutions inside a neural network

Example CNN architecture: The 2012 AlexNet!





"8 layers", really "8 layer blocks"

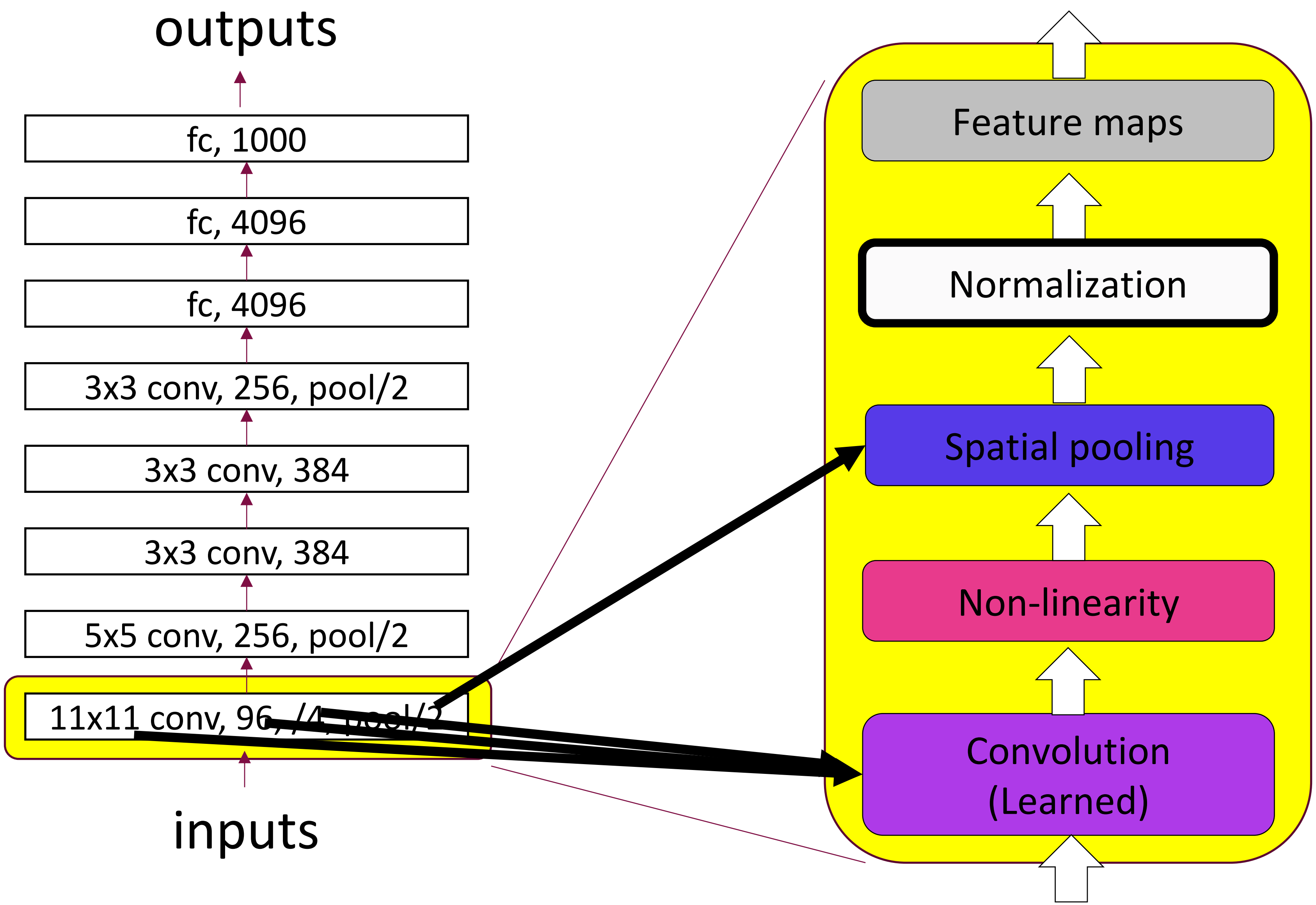
"5 convolution blocks" followed by 3 fully connected layers

More on AlexNet soon!

But first, what is a "convolution block"?
(and what are all the numbers in each layer?)

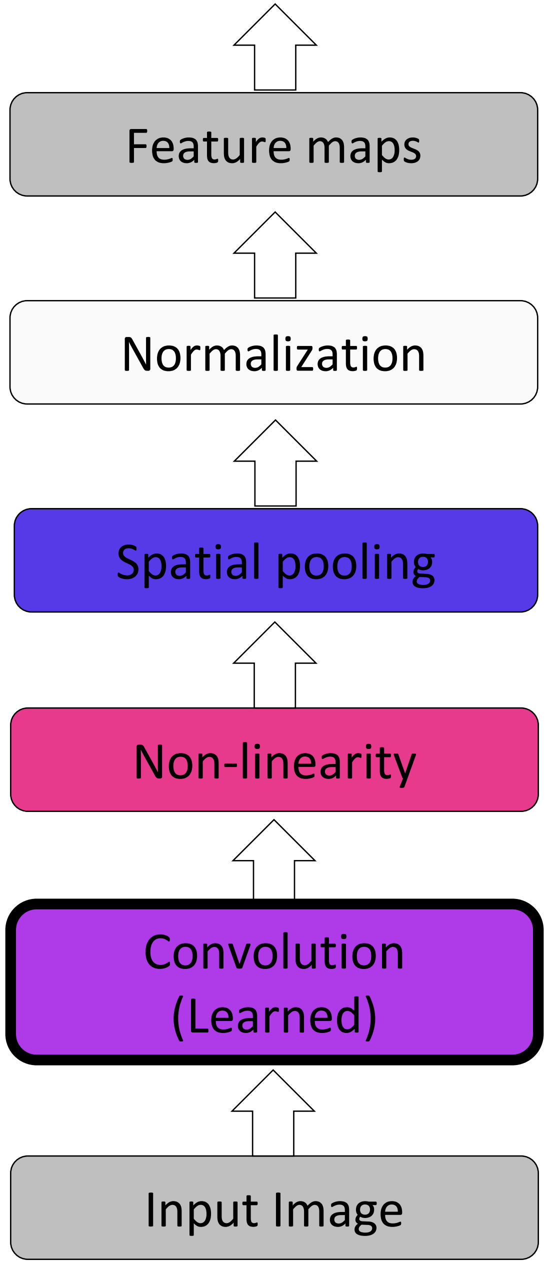
Typical accompaniments to “convolution layers”

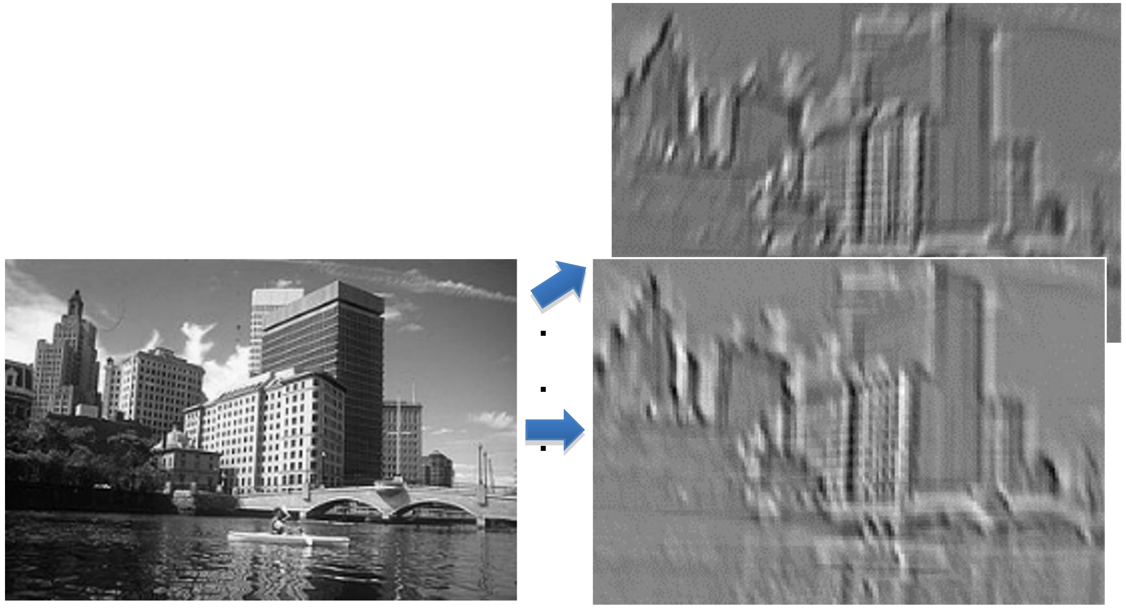
Example CNN architecture



graphic credit: S. Lazebnik

Convolve → activation function → pool → normalize

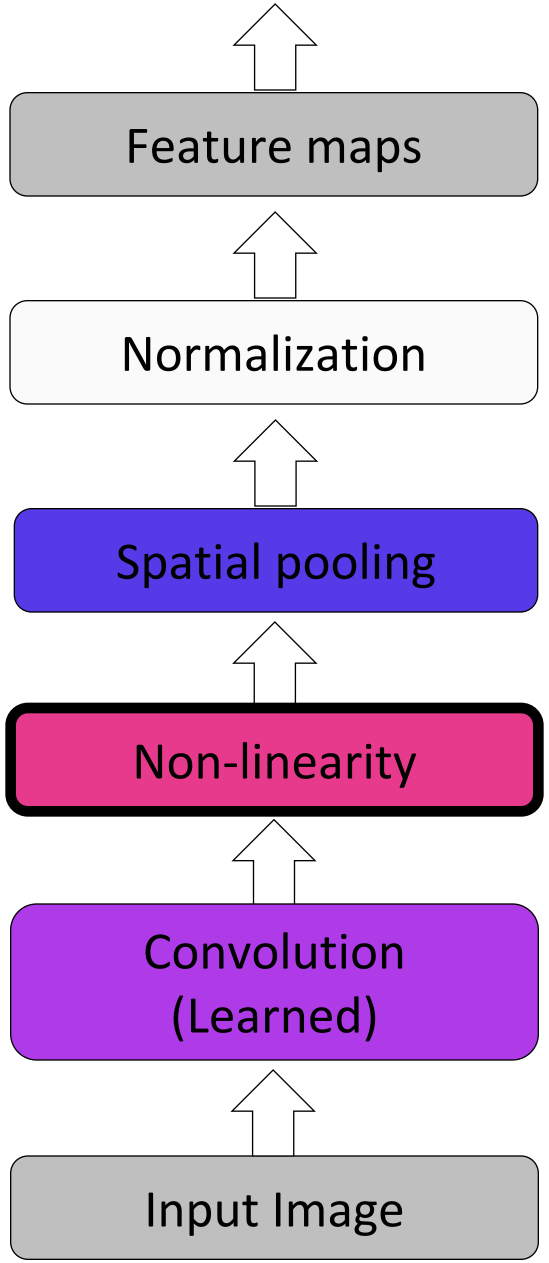




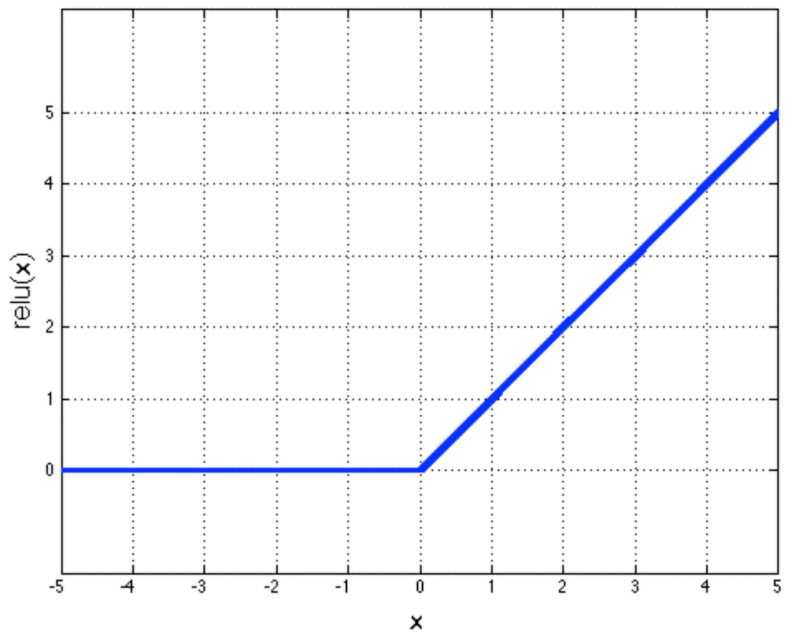
Input

Feature Map

Convolve → activation function → pool → normalize

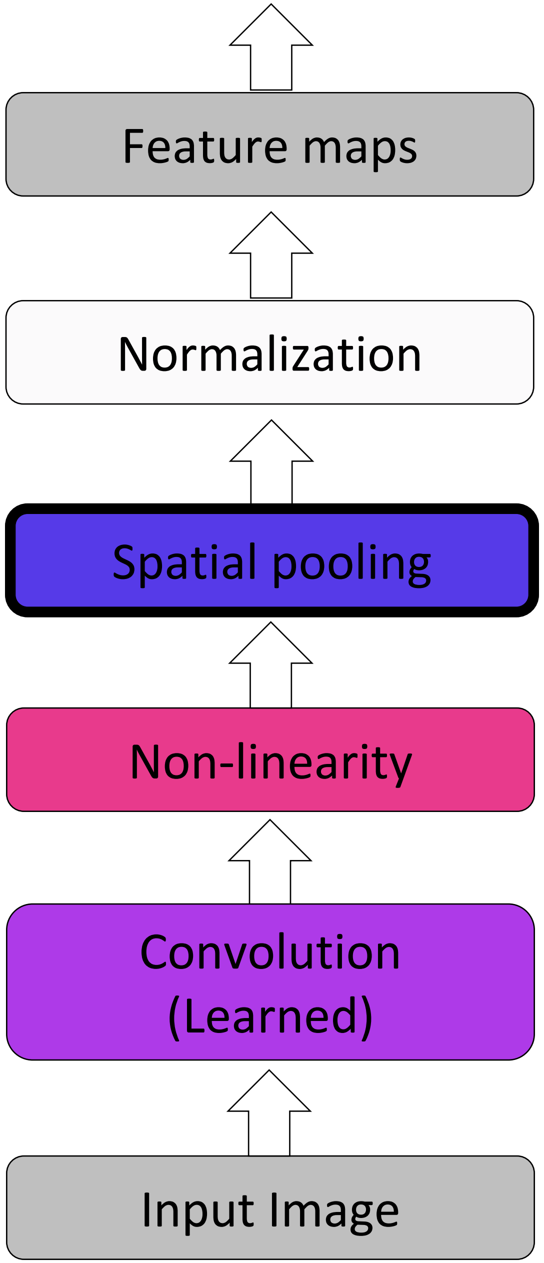


Rectified Linear Unit (ReLU)

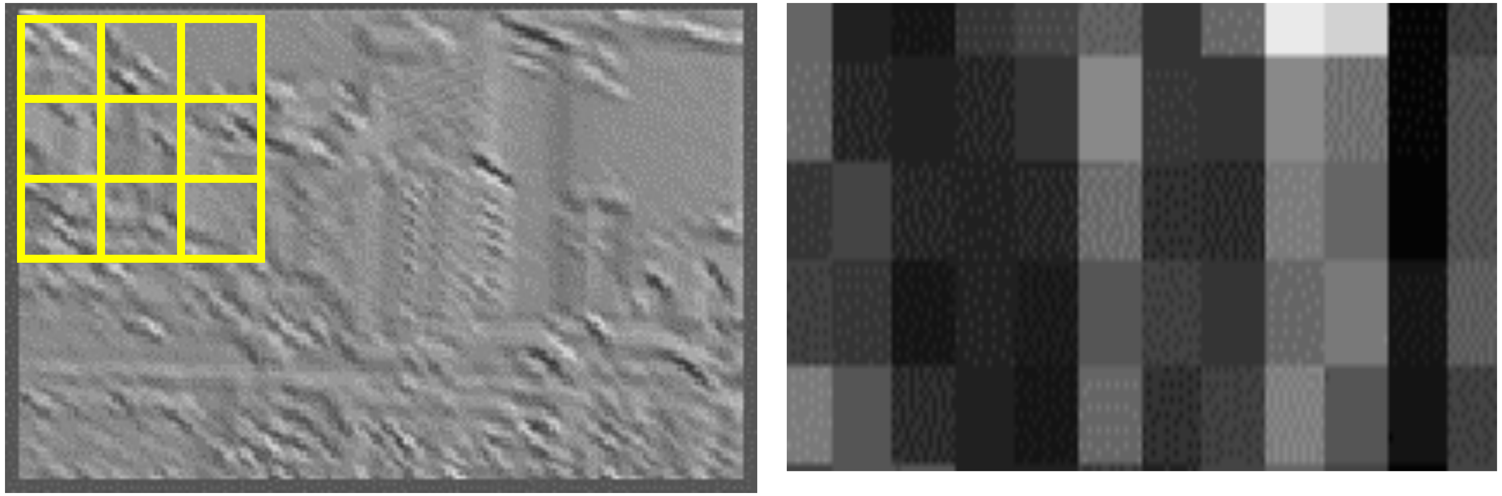


slide credit: S. Lazebnik

Convolve → activation function → pool → normalize



Max pooling



Max-pooling: *translation invariance.*

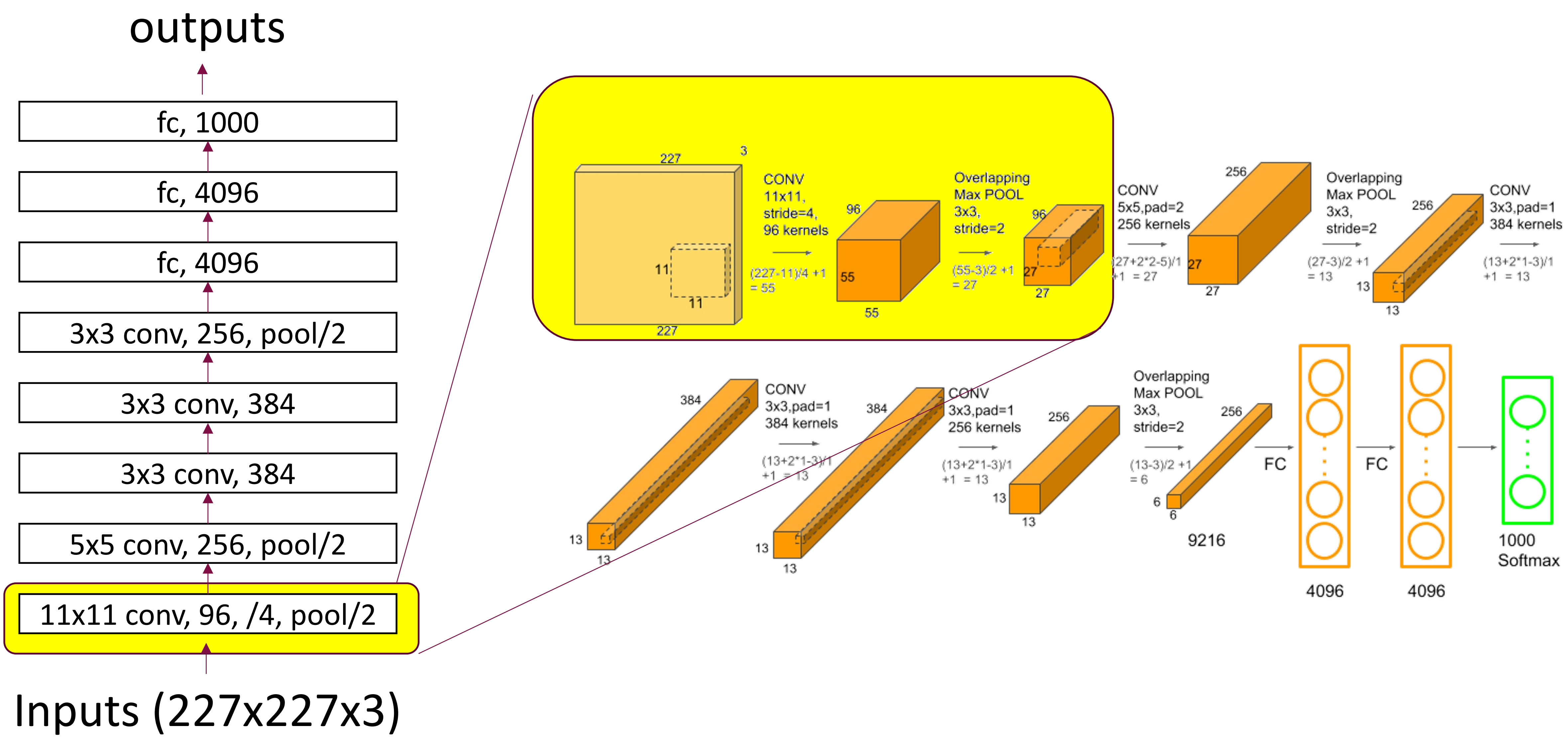
Often applied with a stride.

No learnable parameters.

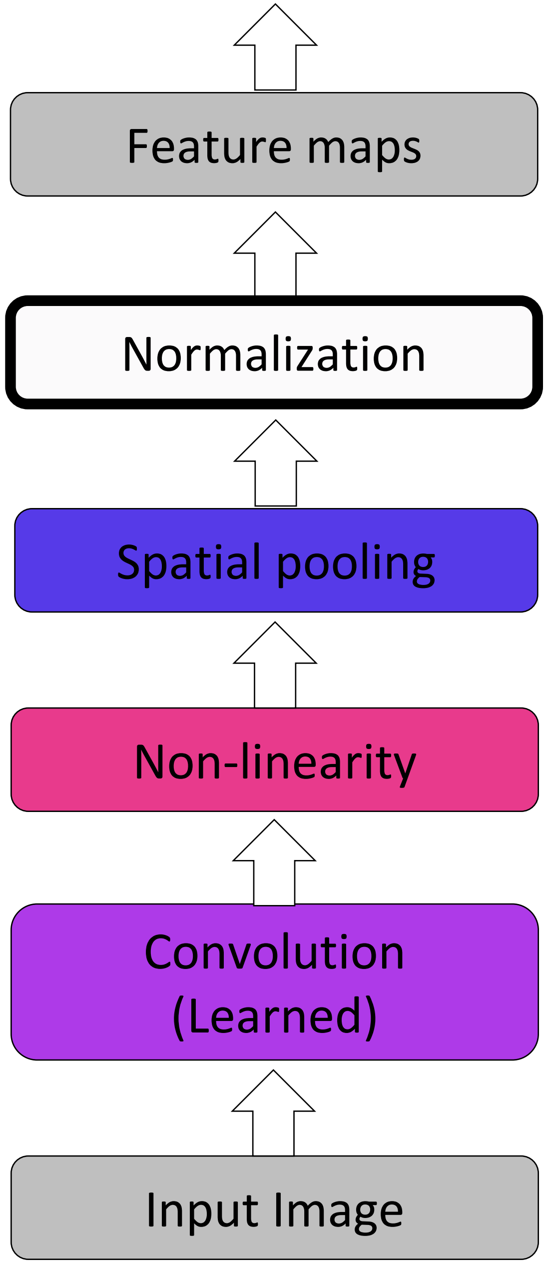
Convolution provides equivariance to shift

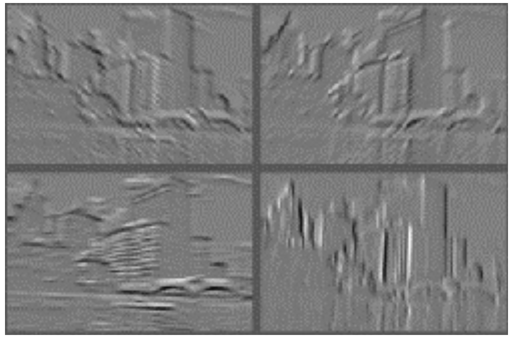
Pooling provides invariance to shift

Back to AlexNet

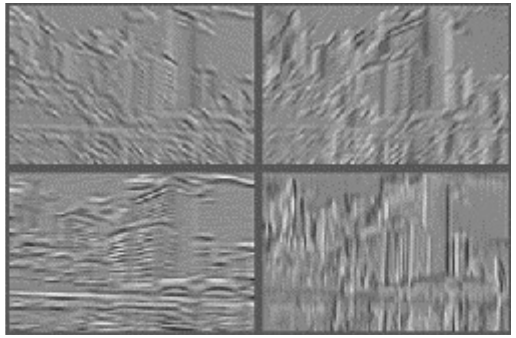


Convolve → activation function → pool → normalize





Feature Maps



Feature Maps
After Contrast
Normalization

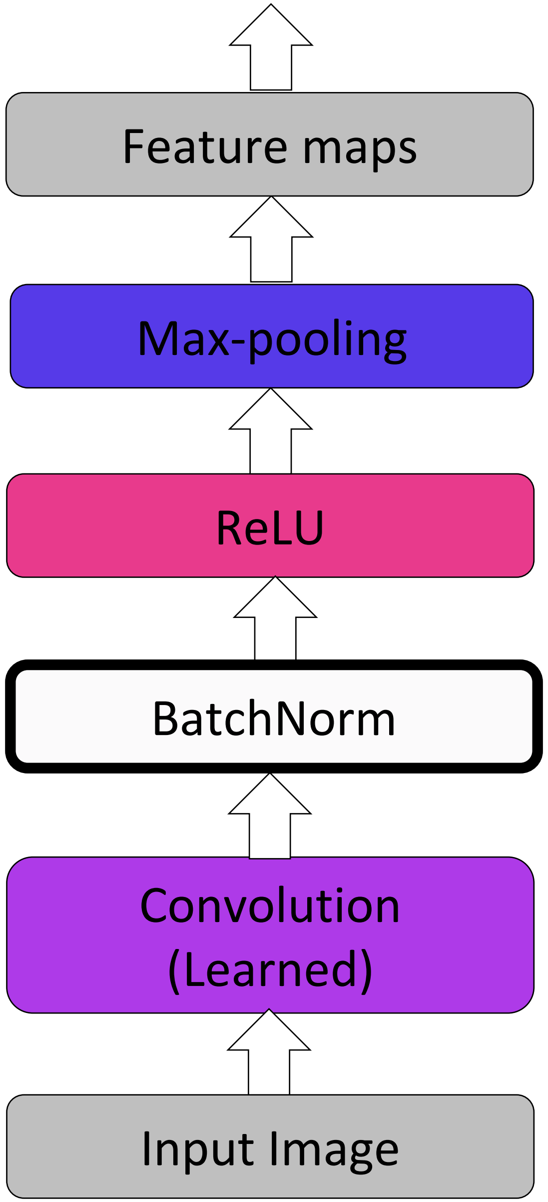
“Contrast normalization” highlights areas where the feature maps change.

More of a historical note at this point than anything else. Used to be a standard component in neural networks. Not used in modern architectures.

graphic credit: S. Lazebnik

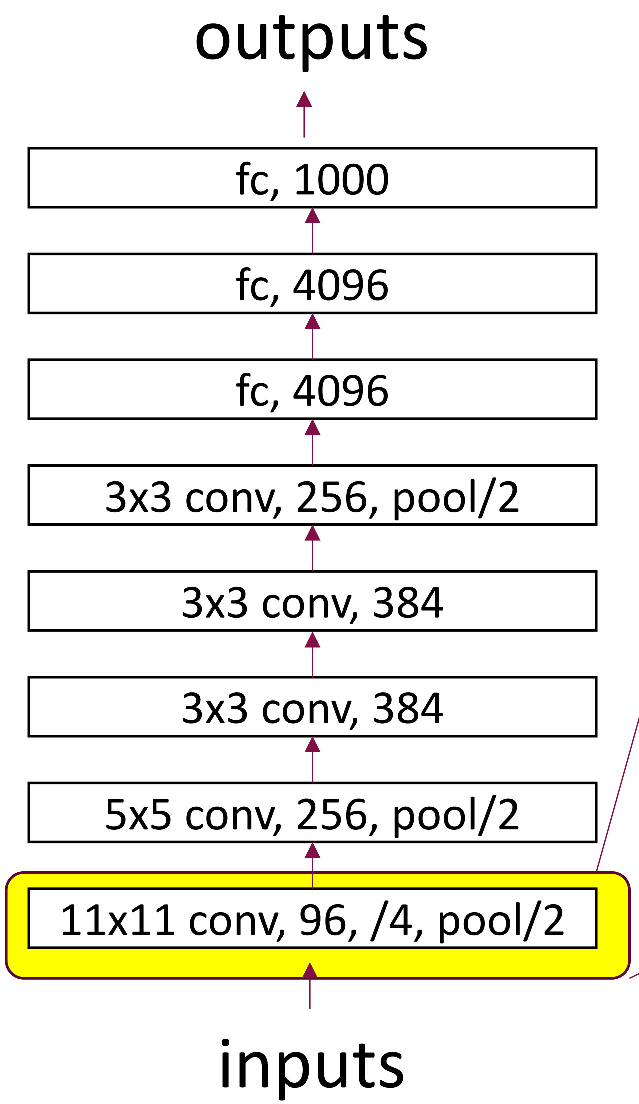
Modern variants

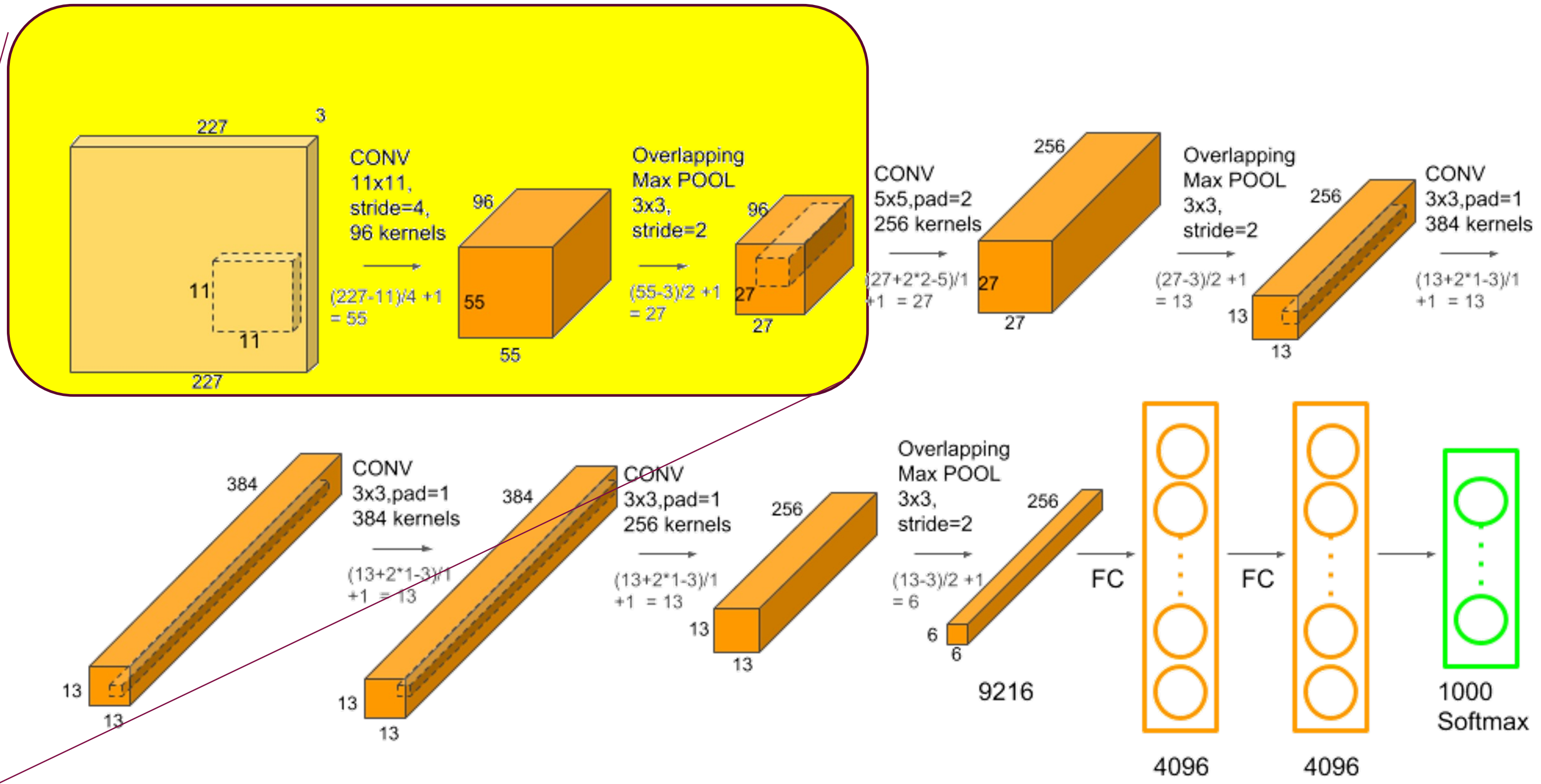
- BatchNorm is very commonly used.
- Most common variants of a convolutional block:
  - Conv-BatchNorm-Maxpool-ReLU, or
  - Conv-BatchNorm-ReLU-Maxpool
- Sometimes even no Maxpool, to keep feature map spatial dimensions large. Often in very deep networks.



Often, when people say “convolution layer”, it is implicit that they mean a full convolutional block with various layers following the actual convolutional layer

Back to AlexNet

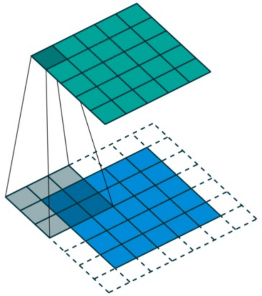




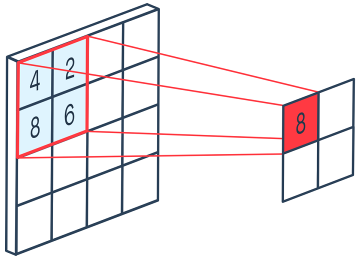
Exercise: work through the rest of the dimensions in this network!

Summary: Image-specific operations in neural nets

- Machinery to convert image matrices into vectors of reasonable dimensions, retaining useful location associations. Two main workhorses:
  - Convolution layers – Location-independent processing. Shift equivariance.
    - Convolutions produce “image”-like feature maps, which retain associations with input pixels.
  - Pooling layers – Binning to make outputs insensitive to translation and reduce dimensionality. Shift invariance.
    - A dog is a dog even if its image is shifted by a few pixels.



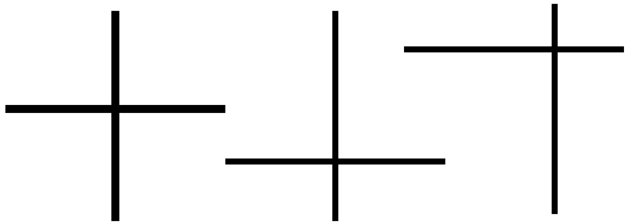
Convolution layers



Pooling layers

Convolution Filter Banks As Pattern Detectors

A Convolution Exercise



Suppose we want to find out whether the following image depicts Cartesian axes.

$$\begin{bmatrix} 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -2 \end{bmatrix}$$

As a step towards this, we convolve the image with two filters (no padding, stride of 1).

$$\begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix}, \begin{bmatrix} -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\ 1 & 1 & 1 \\ -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix}$$

Compute the output by hand.

A Convolution Exercise

$$\begin{bmatrix} 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -2 \end{bmatrix} \qquad \begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix}$$

A Convolution Exercise

$$\boxed{\begin{matrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{matrix}} \quad \begin{bmatrix} 0 & 1 & 0 & \\ 0 & 1 & 0 & \\ 1 & 1 & 1 & \\ & & & 2 \end{bmatrix} \quad \begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} \Rightarrow \begin{bmatrix} 2 & \cdot \\ \cdot & \cdot \end{bmatrix}$$

$$\left(0 \times \frac{-1}{2}\right) + (1 \times 1) + \left(0 \times \frac{-1}{2}\right)$$
$$\left(0 \times \frac{-1}{2}\right) + (1 \times 1) + \left(0 \times \frac{-1}{2}\right)$$
$$\left(0 \times \frac{-1}{2}\right) + (1 \times 1) + \left(0 \times \frac{-1}{2}\right) = 2$$

A Convolution Exercise

$$\begin{bmatrix} 1 & 0 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad \begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} \Rightarrow \begin{bmatrix} 2 & -2 \\ \cdot & \cdot \end{bmatrix}$$

A Convolution Exercise

$$\begin{bmatrix} & & & \\ 0 & 1 & 0 & \\ 1 & 1 & 1 & \\ 0 & -2 & 0 & 2 \end{bmatrix} \quad \begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} \Rightarrow \begin{bmatrix} 2 & -2 \\ -1 & \cdot \end{bmatrix}$$

A Convolution Exercise

$$\begin{bmatrix} 0 & & & \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -2 \end{bmatrix} \quad \begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} \Rightarrow \begin{bmatrix} 2 & -2 \\ -1 & 1 \end{bmatrix}$$

Convolution Exercise Solution

$$\begin{bmatrix} 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -2 \end{bmatrix}$$

$$\begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} \longrightarrow \begin{bmatrix} 2 & -2 \\ -1 & 1 \end{bmatrix}$$

$$\begin{bmatrix} -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\ 1 & 1 & 1 \\ -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix} \longrightarrow \begin{bmatrix} -1 & -\frac{1}{2} \\ \frac{7}{2} & 4 \end{bmatrix}$$

Grayscale image

Filters

Output of filters

Convolutional Exercise Solution

Next, what happens if we run max-pooling on the filter outputs?

Grayscale image

$$\begin{bmatrix} 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -2 \end{bmatrix}$$

Filters

$$\begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} \qquad \begin{bmatrix} -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\ 1 & 1 & 1 \\ -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix}$$

Output of filters

$$\begin{bmatrix} 2 & -2 \\ -1 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & -\frac{1}{2} \\ \frac{7}{2} & 4 \end{bmatrix}$$

Output of max-pool

$$\begin{bmatrix} 2 \\ 4 \end{bmatrix}$$

Pretty clear vertical line

and

Pretty clear horiz line

Example architectures

Architecture Design

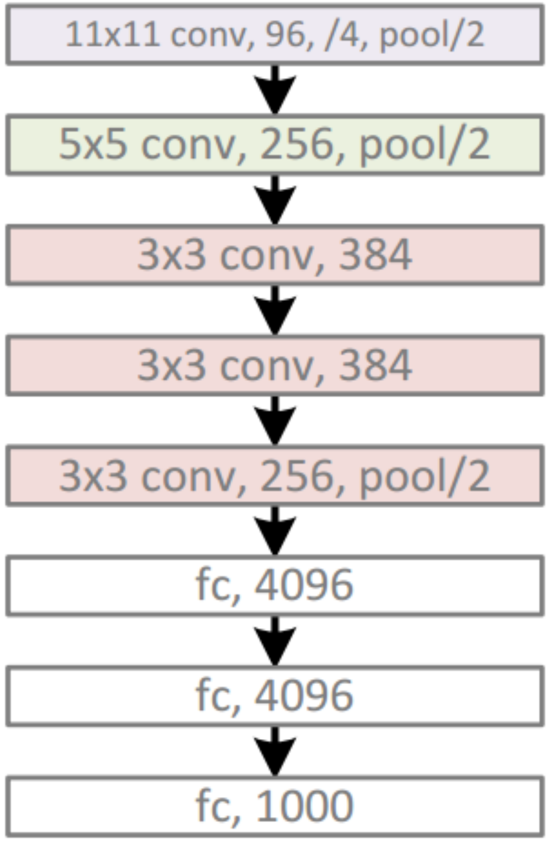
- Compose layers until you have a feature representation of the input you want to use to do linear prediction for whatever problem you have in mind (e.g., classification)
- Exact architectural choices are nearly always empirically driven
  - Lots of trial and error
  - Many choices may not be fully justified but work well enough that we accept them.
- Many choices we have learned work better over time, but these choices may not be good for all settings
- Proposing new architecture is very risky!
  - No guarantee it will optimize well with current tools

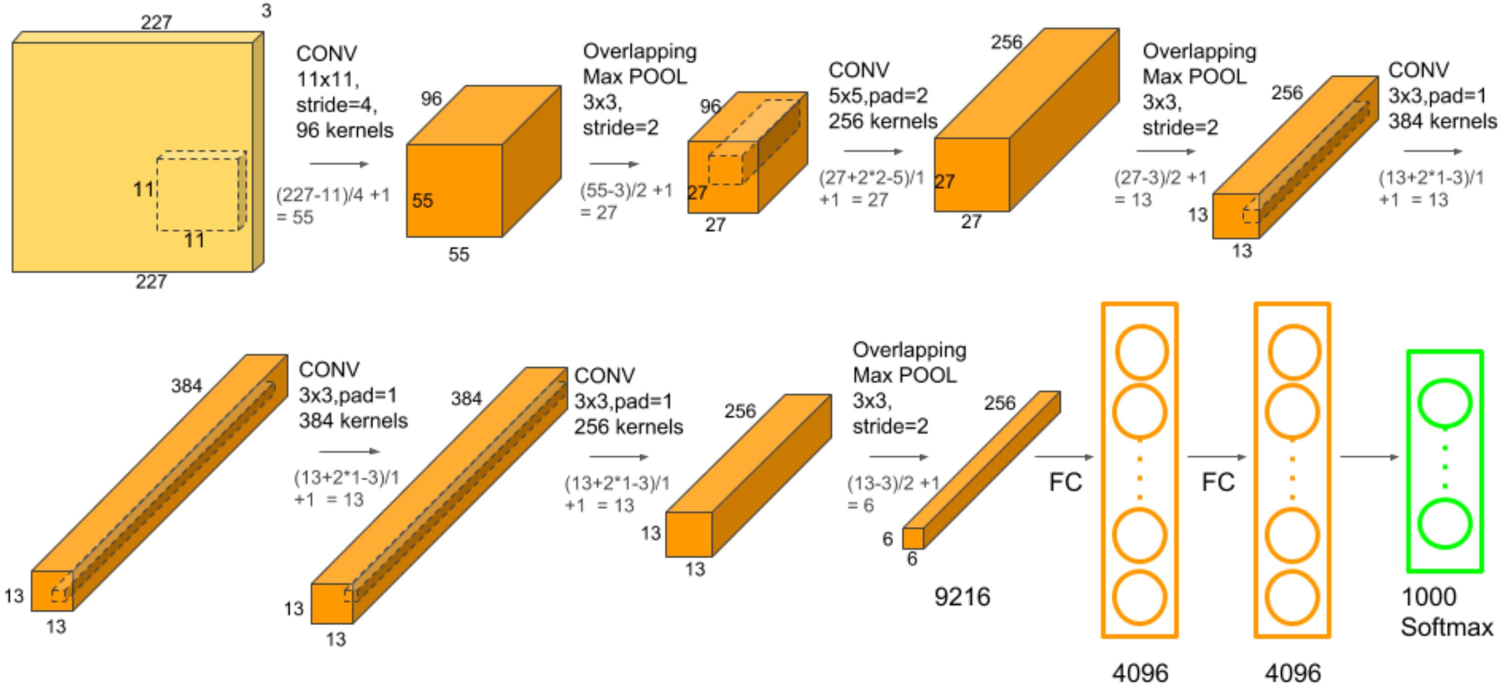
Example architectures

AlexNet, 8 layers
(ILSVRC 2012)

~60M params

“Standard” scheme
[Conv-ReLU-pool?]
[Conv-ReLU-pool?]
[Conv-ReLU-pool?]
…
Fully connected
…
Fully connected





Q: Where are most of the 60M parameters?

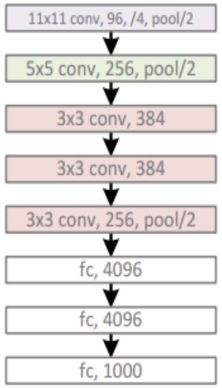
Source: MSRA slides at ILSVRC15

https://learnopencv.com/understanding-alexnet/

Example architectures

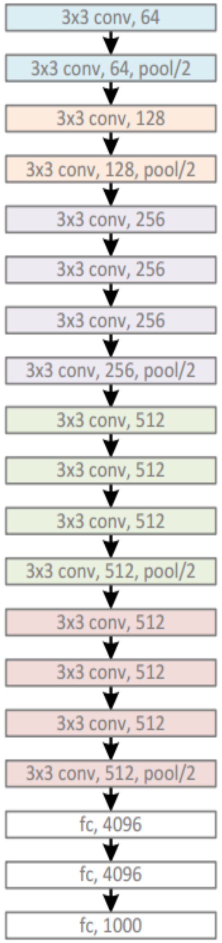
AlexNet, 8 layers
(ILSVRC 2012)

~60M params



VGG, 19 layers
(ILSVRC 2014)

~140M params



“Standard” scheme
[Conv-ReLU-pool?]
[Conv-ReLU-pool?]
[Conv-ReLU-pool?]
…
Fully connected
…
Fully connected

ICCV15

[Source: MSRA slides at ILSVRC15]

Example architectures

AlexNet, 8 layers
(ILSVRC 2012)
~60M params

VGG, 19 layers
(ILSVRC 2014)
~140M params

ResNet, 152 layers
(ILSVRC 2015)

Less computation in forward pass than VGGNet!

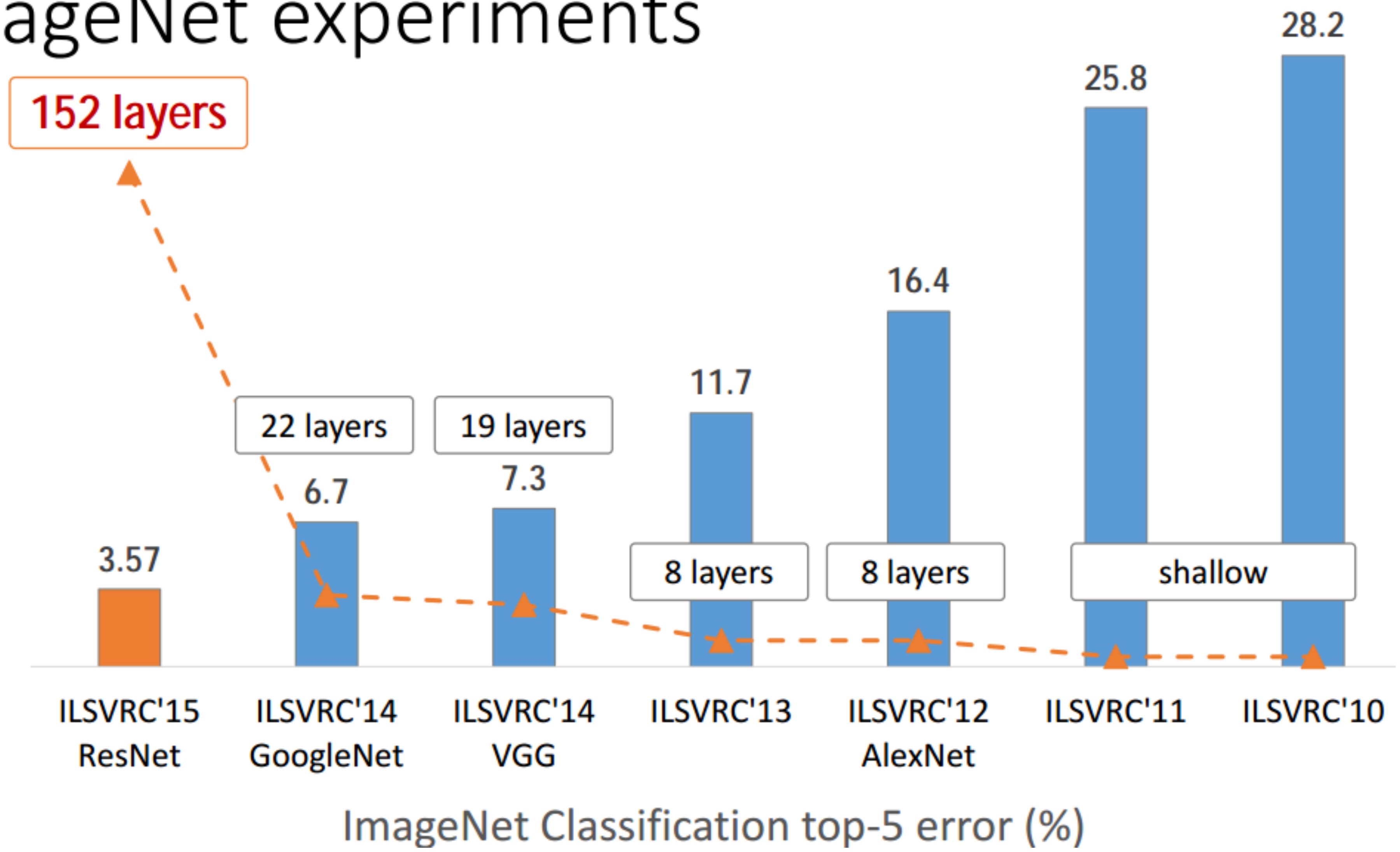
Back to 60M params

GoogleNet, 22 layers
(ILSVRC 2014)
~5M params

ICCV15

[Source: MSRA slides at ILSVRC15]

ImageNet experiments



[Source: MSRA slides at ILSVRC15]()

Residual Network

- Q: Why are deeper networks not always better?
- Hypothesis 1: Because of overfitting.

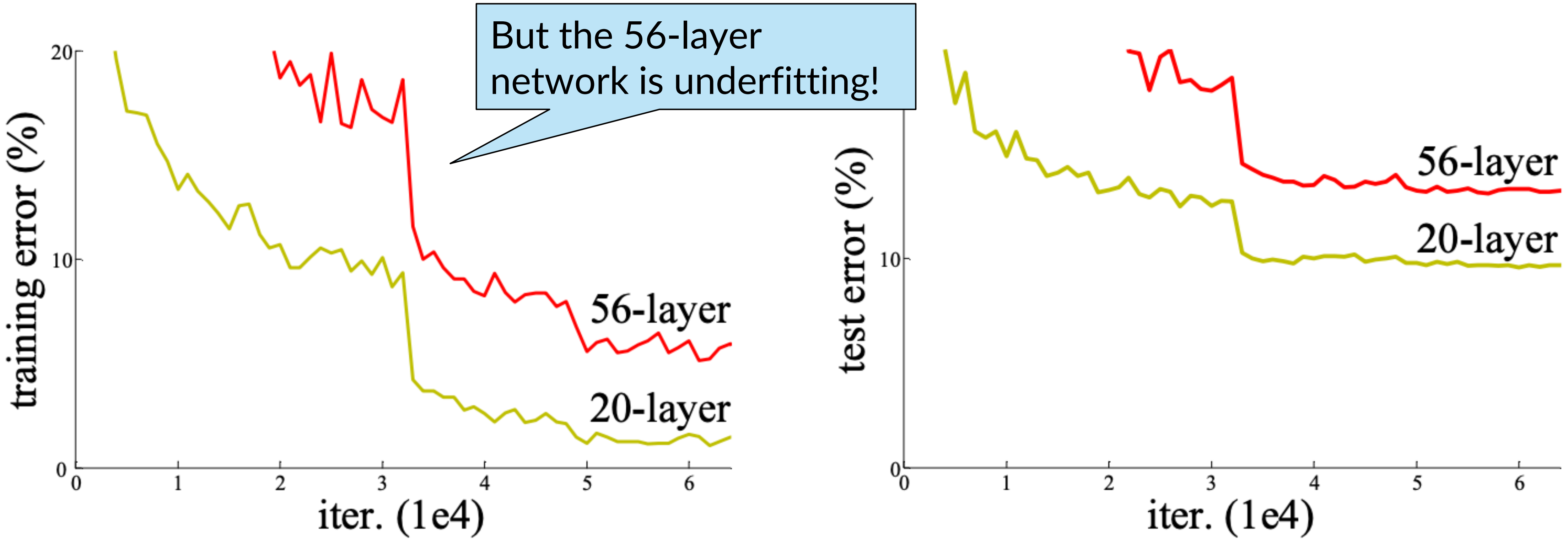


Image credit: He et al, Residual Nets, 2015

Residual Network

- Q: Why are deeper networks not always better?
- Hypothesis 2: Because of optimization issues with deeper networks.

Idea: *Skip connections* that facilitate more direct feedback from the loss to the weights.

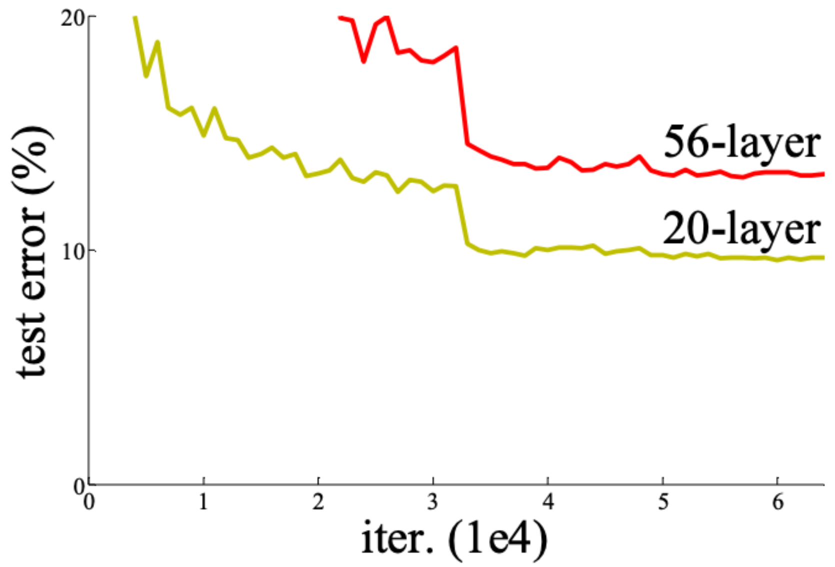


Image credit: He et al, Residual Nets, 2015

Residual Network

Two views of residual connections:

1. Providing shortcuts to gradients on the backward pass.
2. Allowing each “residual block” to fit the residual error function $F(x) = H(x) - x$.

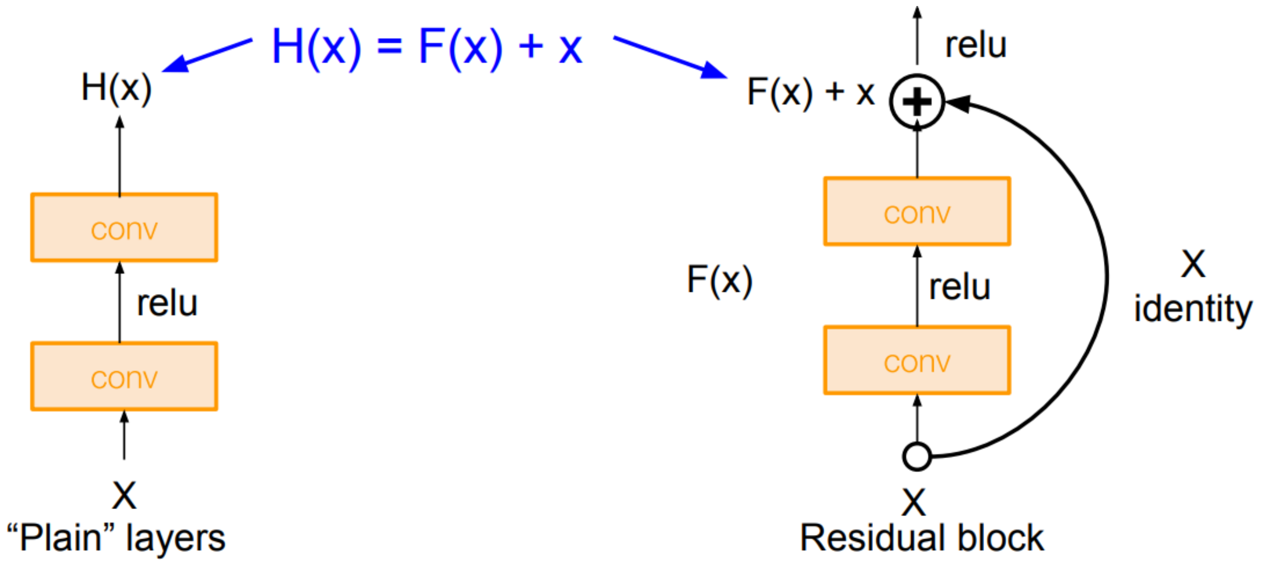
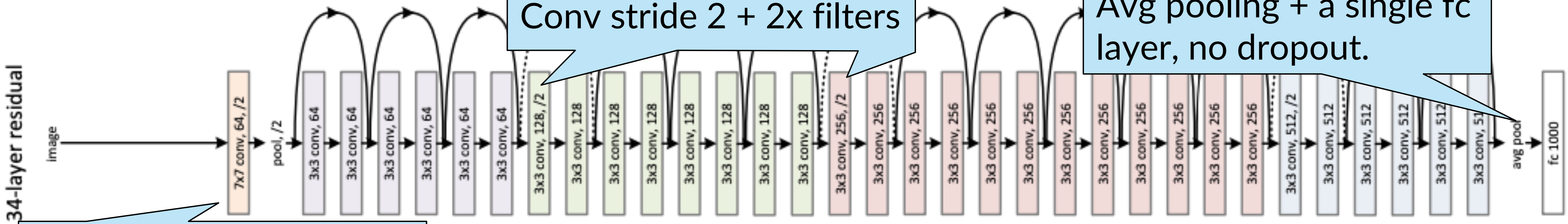


Image credit: Fei-Fei Li, Justin Johnson, Serena Yeung

Residual Network

- Stack lots of residual blocks.
- Zero-padded stride-1 3x3 convolutions + no max-pooling ⇒ maintains feature map size to build very deep nets.
- Reduce dimensions through stride 2 once every K blocks, increase #channels.



Conv stride 2 + 2x filters

Avg pooling + a single fc layer, no dropout.

Larger conv kernel before residual blocks.

Image credit: He et al, Residual Nets, 2015

Residual block designs

- For deeper networks, improve efficiency through 1x1 convolutions.

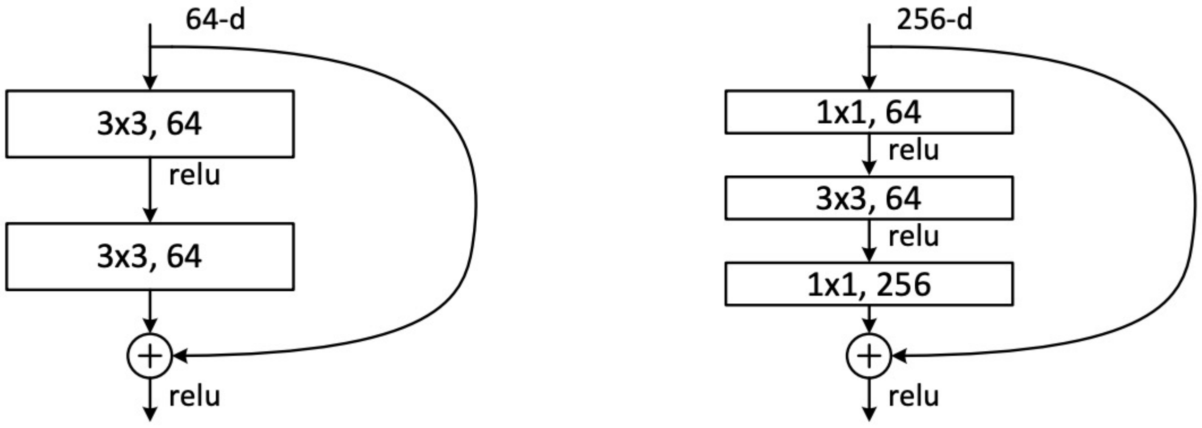


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.

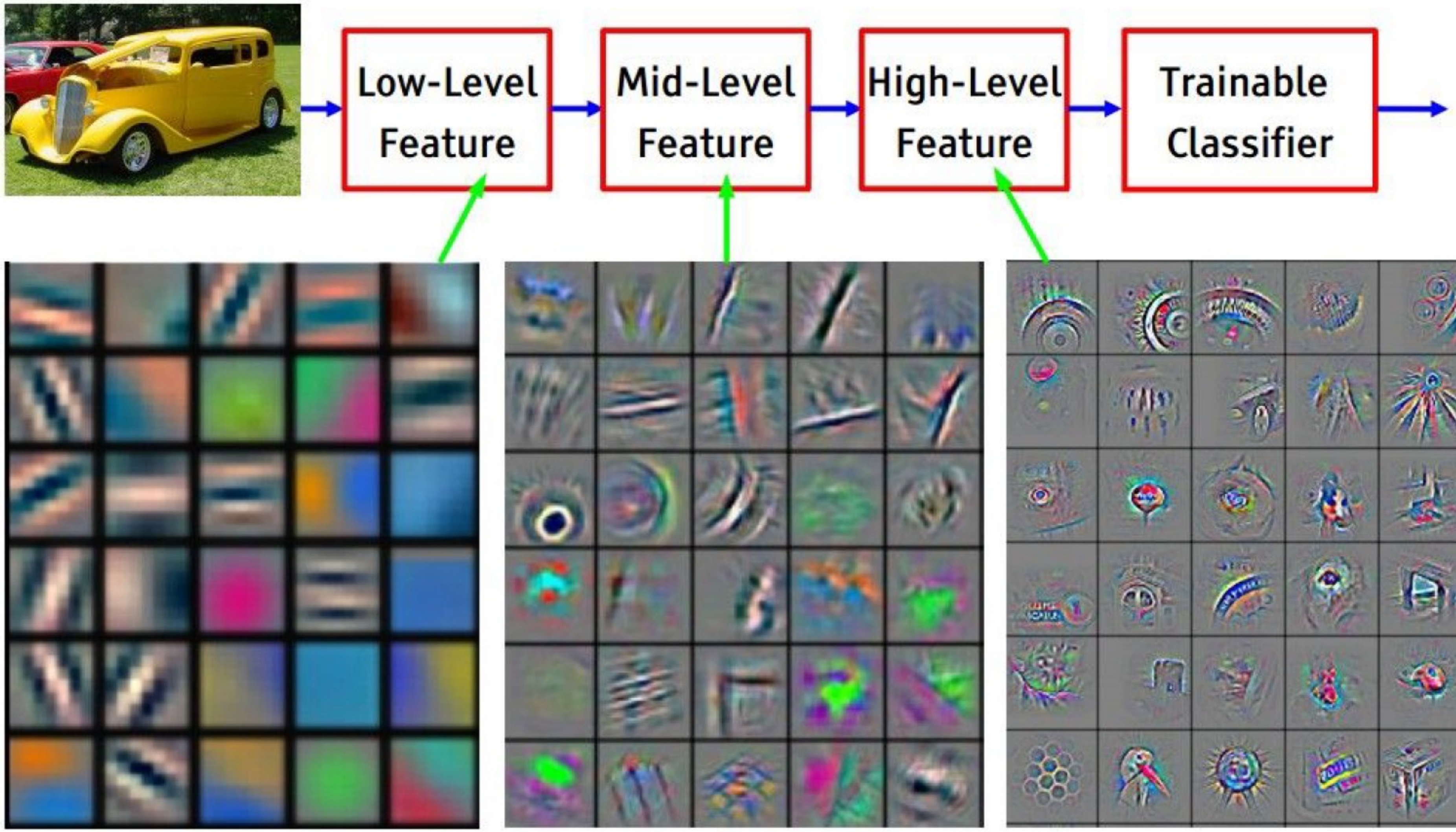
Many other improvements since 2015! E.g. "ResNeXt", "Identity Mappings", "ConvNeXt" etc.

Image credit: He et al, Residual Nets, 2015

What do CNNs learn?

Visualizing and Understanding CNNs

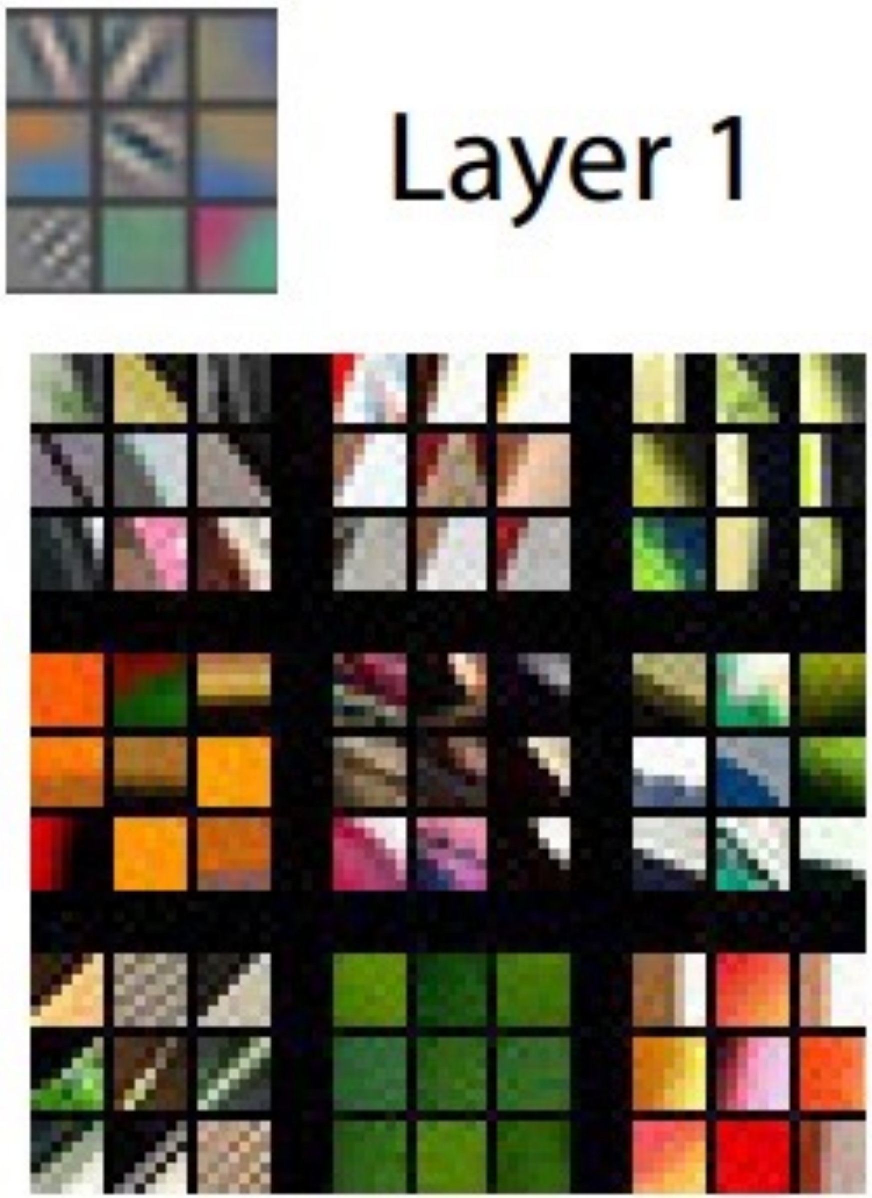
Feature visualization



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Slide credit: Yann LeCun

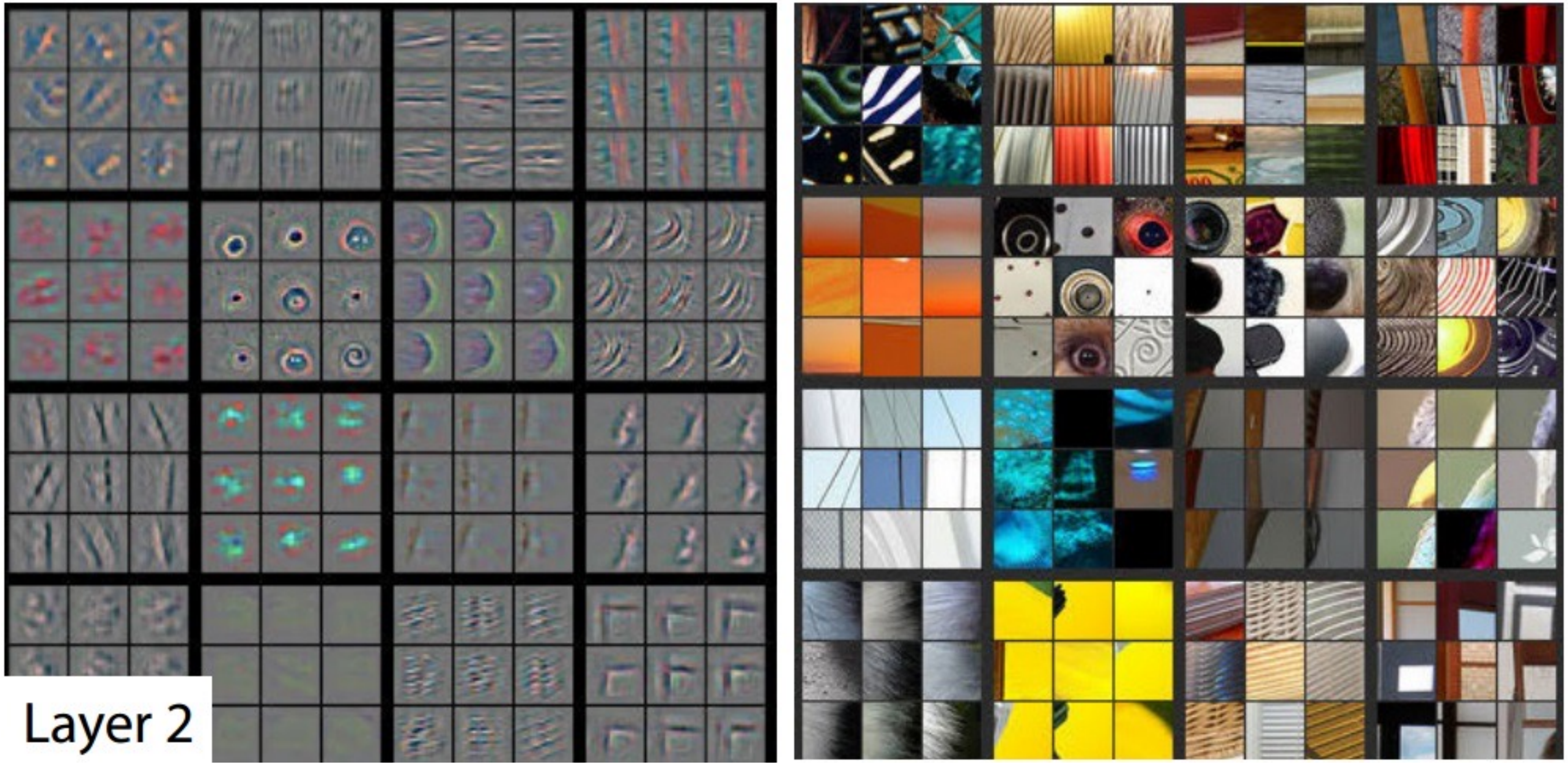
Layer 1



Slide credit: Jia-Bin Huang

Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

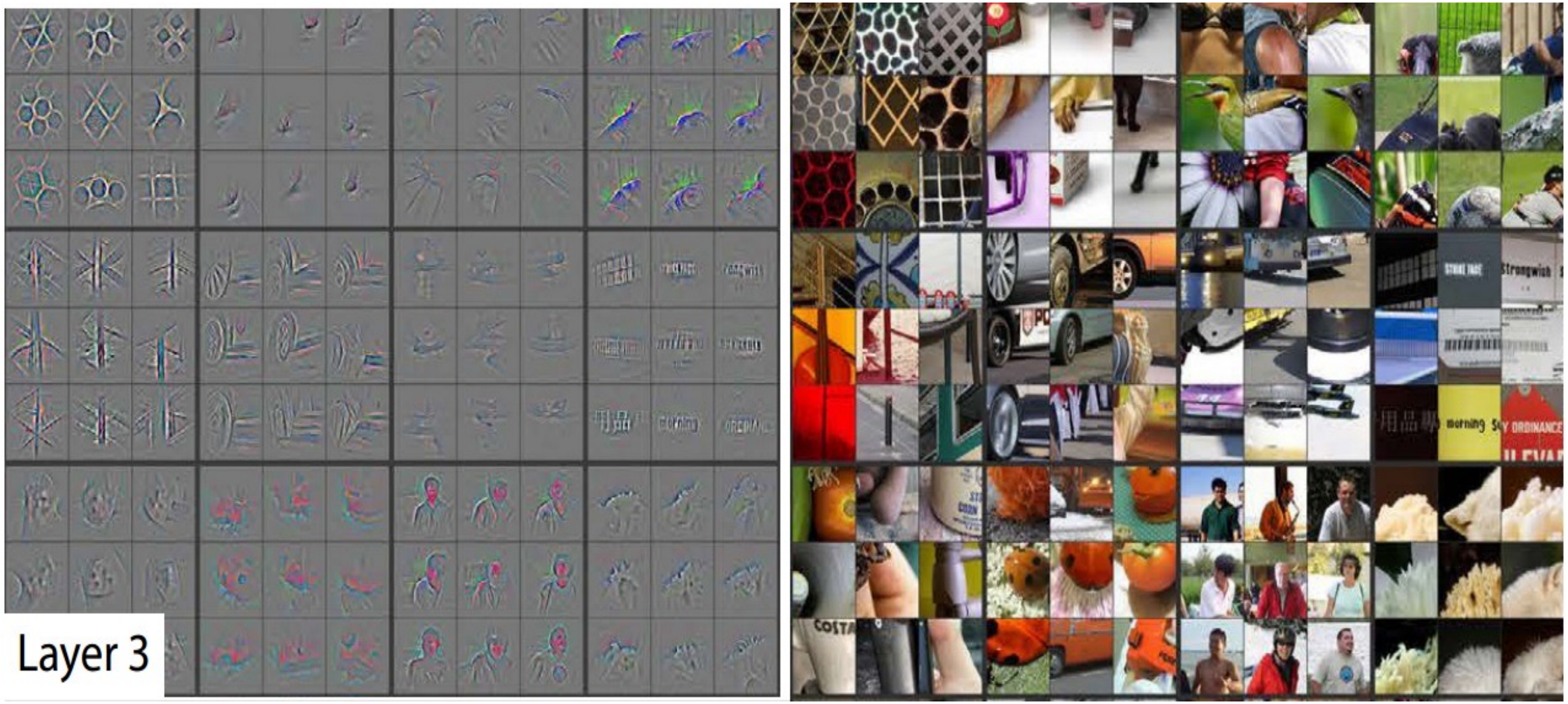
Layer 2



Slide credit: Jia-Bin Huang

Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

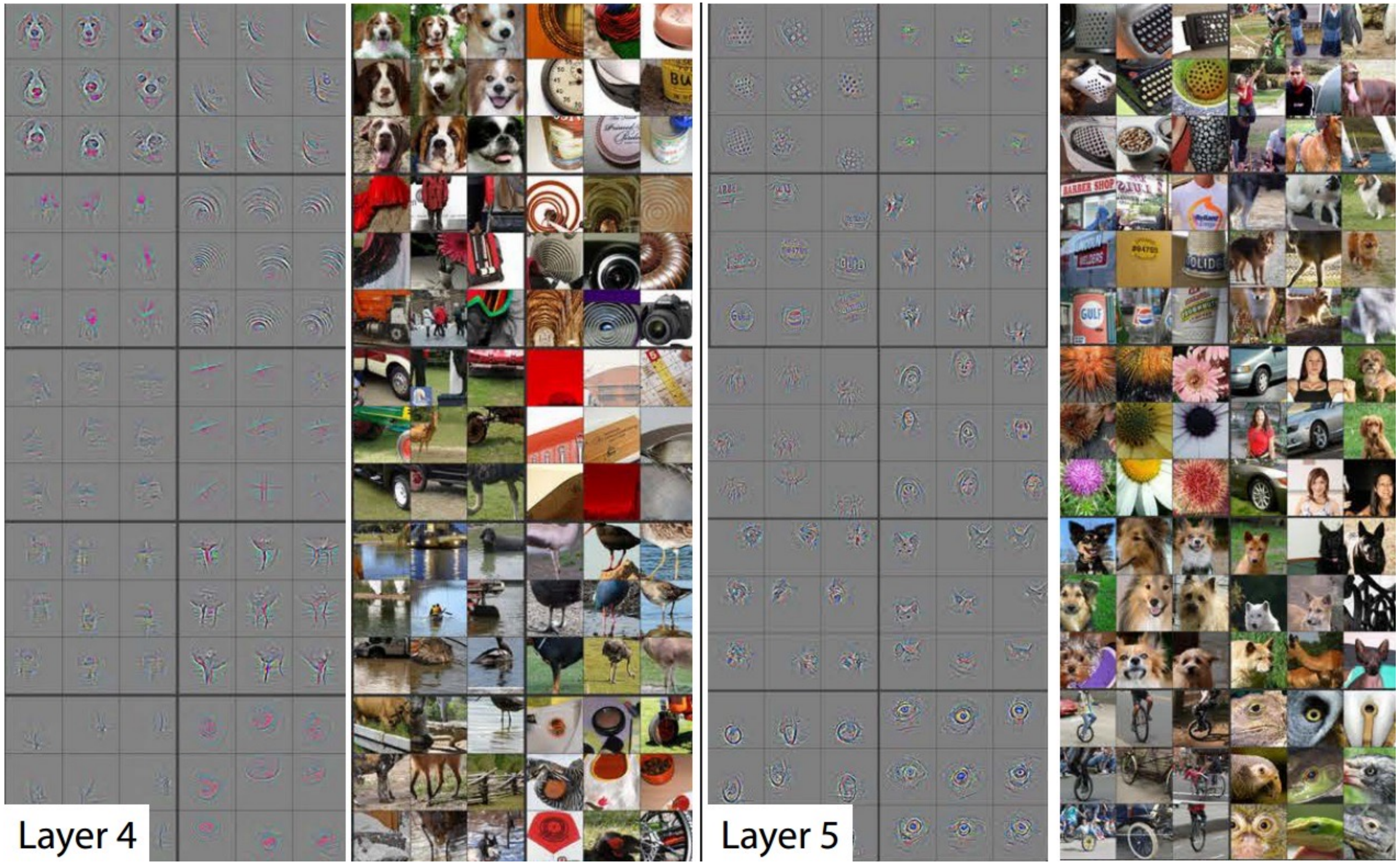
Layer 3



Slide credit: Jia-Bin Huang

Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

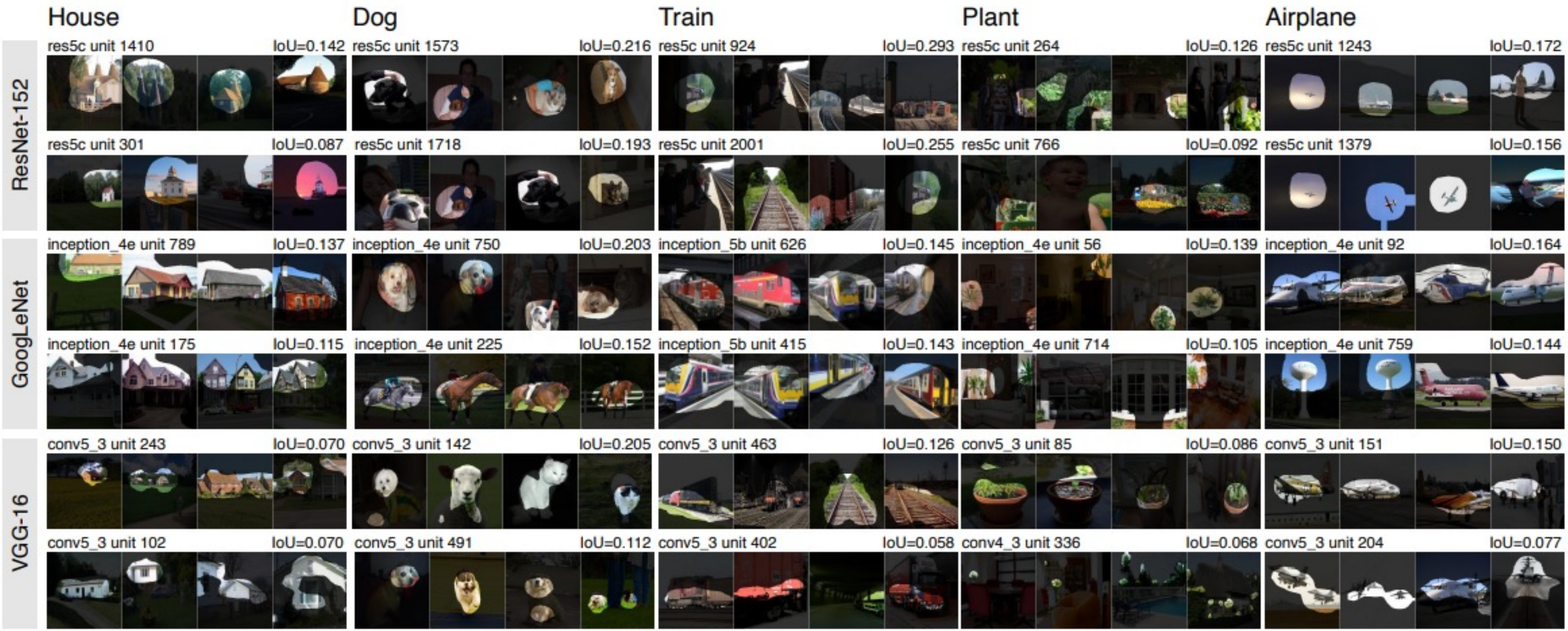
Layer 4 and 5



Slide credit: Jia-Bin Huang

Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

Network dissection



http://netdissect.csail.mit.edu/

CNNs with small datasets

Can we reuse trained concepts?

Since CNN’s trained for ImageNet object category classification appear to learn many apparently general features, why not reuse these models in some way to perform new tasks?

Transfer learning with CNNs

What if your task doesn't have Imagenet-sized data?

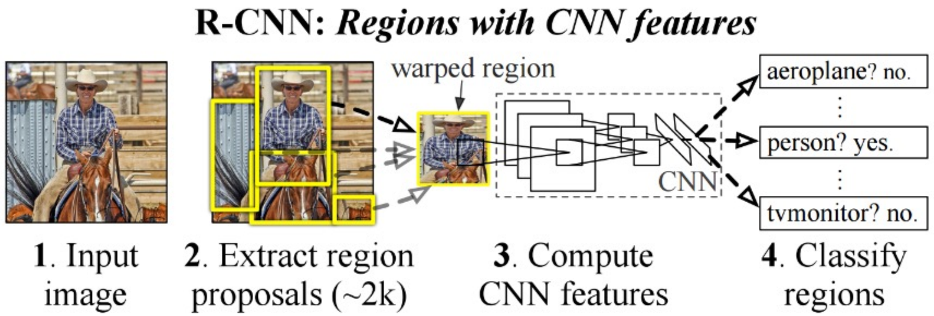
For tasks close to original task, can make do with small datasets + feature extraction or shallow finetuning.

For tasks far from original task, you will need to use moderate-sized datasets + deeper finetuning

Slide credit: Fei-Fei Li and Andrej Karpathy

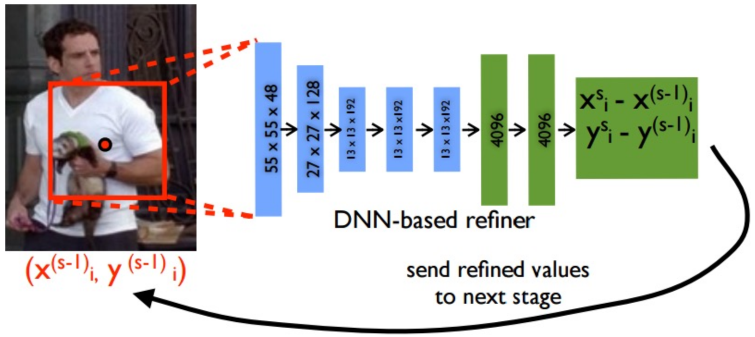
Some sample applications

[Girshick et al. CVPR14]



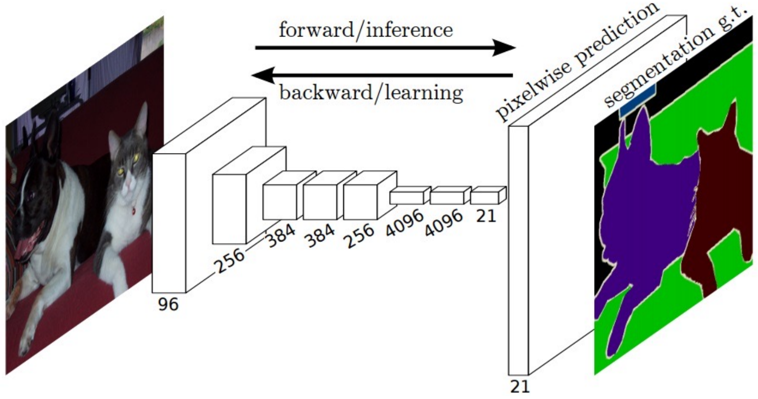
Object detection

[Toshev et al. CVPR14]



Pose detection (regression)

[Long et al. CVPR15]

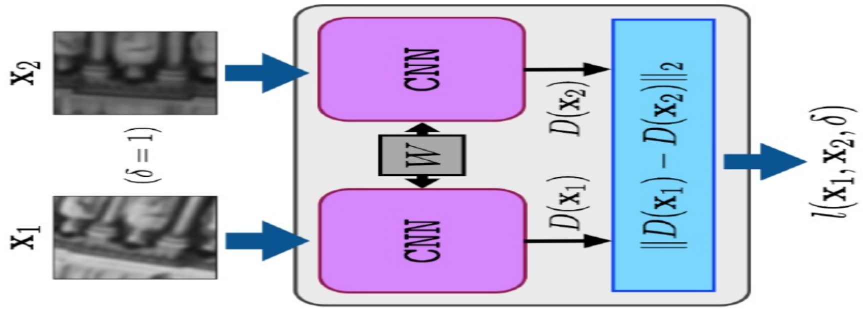


Semantic segmentation

Examples courtesy Jia-Bin Huang

Some sample applications

[Chopra et al. CVPR05]



Picture source

Similarity metric learning

[Dosovitskiy et al. CVPR15]

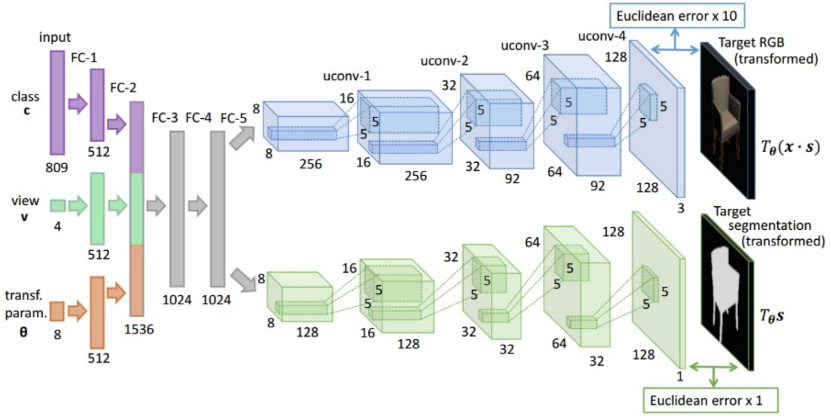
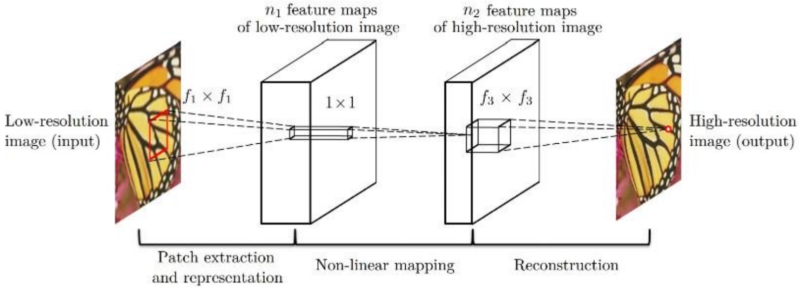


Image generation

[Dong et al. ECCV 2014]



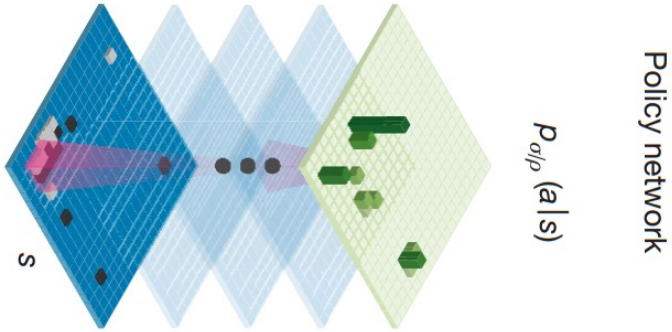
Low-level image processing: (superresolution, deblurring, image quality etc.)

Examples courtesy Jia-Bin Huang

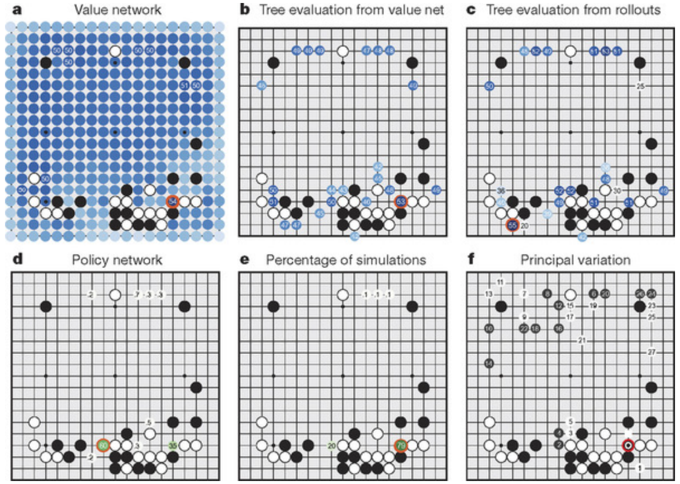
Game playing!

CNN + Reinforcement learning

[Mnih et al, Nature' 15]



[Silver et al, Nature '16]



ConvNet Art!

Paper: Gatys et al, “Neural ... Style”, arXiv ‘15
Code (torch): https://github.com/jcjohnson/neural-style

See if you can tell artists’ originals from machine style imitations at: http://turing.deepart.io/

Pytorch Training Loop

Pytorch Training Loop

```python
def train(args, model, device, train_loader, optimizer, epoch):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % args.log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.item()))
```

Looping over mini-batches

Zero out all old gradients

Runs forward pass model.forward(data)

Loss computation

Backpropagation

Gradient step

Pytorch Training Loop

```python
def main():
    torch.manual_seed(1)
    device = torch.device("cuda")
    train_loader = torch.utils.data.DataLoader(
        datasets.MNIST('../data', train=True, download=True,
                       transform=transforms.Compose([
                           transforms.ToTensor(),
                           transforms.Normalize((0.1307,), (0.3081,))
                       ])),
        batch_size=64, shuffle=True)

    model = Net().to(device)
    optimizer = optim.Adam(model.parameters(), lr=1e-4)
    sc[illegible]e=1, gamma=0.9)
    for epoch in range(1, 15):
        train(model, device, train_loader, optimizer, epoch)
        scheduler.step()
```

Load dataset

Loop over epochs (full passes over data)

Minibatch SGD for one epoch

Update base learning rate

Pytorch Model

- To use your model (once it has been trained):

```
model.eval()     # puts model in evaluation mode
label = model(input)    # forward pass to compute
outputs
```