Announcements

- Quiz 7 due **Thursday, November 2 at 8pm**
- HW 5 due **Wednesday, November 8 at 8pm**
- Project Milestone 2 Template:
  - https://docs.google.com/document/d/1VUt_oBhFte5yC4SxQ4ZwSE0bMLN0wxdv/edit?usp=sharing&ouid=104445367729520435803&rtpof=true&sd=true
  - Due Wednesday, November 15

Lecture 17: Computer Vision (Part 2)

CIS 4190/5190

Fall 2023

Agenda

- **Convolutional & pooling layers**
- **Convolutional neural networks**
- **Feature visualization**
- **Applications**

Images as 2D Arrays

- Grayscale image is a 2D array of pixel values

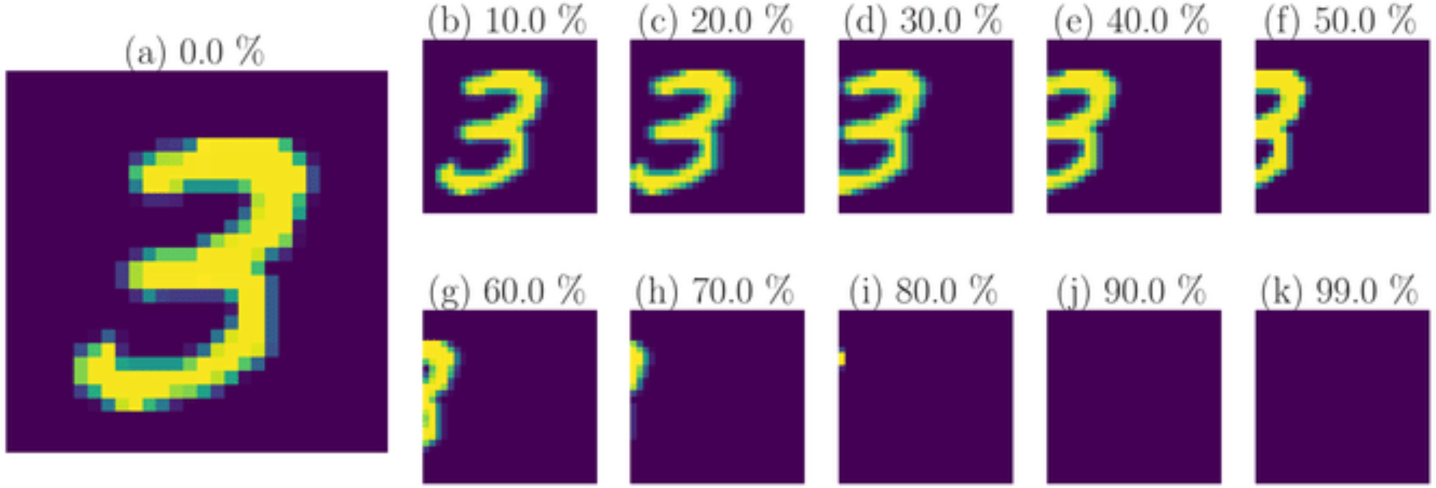
- Color images are 3D array
  - 3rd dimension is color (e.g., RGB)
  - Called “channels”

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

Source: S. Narasimhan, S. Lazebnik

Structure in Images

- **Translation invariance**
  - Consider image classification (e.g., labels are cat, dog, etc.)
  - **Invariance:** If we translate an image, it does not change the category label



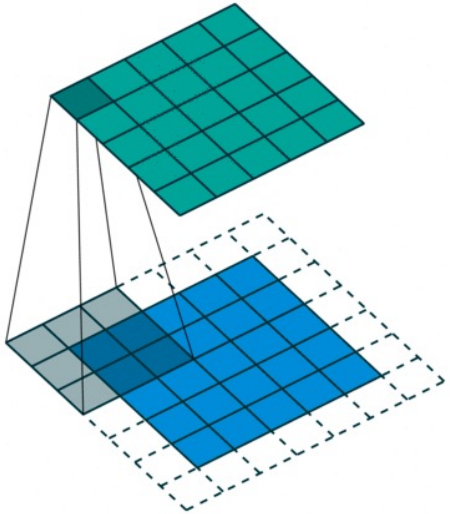
Source: Ott et al., Learning in the machine: To share or not to share?

Structure in Images

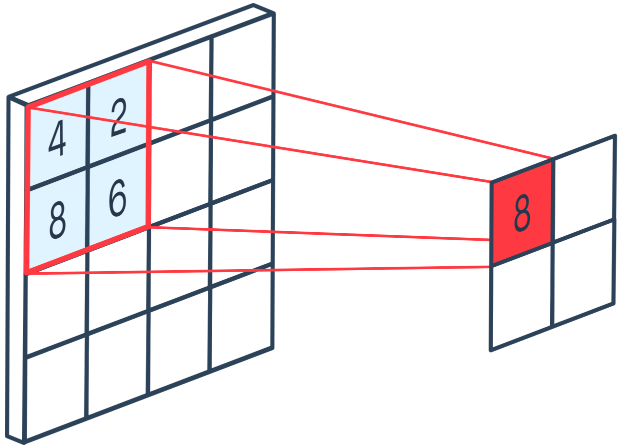
- **Translation equivariance**
  - Consider object detection (e.g., find the position of the cat in an image)
  - **Equivariance:** If we translate an image, the the object is translated similarly

Structure in Images

- Use layers that capture structure



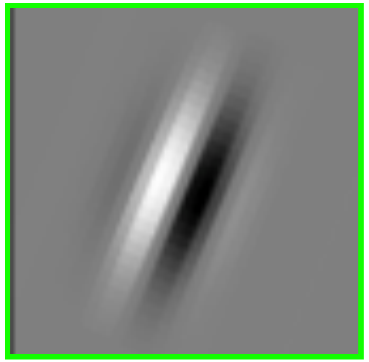
Convolution layers
(Capture equivariance)

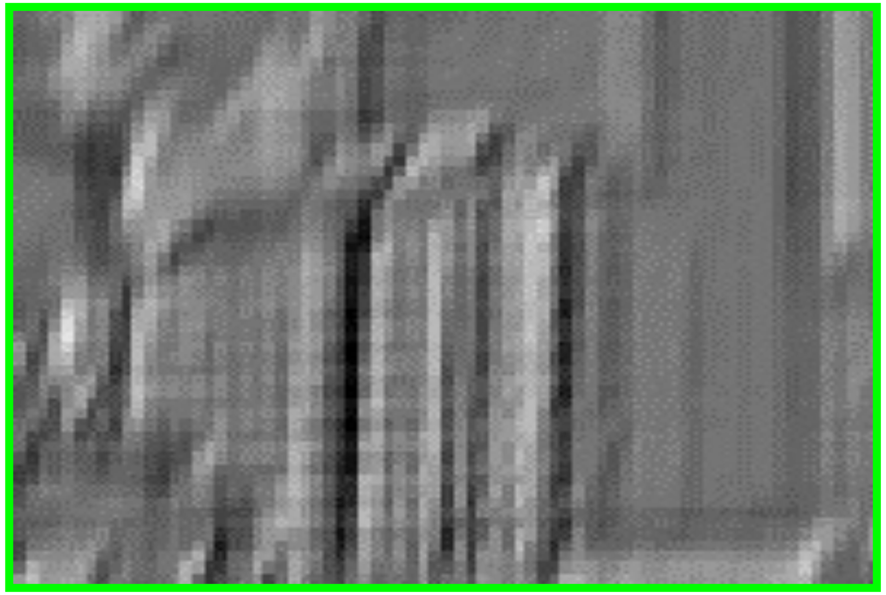


Pooling layers
(Capture invariance)

https://towardsdatascience.com/types-of-convolutions-in-deep-learning-717013397f4d
https://peltarion.com/static/2d_max_pooling_pa1.png

Convolution Filters





$$\text{output}[i,j] = \sum_{\tau=0}^{k-1} \sum_{\gamma=0}^{k-1} \text{filter}[\tau,\gamma] \cdot \text{image}[i+\tau, j+\gamma]$$

graphic credit: S. Lazebnik

2D Convolution Filters

- **Given:**
  - A 2D input x
  - A 2D $h \times w$ kernel k

- The 2D convolution is:

$$y[s,t] = \sum_{\tau=0}^{h-1} \sum_{\gamma=0}^{w-1} k[\tau,\gamma] \cdot x[s+\tau, t+\gamma]$$

2D Convolution Filters

-1	-1	-1
2	2	2
-1	-1	-1

Horizontal lines

-1	2	-1
-1	2	-1
-1	2	-1

Vertical lines

-1	-1	2
-1	2	-1
2	-1	-1

45 degree lines

2	-1	-1
-1	2	-1
-1	-1	2

135 degree lines

Example Edge Detection Kernels

Result of Convolution with Horizontal Kernel

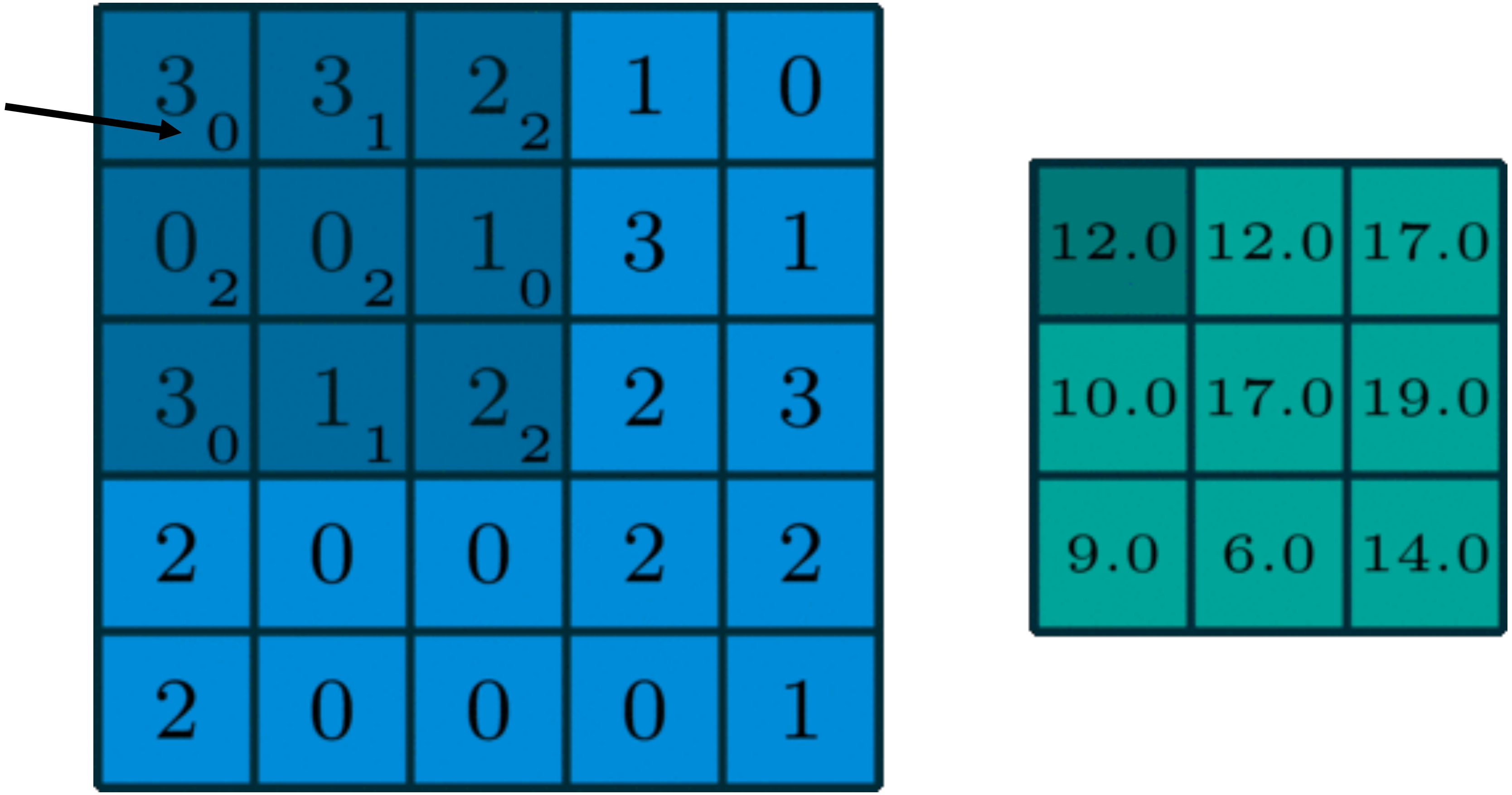
https://aishack.in/tutorials/image-convolution-examples/

2D Convolution Filters

- Historically (until late 1980s), kernel parameters were handcrafted
  - E.g., “edge detectors”
- In convolutional neural networks, they are learned
  - Essentially a linear layer with fewer “connections”
  - Backpropagate as usual!

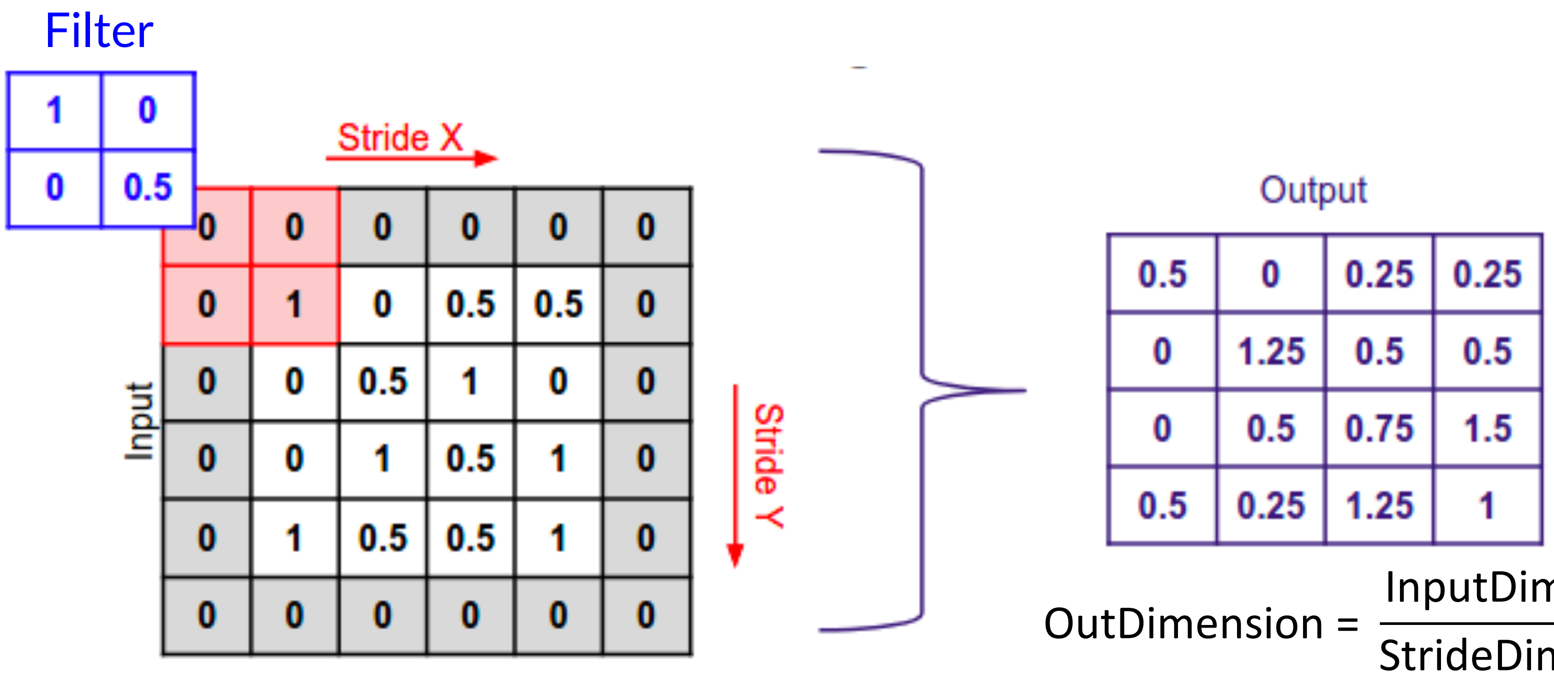
Convolution Layers

Learnable parameters



Convolution Layer Parameters

- **Stride:** How many pixels to skip (if any)
  - **Default:** Stride of 1 (no skipping)

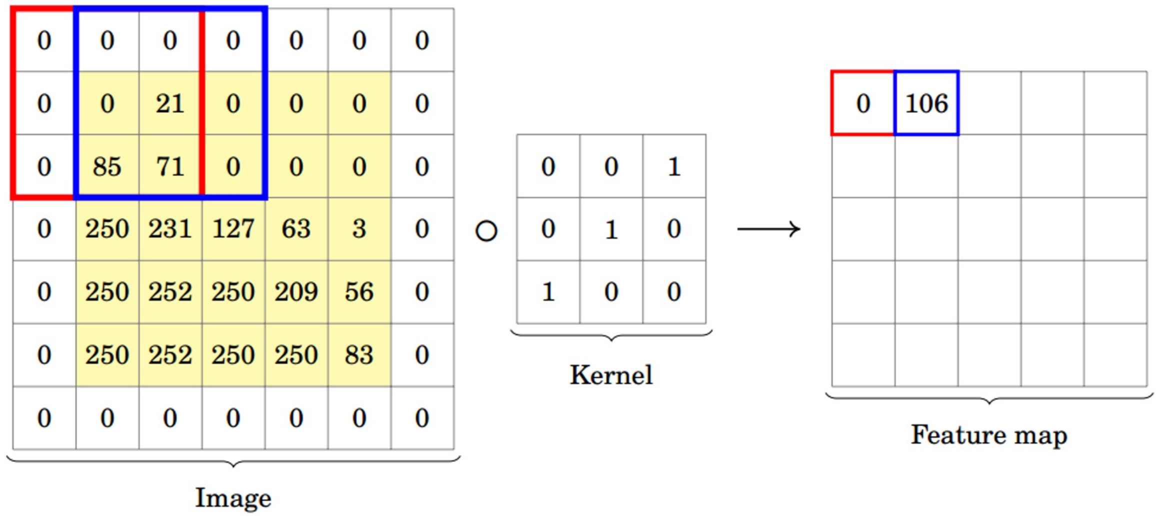


$$\text{OutDimension} = \frac{\text{InputDimension}}{\text{StrideDimension}}$$

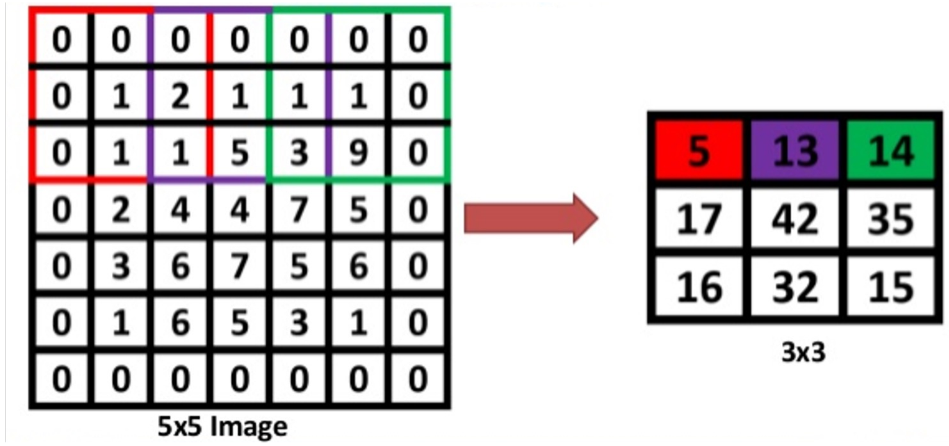
https://medium.com/@ayeshmanthaperera/what-is-padding-in-cnns-71b21fb0dd7

Convolution Layer Parameters

- **Padding:** Add zeros to edges of image to capture ends
    - **Default:** No padding



stride = 1, zero-padding = 1



stride = 2, zero-padding = 1

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

Convolution Layer Parameters

- **Summary:** Hyperparameters
  - Kernel size
  - Stride
  - Amount of zero-padding
  - Output channels

- Together, these determine the relationship between the input tensor shape and the output tensor shape

- Typically, also use a single bias term for each convolution filter

Convolution Layers

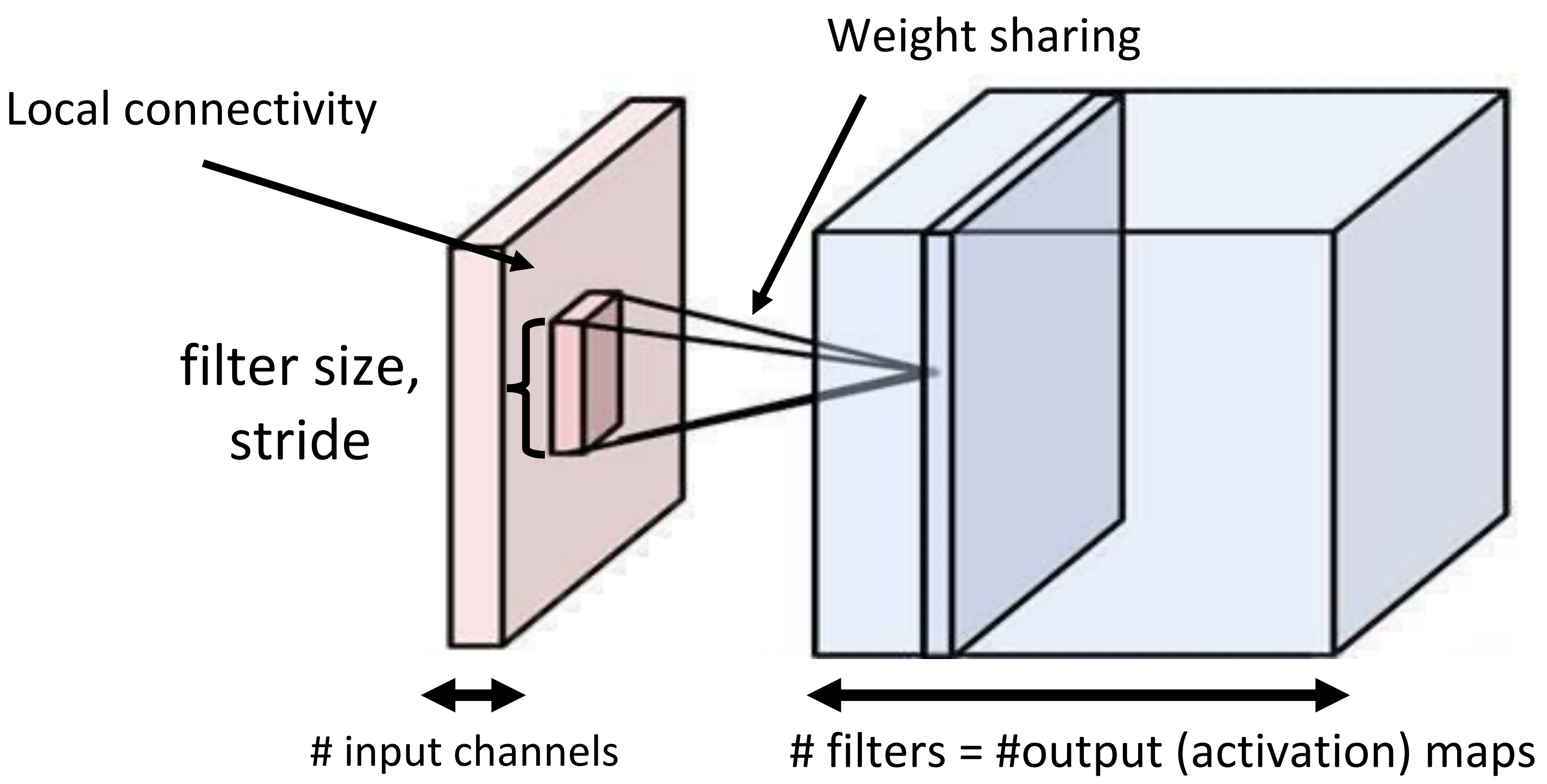
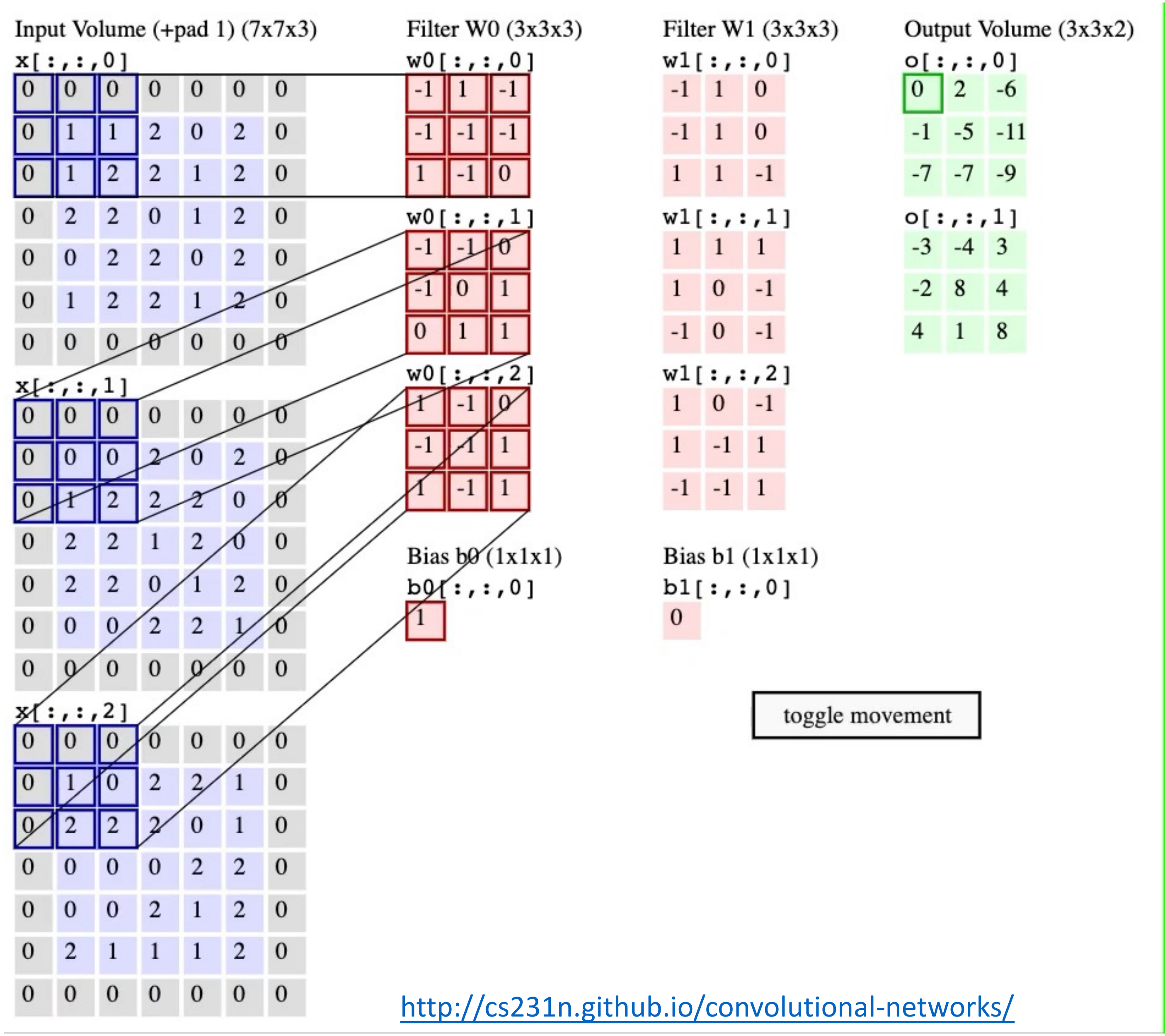


Image credit: A. Karpathy   Slide credit: Jia-Bin Huang

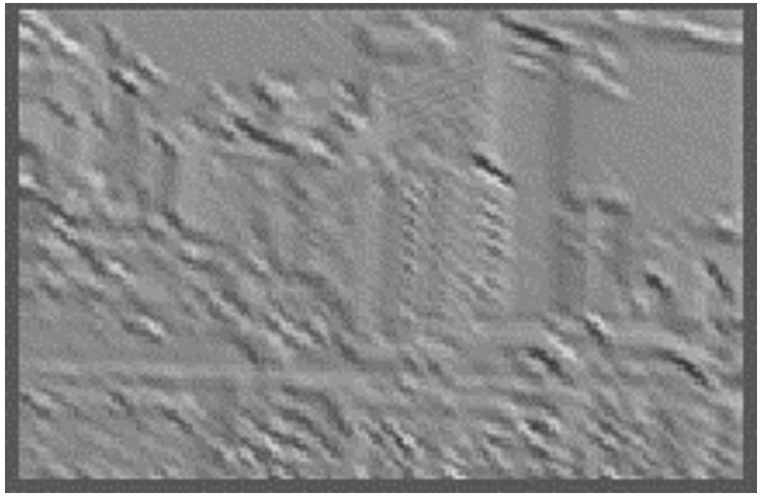
Example

- Kernel size 3, stride 2, padding 1
- 3 input channels
  - Hence kernel size 3×3×3
- 2 output channels
  - Hence 2 kernels
- Total # of parameters:
  - $(3\times3\times3 + 1)\times2 = 56$

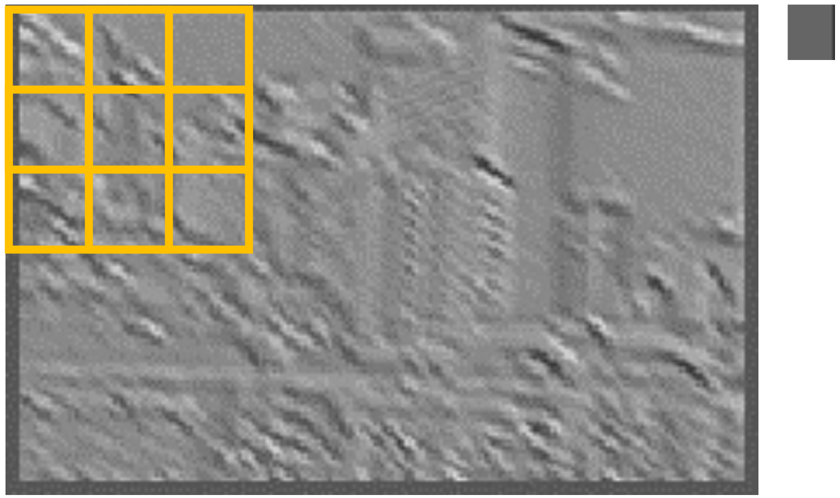


http://cs231n.github.io/convolutional-networks/

Pooling Layers

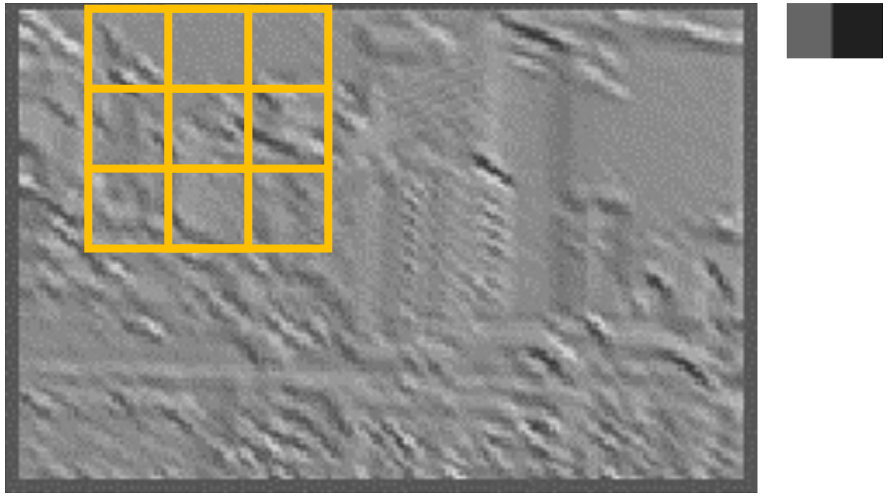


Pooling Layers



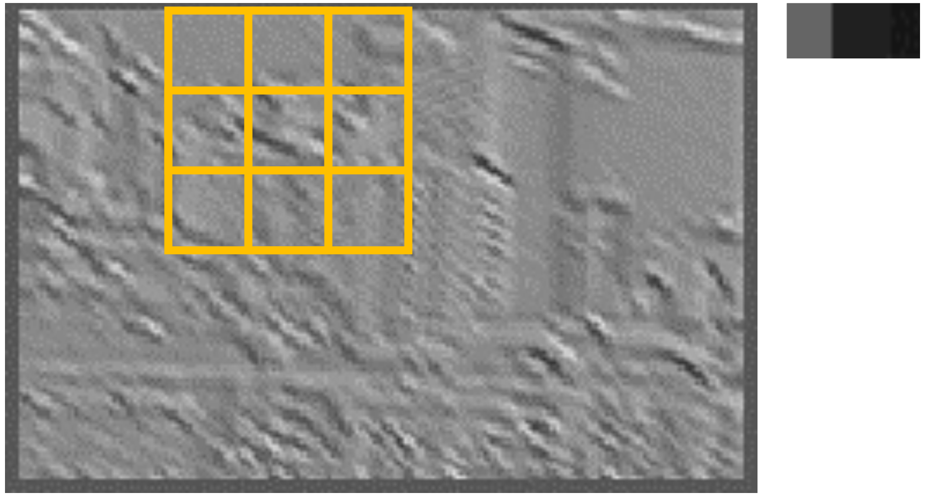
$$\text{output}[0,0] = \max_{0 \le \tau < k} \max_{0 \le \gamma < k} \text{image}[0+\tau, 0+\gamma]$$

Pooling Layers



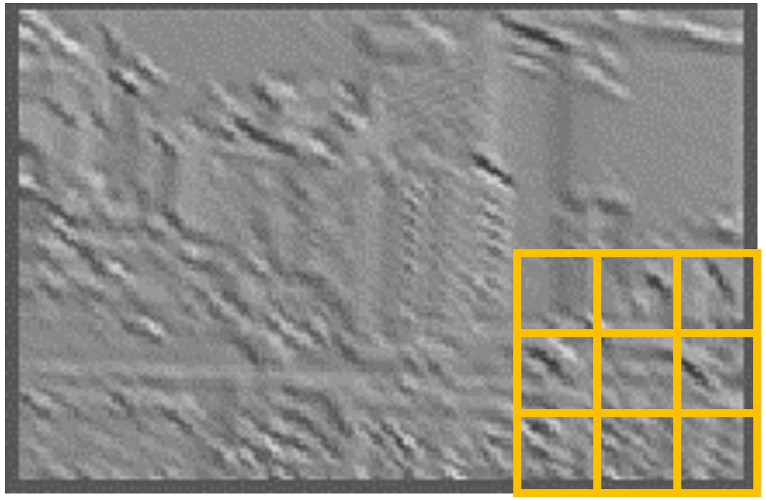
$$\text{output}[0,1] = \max_{0 \le \tau < k} \max_{0 \le \gamma < k} \text{image}[0+\tau, 1+\gamma]$$

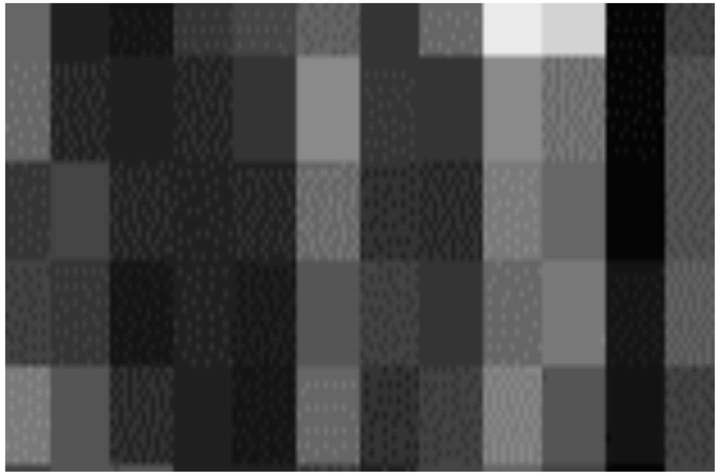
Pooling Layers



$$\text{output}[0,2] = \max_{0 \le \tau < k} \max_{0 \le \gamma < k} \text{image}[0+\tau, 2+\gamma]$$

Pooling Layers





$$\text{output}[i,j] = \max_{0\le\tau<k} \max_{0\le\gamma<k} \text{image}[i+\tau, j+\gamma]$$

Pooling Layers

- **Summary:** Hyperparameters
  - Kernel size
  - Stride (usually >1)
  - Amount of zero-padding
  - Pooling function (almost always "max")

- Together, these determine the relationship between the input tensor shape and the output tensor shape

- **Note:** Unlike convolution, pooling operates on channels separately
  - Thus, n input channels → n output channels

Summary: Convolution vs. Pooling

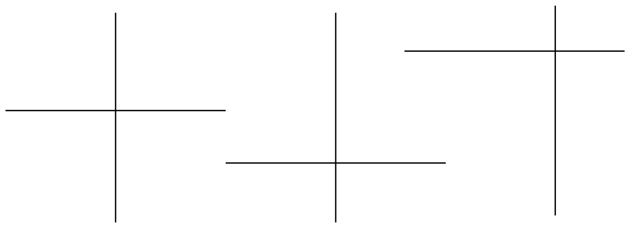
- **Convolution layers:** Translation equivariant
  - If object is translated, convolution output is translated by same amount
  - Produce “image-shaped” features that retain associations with input pixels
- **Pooling layers:** Translation invariant
  - Binning to make outputs insensitive to translation
  - Also reduces dimensionality
- Combined in modern architectures
  - Convolution to construct equivariant features
  - Pooling to enable invariance

Example

- Suppose we want to predict whether an image depicts Cartesian axes

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

input image



?

target (binary) label

Example

- **Step 1:** Convolve the image with two filters
  - No padding, stride 1

- **Step 2:** Run max pooling

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

convolution filters

Example

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

Example

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

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

Example

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

Example

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

Example

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

Example

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

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

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

Input image Convolution Features

Example

$$\begin{tikzcd}[column sep=large]
 & \begin{bmatrix} -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \end{bmatrix} \arrow[r] & \begin{bmatrix} 2 & -2 \\ -1 & 1 \end{bmatrix} \arrow[dr] & \\
\begin{bmatrix} 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -2 \end{bmatrix} \arrow[ur] \arrow[dr] & & & \begin{bmatrix} 2 \\ 4 \end{bmatrix} \\
 & \begin{bmatrix} -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\ 1 & 1 & 1 \\ -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \end{bmatrix} \arrow[r] & \begin{bmatrix} -1 & -\frac{1}{2} \\ \frac{7}{2} & 4 \end{bmatrix} \arrow[ur] &
\end{tikzcd}$$

Input image | Convolution | Features | Pooling

Example

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

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

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

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

Clear vertical line

Clear horizontal line

Input image

Convolution

Features

Pooling

Agenda

- **Convolutional & pooling layers**
- **Convolutional neural networks**
- **Feature visualization**
- **Applications**

Example Architecture: AlexNet

- **ImageNet dataset**
  - 1000 class image classification problem (e.g., grey fox, tabby cat, barber chair)
  - >1M image-label pairs gathered from internet and crowdsourced labels

- **AlexNet Architecture (Krizhevsky 2012)**
  - Historically important architecture
  - Image classification network (~60M parameters)
  - Trained using GPUs on ImageNet dataset
  - Huge improvement in performance compared to prior state-of-the-art

Example Architecture: AlexNet

Fully connected (i.e., linear) layers

output

fc, 1000

fc, 4096

fc, 4096

Input

3x3 conv, 256, pool/2

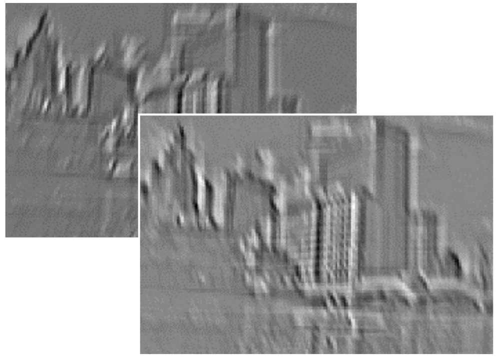
3x3 conv, 384

3x3 conv, 384

5x5 conv, 256, pool/2

11x11 conv, 96, /4, pool/2

input



Local Response Normalization

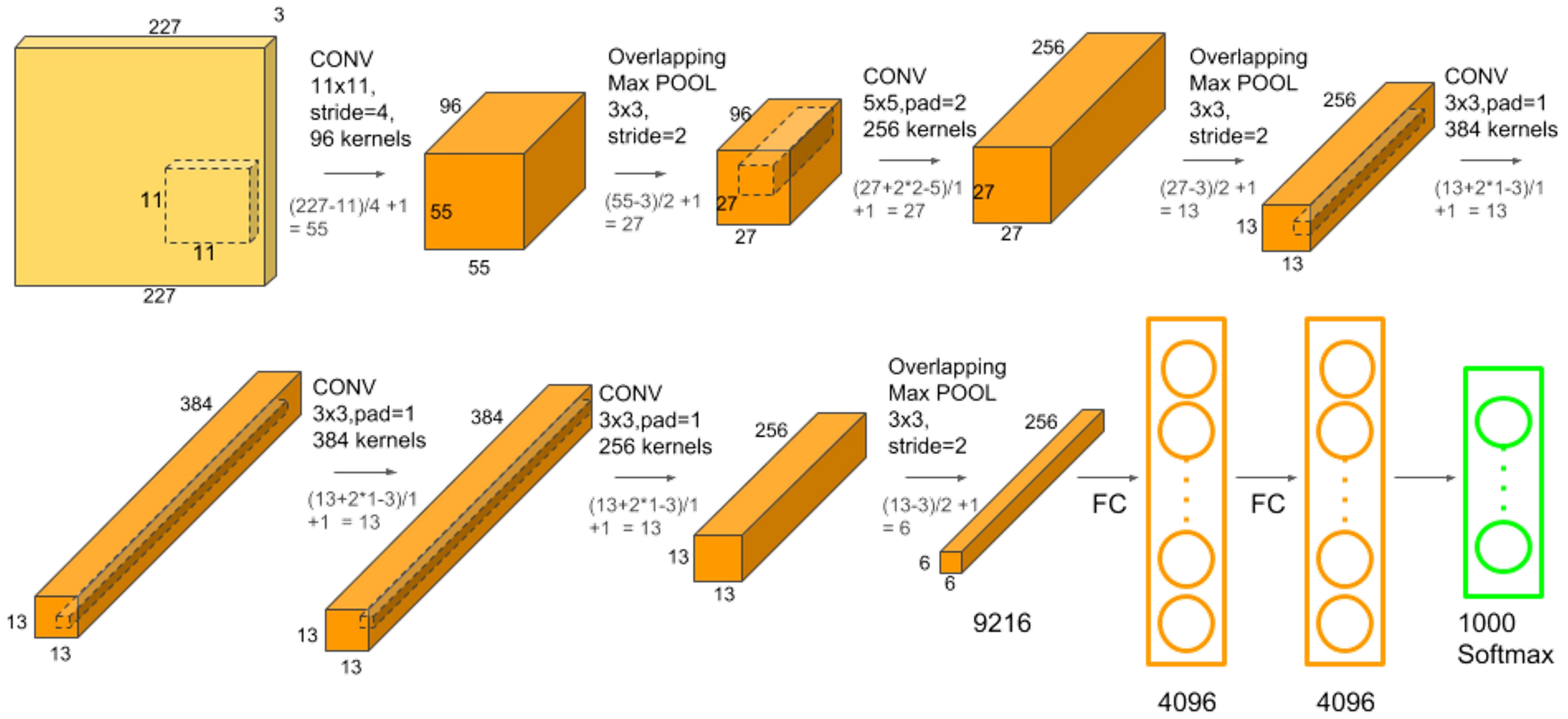
Pooling (kernel size 3, stride 2, no padding)

ReLU Activation

Convolution (kernel size 11, stride 4, 96 output channels, no padding)

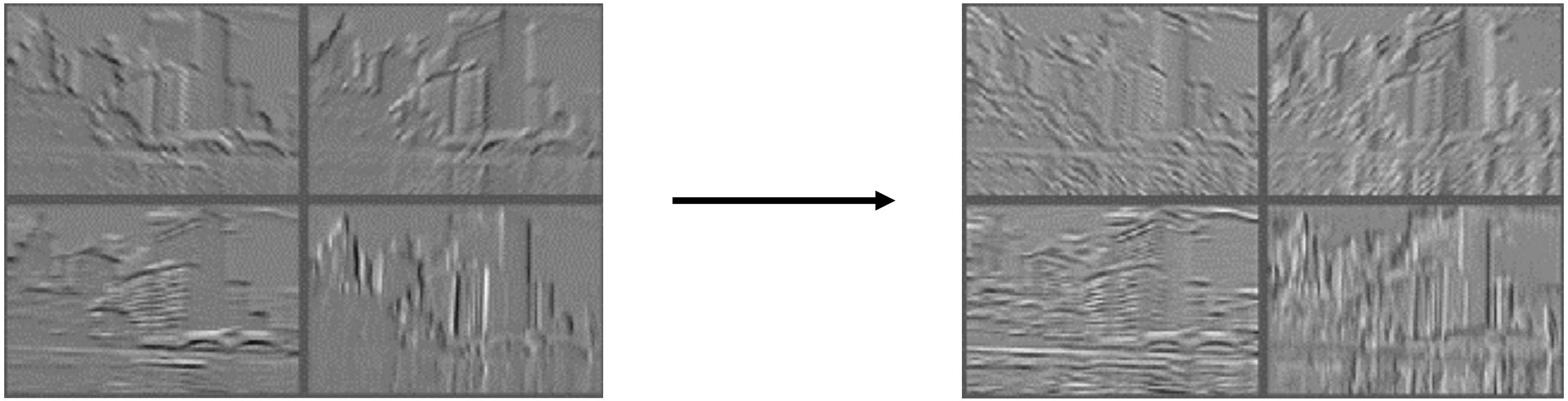
slide credit: S. Lazebnik

Example Architecture: AlexNet



Aside: Local Response Normalization

- Highlights areas where the feature maps change
- Historically a standard layer, but no longer used
- Also called “contrastive normalization”



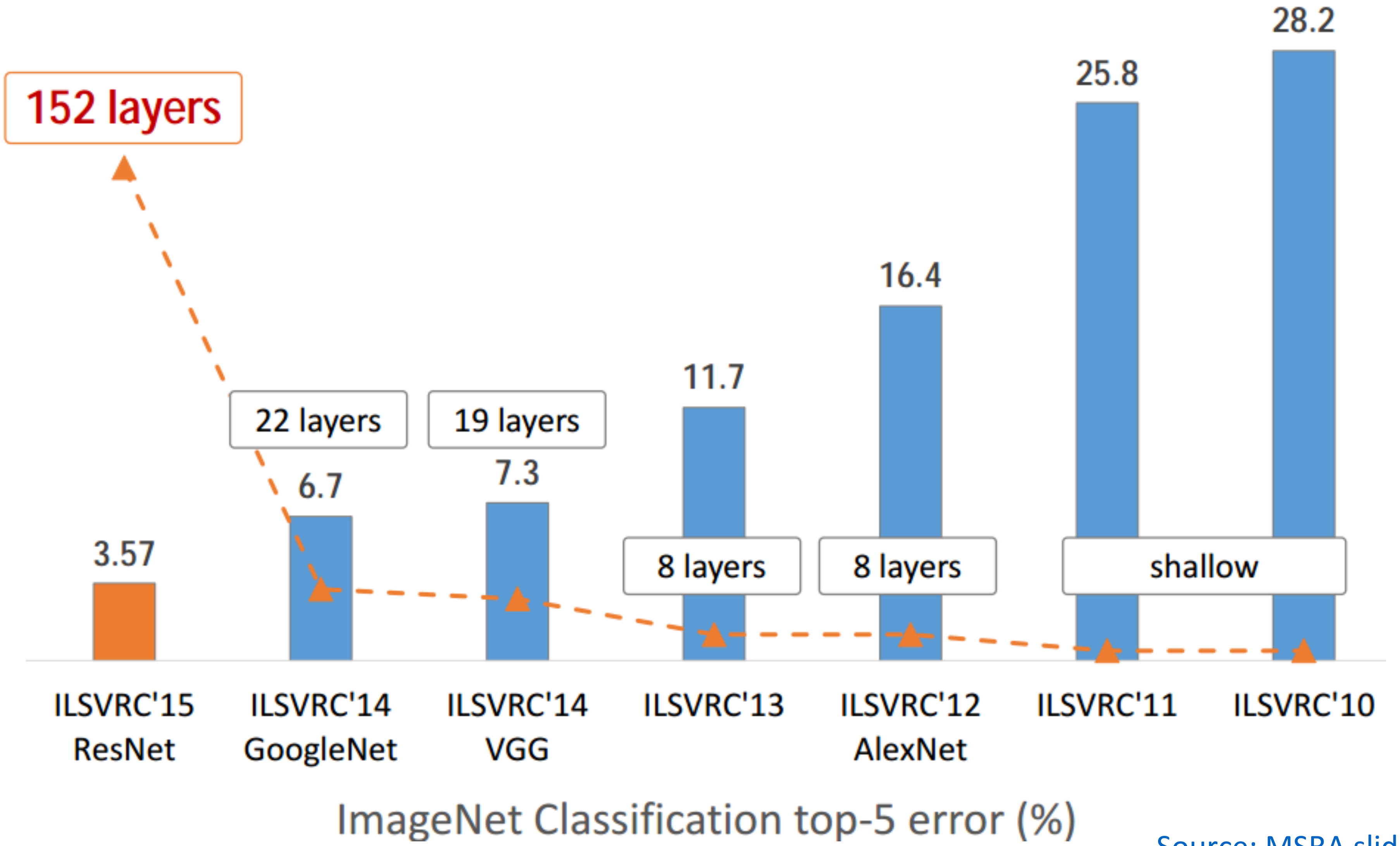
Convolutional Neural Networks

- “Convolutional layer” often refers to sequence of layers

- **Modern sequence of layers**
  - Convolution → Batch Normalization → Pooling → ReLU
  - Convolution → Batch Normalization → ReLU → Pooling

- Can also omit pooling (especially for very deep neural networks)

Evolution of Neural Networks



[Source: MSRA slides at ILSVRC15]()

Evolution of Neural Networks

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

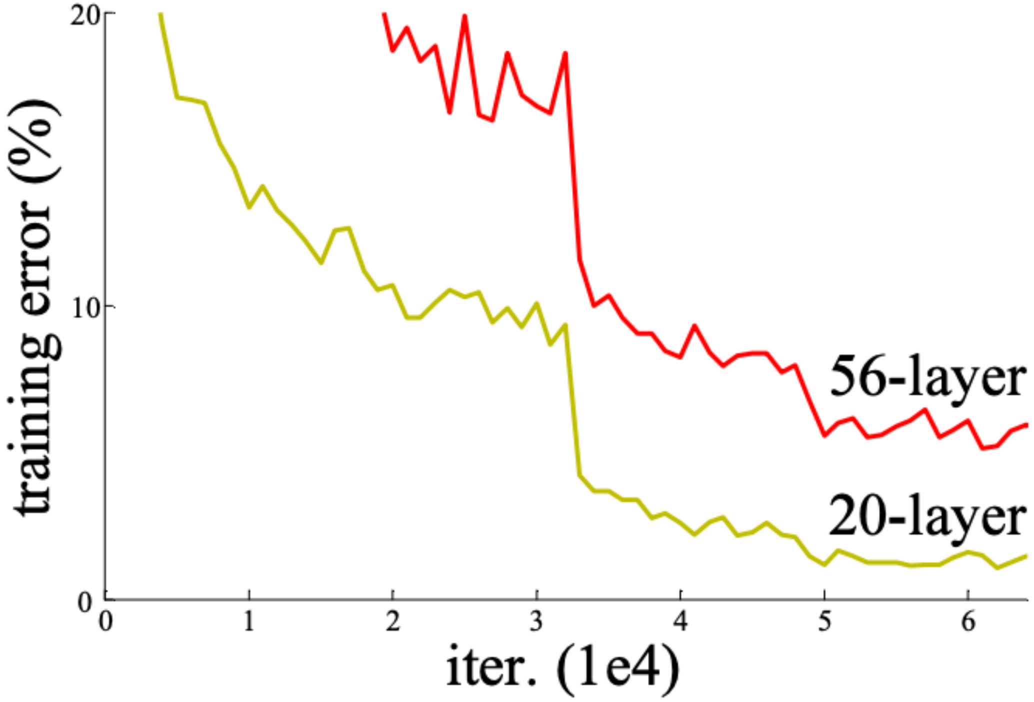
GoogleNet, 22 layers
(ILSVRC 2014)
~5M params

ICCV15

[Source: MSRA slides at ILSVRC15]

Residual Connections

- **Challenges with deeper networks**
  - Overfitting?
  - No, 56 layer network underfits!



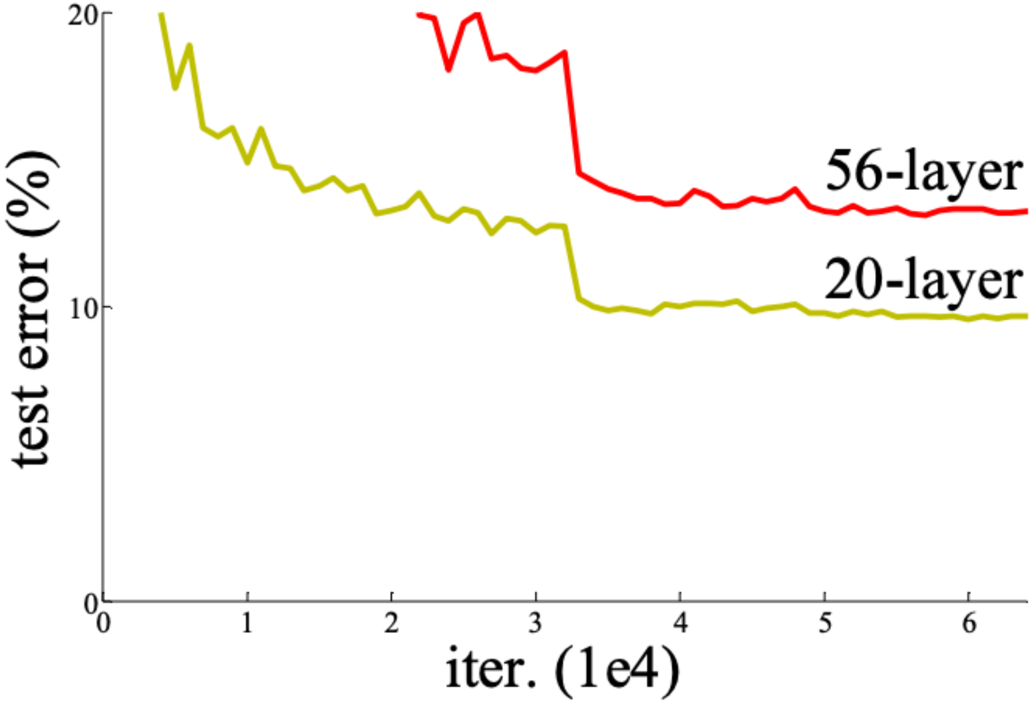


Image credit: He et al, Residual Nets, 2015

Residual Connections

- **Challenges with deep networks**
  - Overfitting?
  - No, 56 layer network underfits!
- **Optimization/representation**
  - Difficulty representing the identity function!
- **Solution:** “Skip” connections
  - Facilitate direct feedback from loss
  - Easy to represent identity function

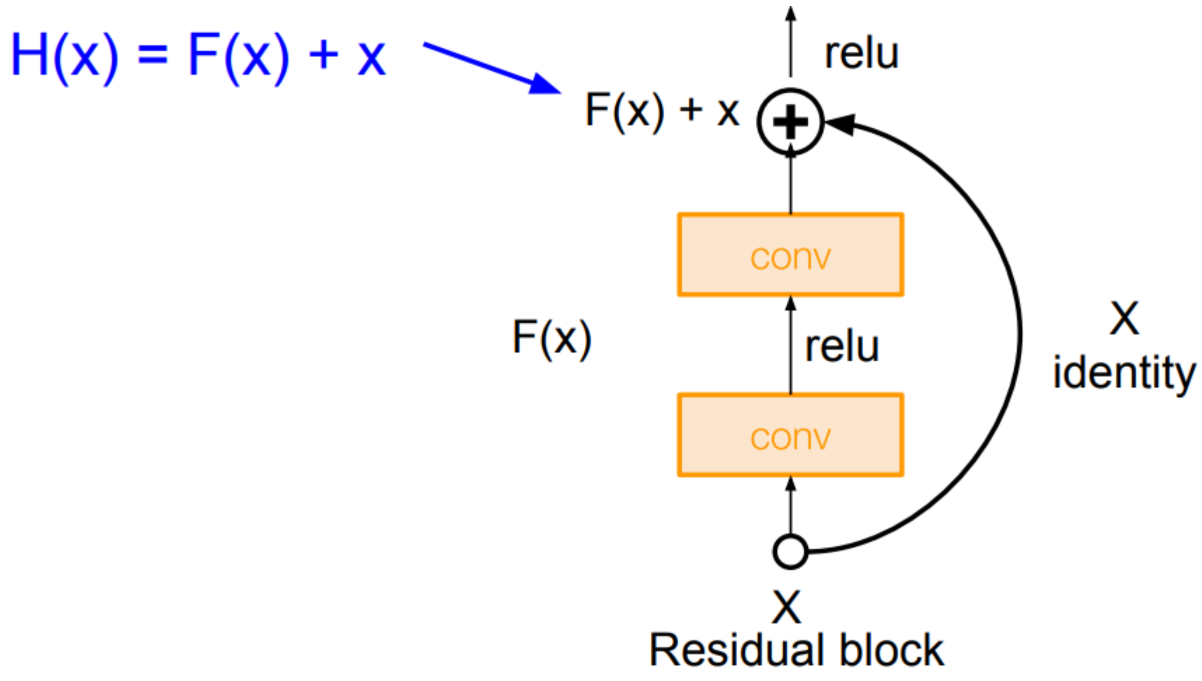


Image credit: Fei-Fei Li, Justin Johnson, Serena Yeung

Residual Connections

- **Residual layers:** Given any convolutional layer $F(x)$, use

$$H(x) = F(x) + x$$

- Two views of residual connections:
  - **View 1:** Providing shortcuts to gradients on the backward pass
  - **View 2:** Allow each "residual block" to fit the residual error (boosting!)

$$F(x) = H(x) - x$$

Residual Networks

- Stack lots of residual blocks!
  - Kernel size 3, no padding, stride 1, no pooling
  - Reduce feature dimensions by using stride 2 once every K blocks
  - Maintains feature size to build very deep nets

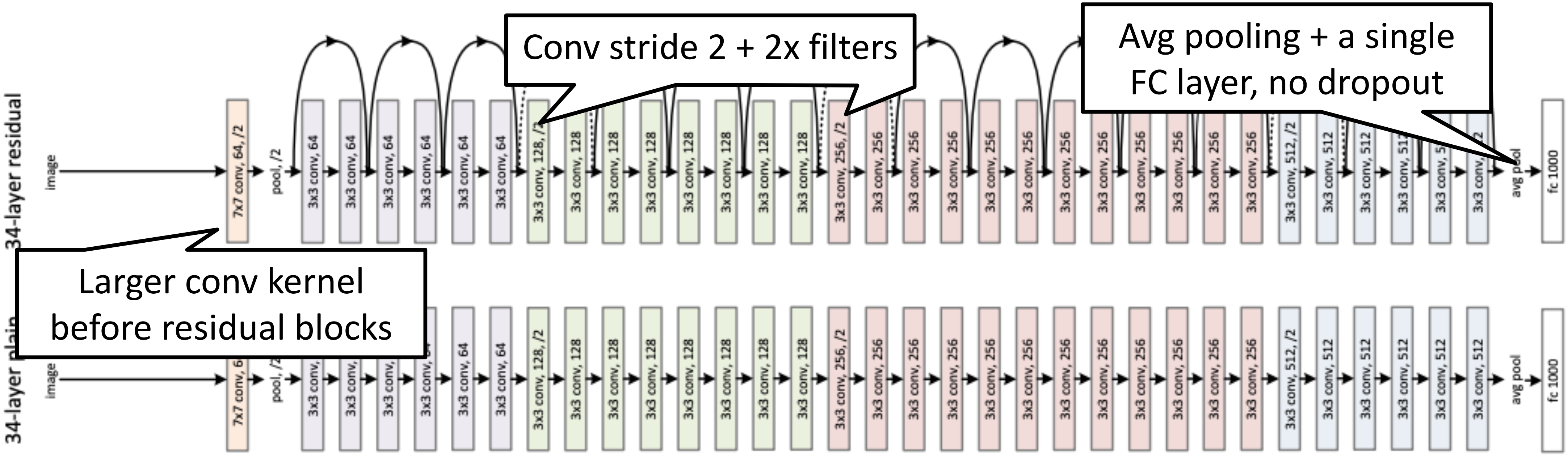


Image credit: He et al, Residual Nets, 2015

Residual Networks

- For deeper networks, improve efficiency through 1x1 convolutions
- Many other improvements since 2015!
  - E.g., “ResNeXt”, “Identity Mappings”, “ConvNeXt” etc.

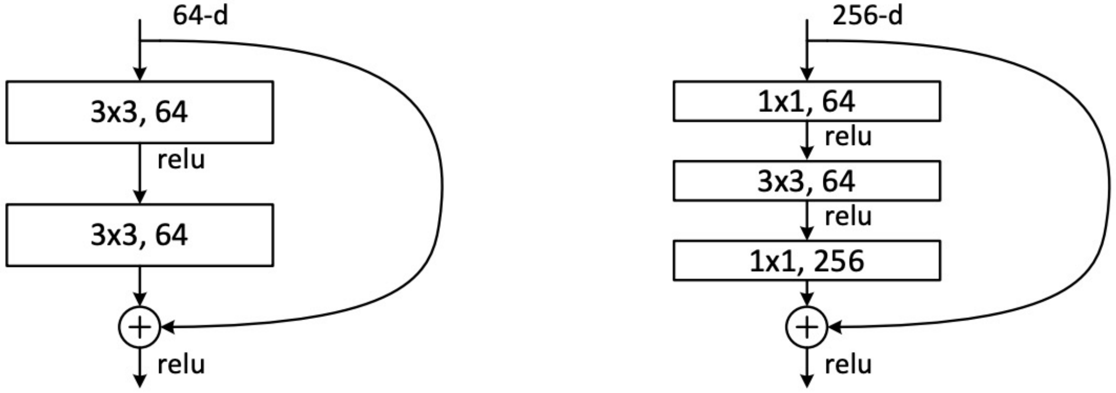


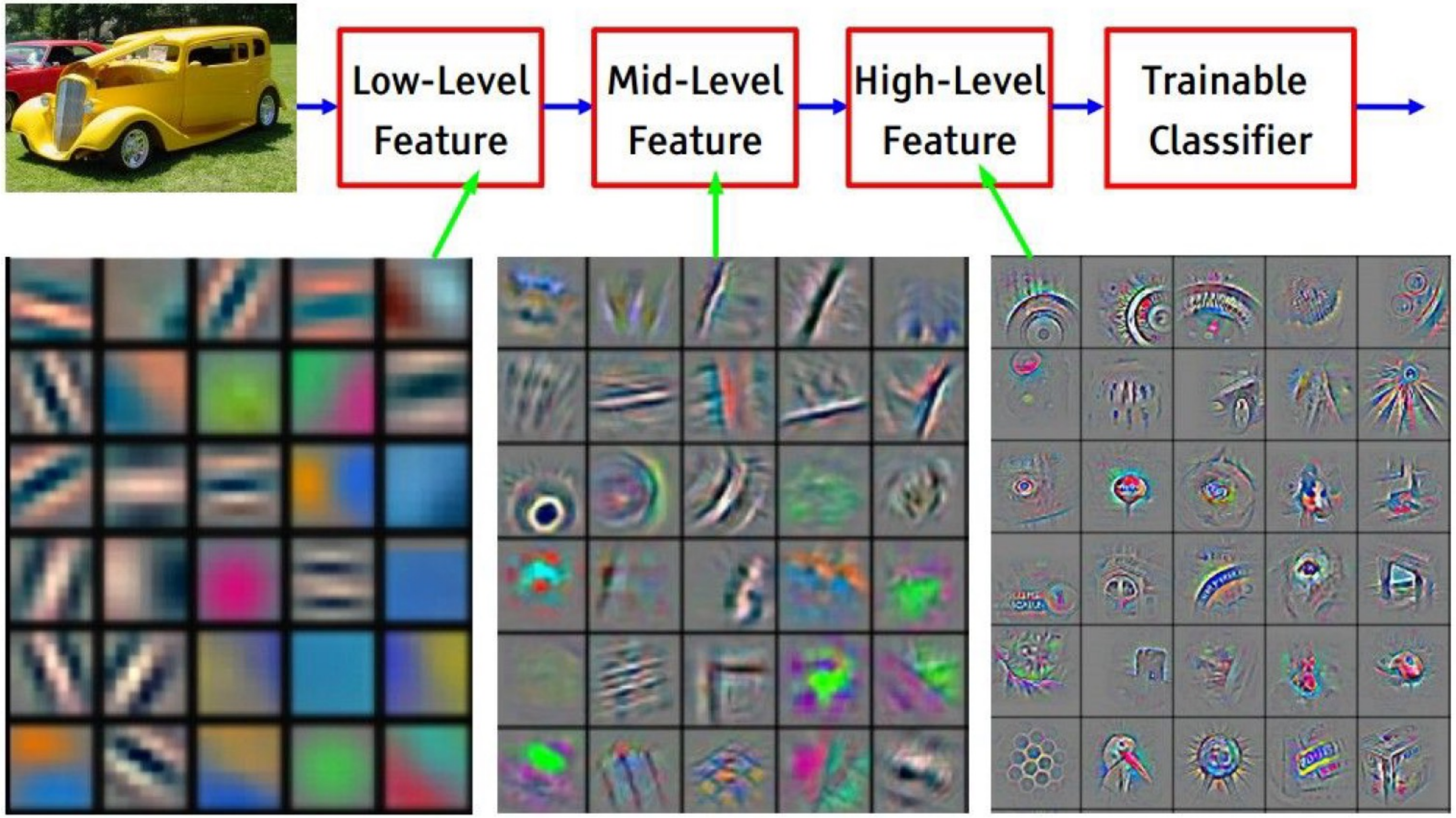
Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

Image credit: He et al, Residual Nets, 2015

Agenda

- **Convolutional & pooling layers**
- **Convolutional neural networks**
- **Feature visualization**
- **Applications**

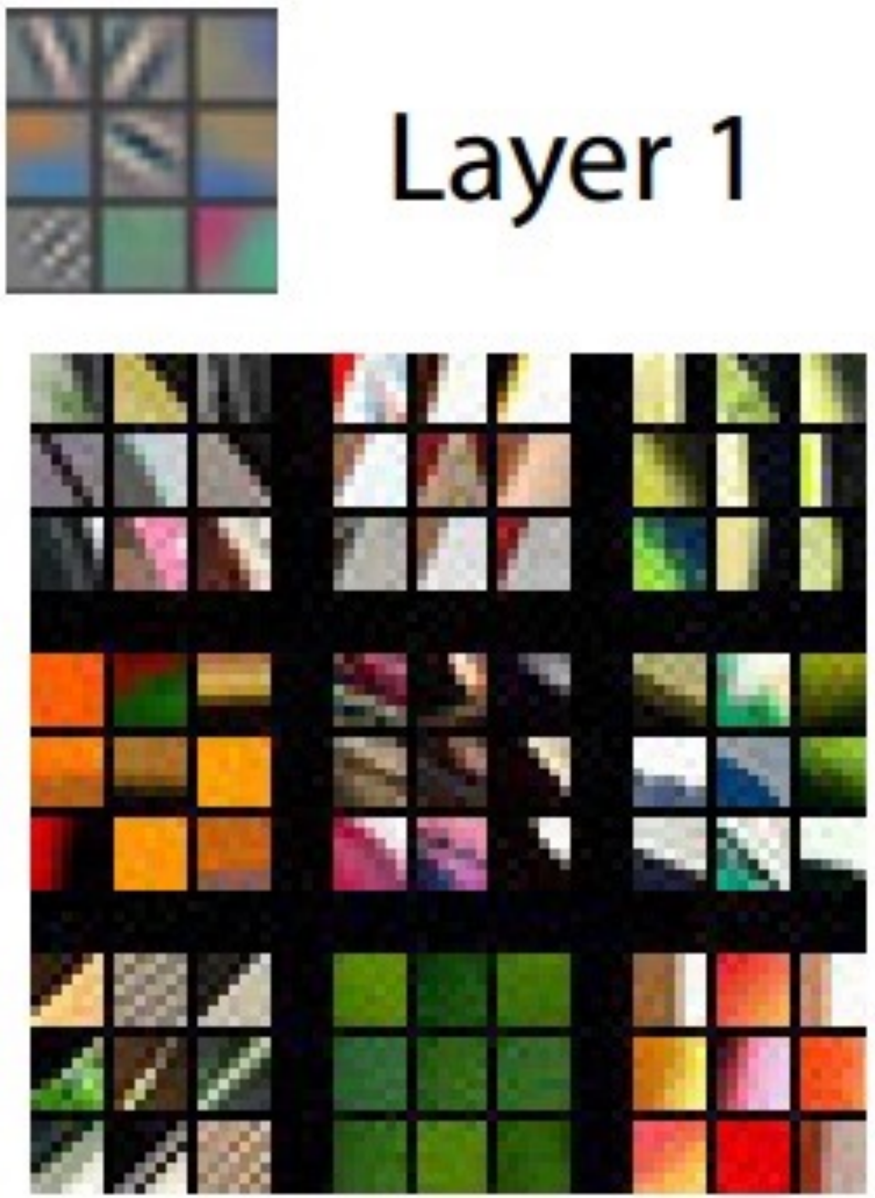
Feature Visualization



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

Slide credit: Yann LeCun

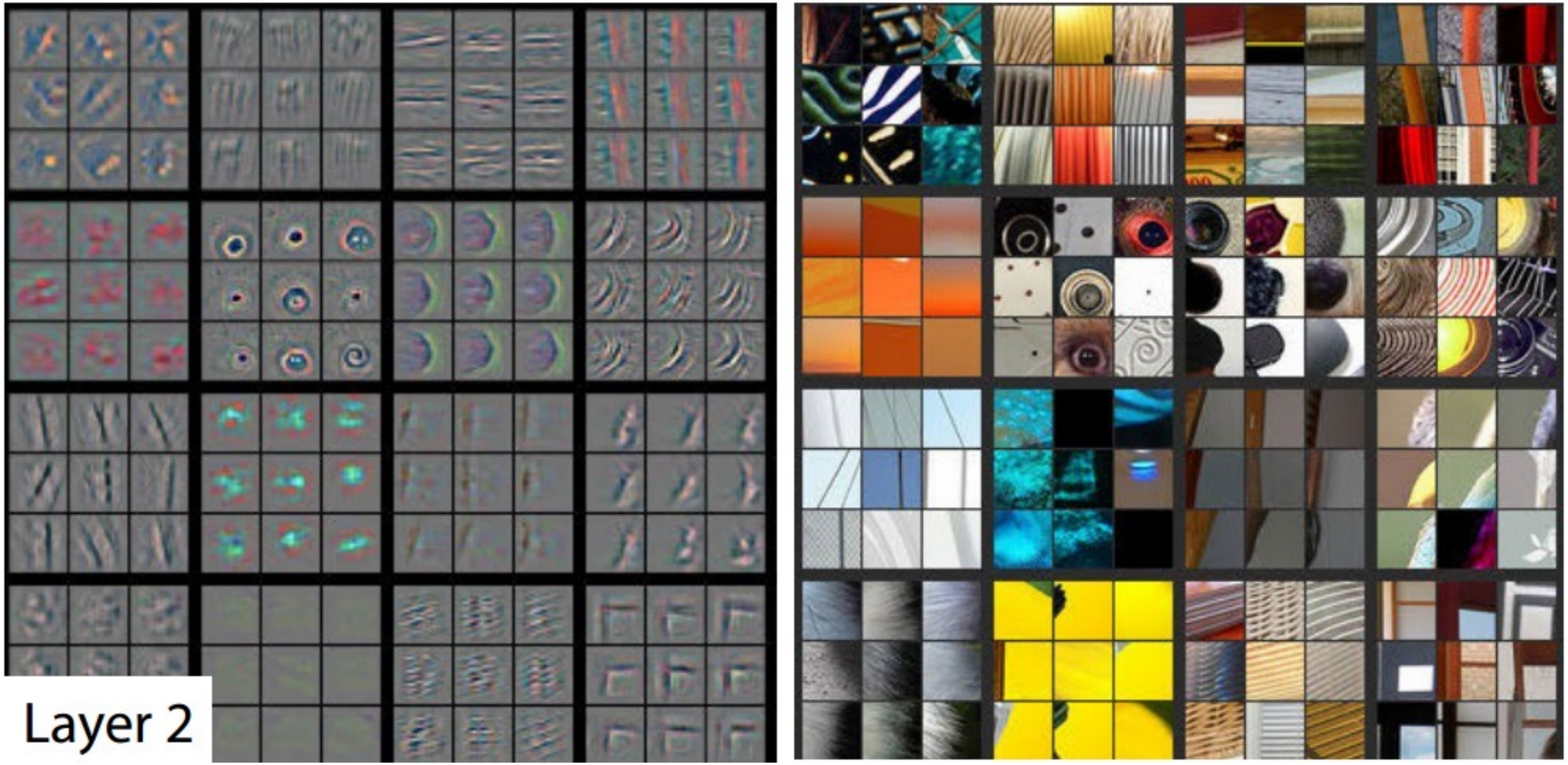
Layer 1



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

Slide credit: Jia-Bin Huang

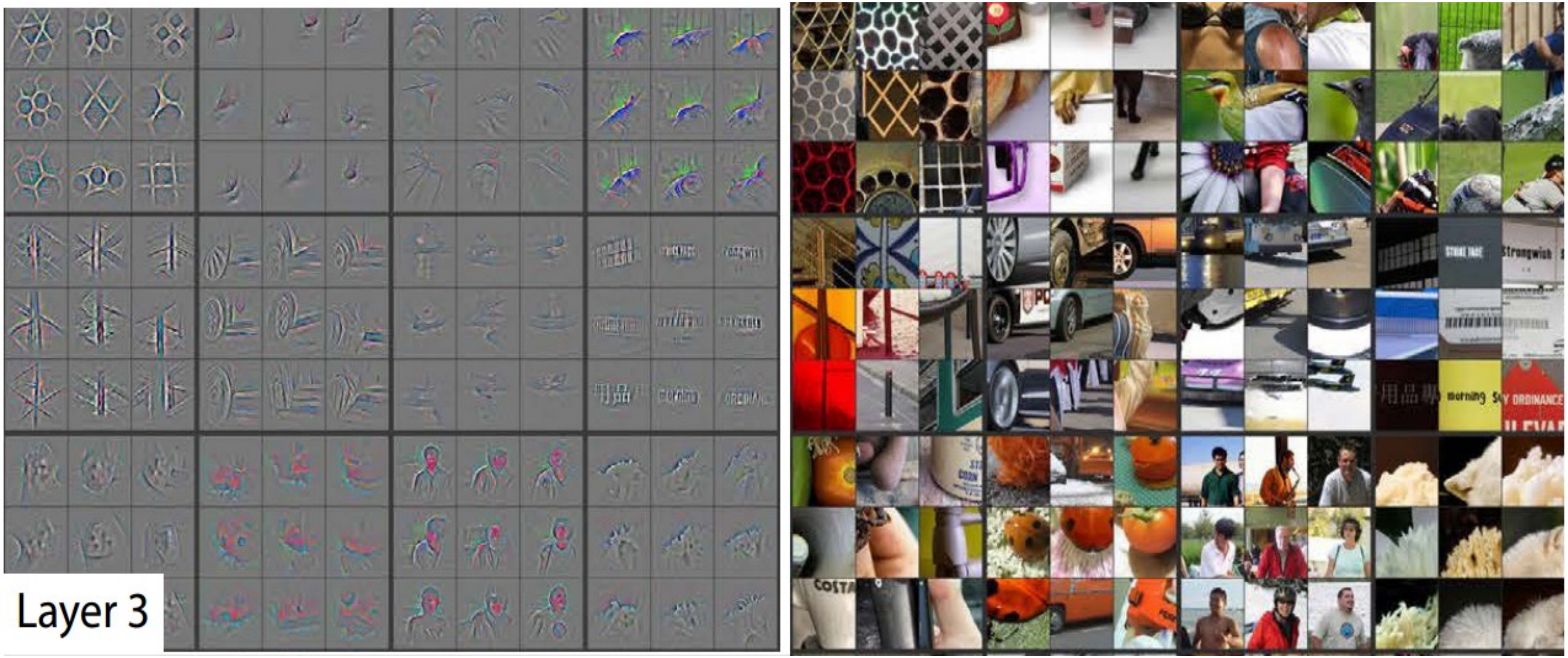
Layer 2



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

Slide credit: Jia-Bin Huang

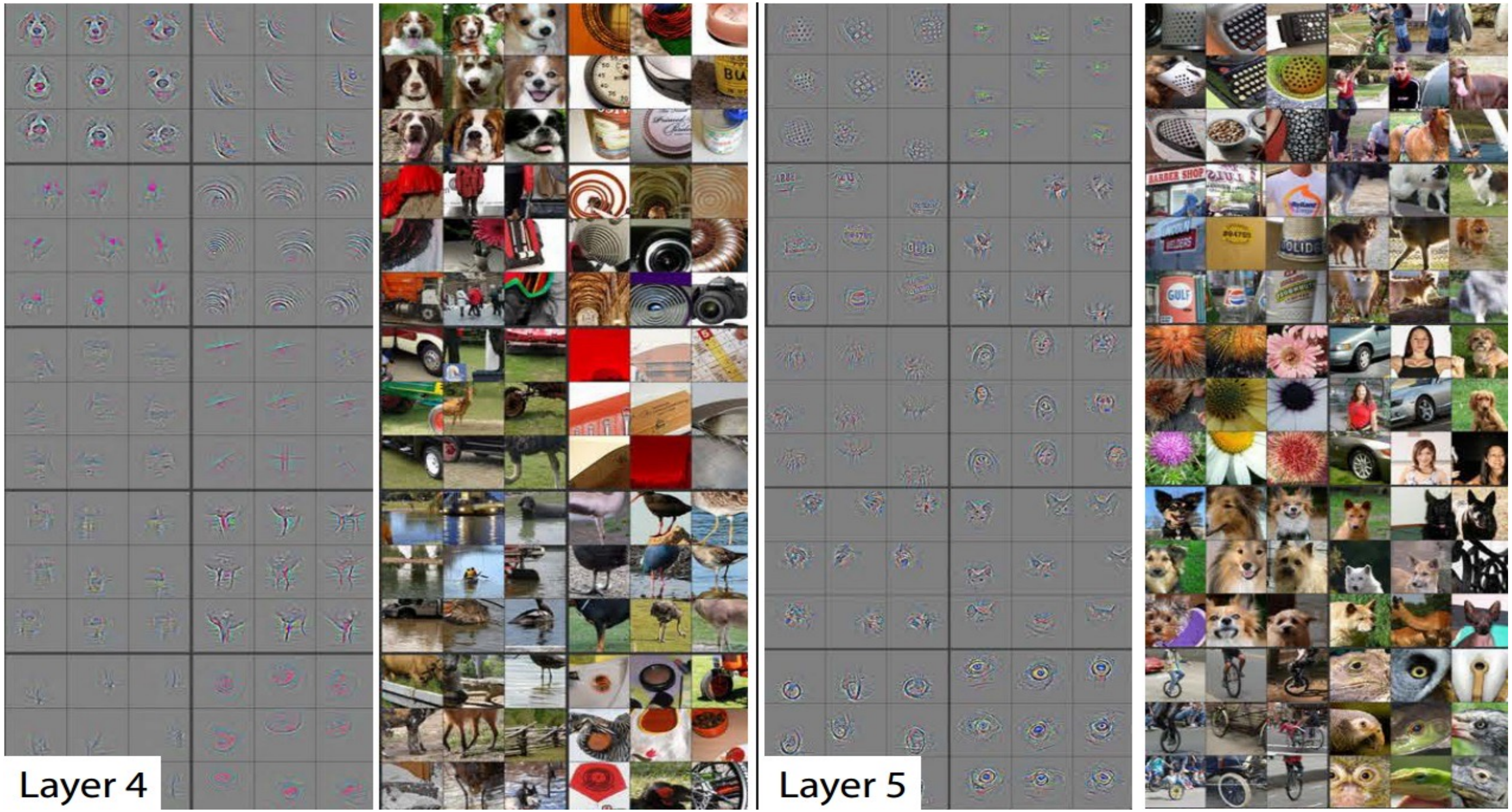
Layer 3



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

Slide credit: Jia-Bin Huang

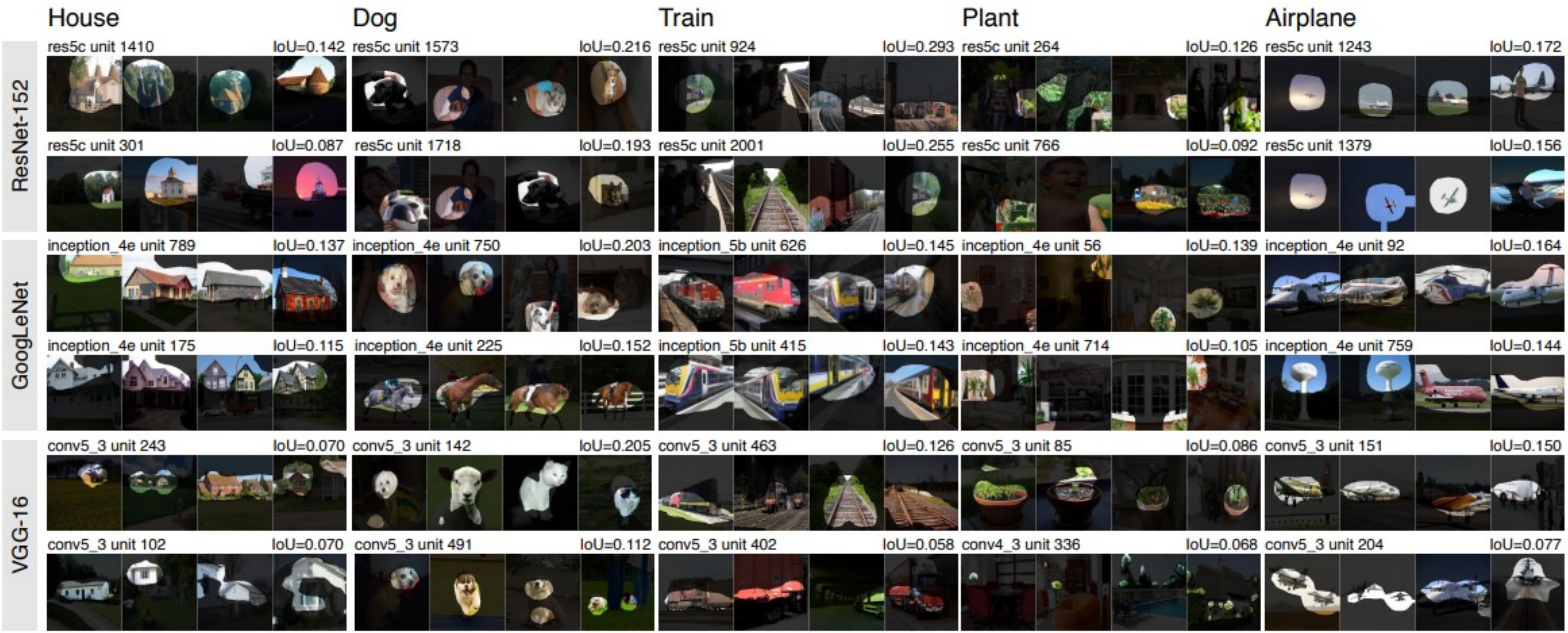
Layer 3



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

Slide credit: Jia-Bin Huang

Neural Network Dissection



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

What About Small Datasets?

- **Transfer learning:** We can reuse trained concepts!
  - Since CNNs trained on ImageNet appear to learn general features
  - We can reuse these models in some way to perform new tasks
- **Strategy 1:** Feature extraction
  - Remove final (softmax) layer and replace with a new one
  - Train only the new layer
- **Strategy 2:** Finetuning
  - Do the same thing but train end-to-end

What About Small Datasets?

- **New dataset is similar to the original dataset**
  - Can use very small datasets
  - Both strategies work

- **New dataset is different from original dataset**
  - Transfer learning still works!
  - Moderate-sized datasets
  - Finetune end-to-end
  - **Examples:** Medical images, audio spectrograms, etc.

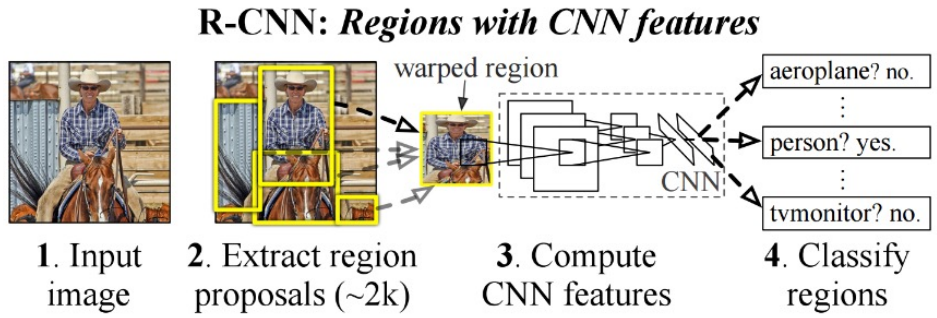
Agenda

- **Convolutional & pooling layers**
- **Convolutional neural networks**
- **Feature visualization**
- **Applications**

Applications

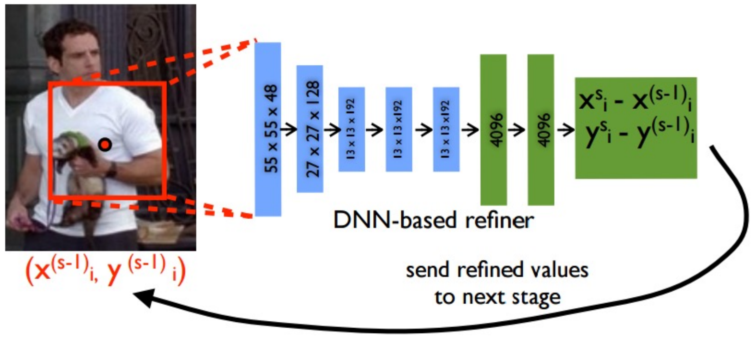
Object detection

[Girshick et al. CVPR14]



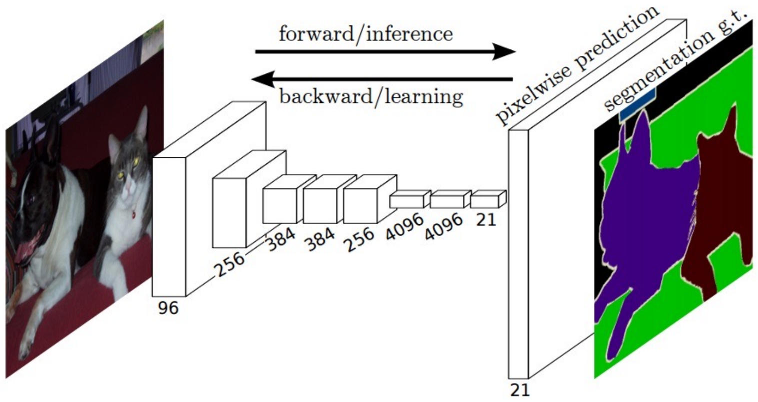
Pose detection (regression)

[Toshev et al. CVPR14]



Semantic segmentation

[Long et al. CVPR15]

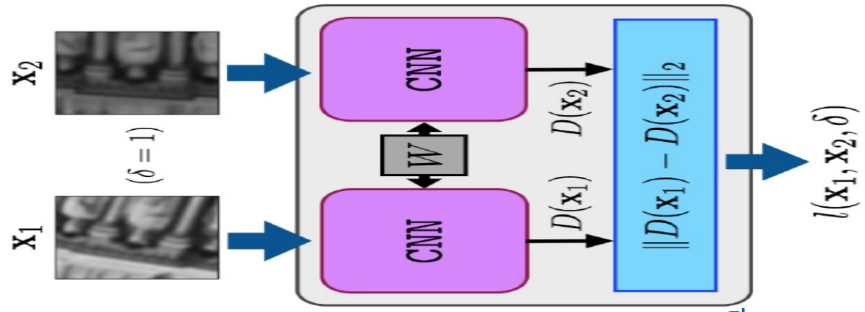


Examples courtesy Jia-Bin Huang

Applications

Similarity metric learning

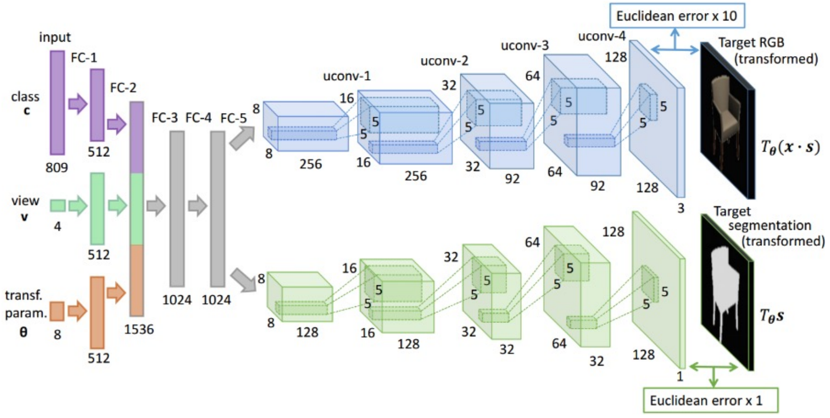
[Chopra et al. CVPR05]



Picture source [Girsh]

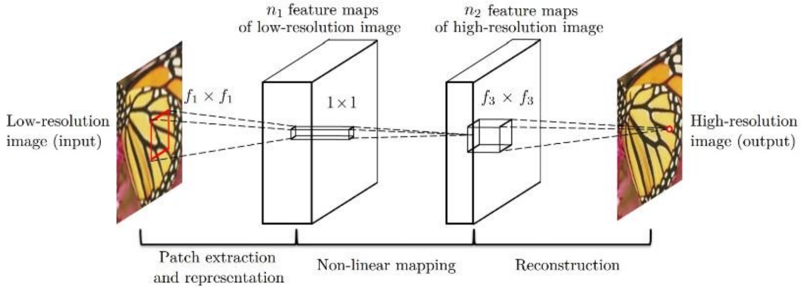
Image generation

[Dosovitskiy et al. CVPR15]



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

[Dong et al. ECCV 2014]



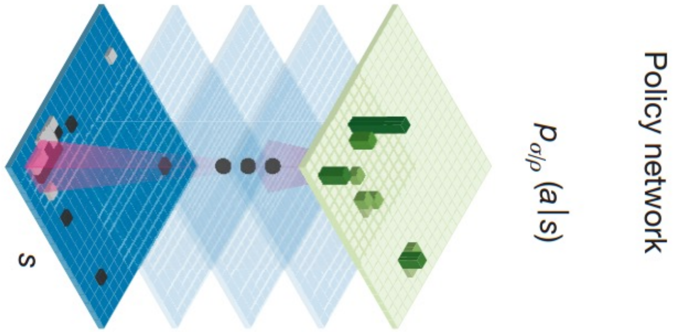
Examples courtesy Jia-Bin Huang

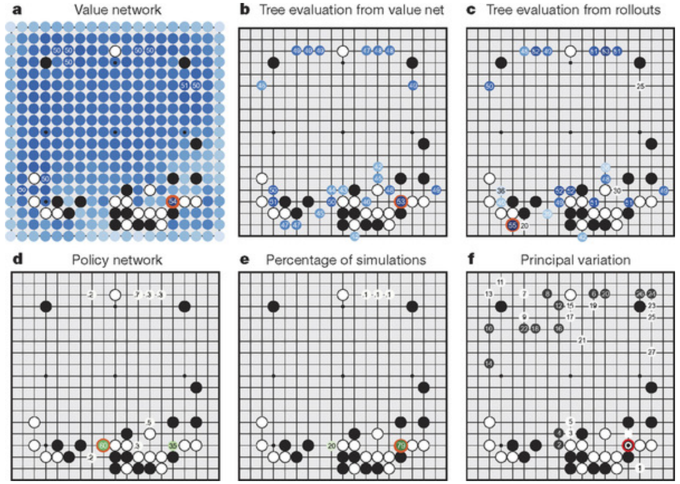
Applications: Game Playing

CNN + Reinforcement learning

[Mnih et al, Nature’ 15]

[Silver et al, Nature ‘16]





Applications: Art Generation

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

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