CNNs and Key Ingredients of Deep Learning

Applied Machine Learning
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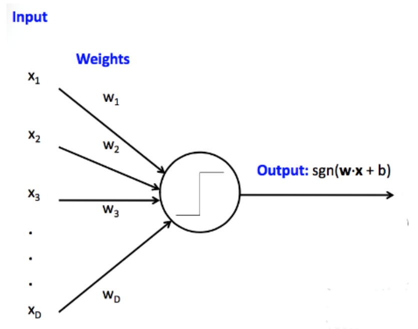
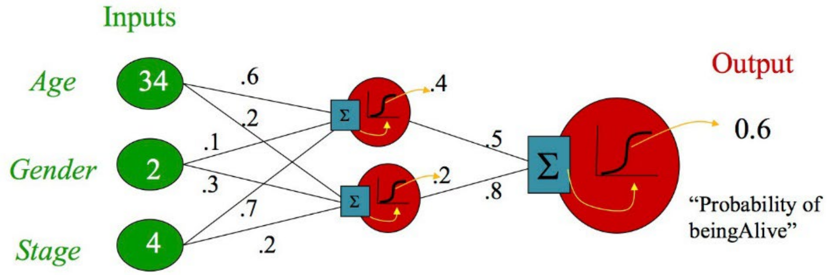
Dall-E

Last class

- Perceptrons are linear prediction models
- MLPs are non-linear prediction models, composed of multiple linear layers with non-linear activations
- MLPs can model more complex functions, but are harder to optimize
- Optimization is by stochastic gradient descent





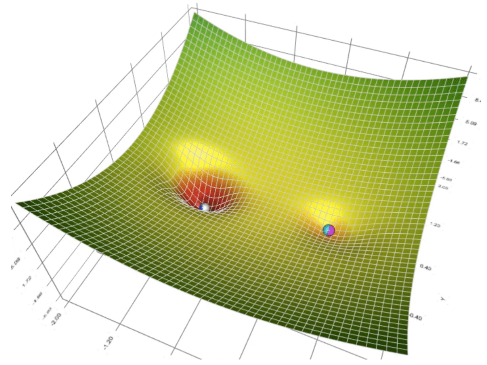
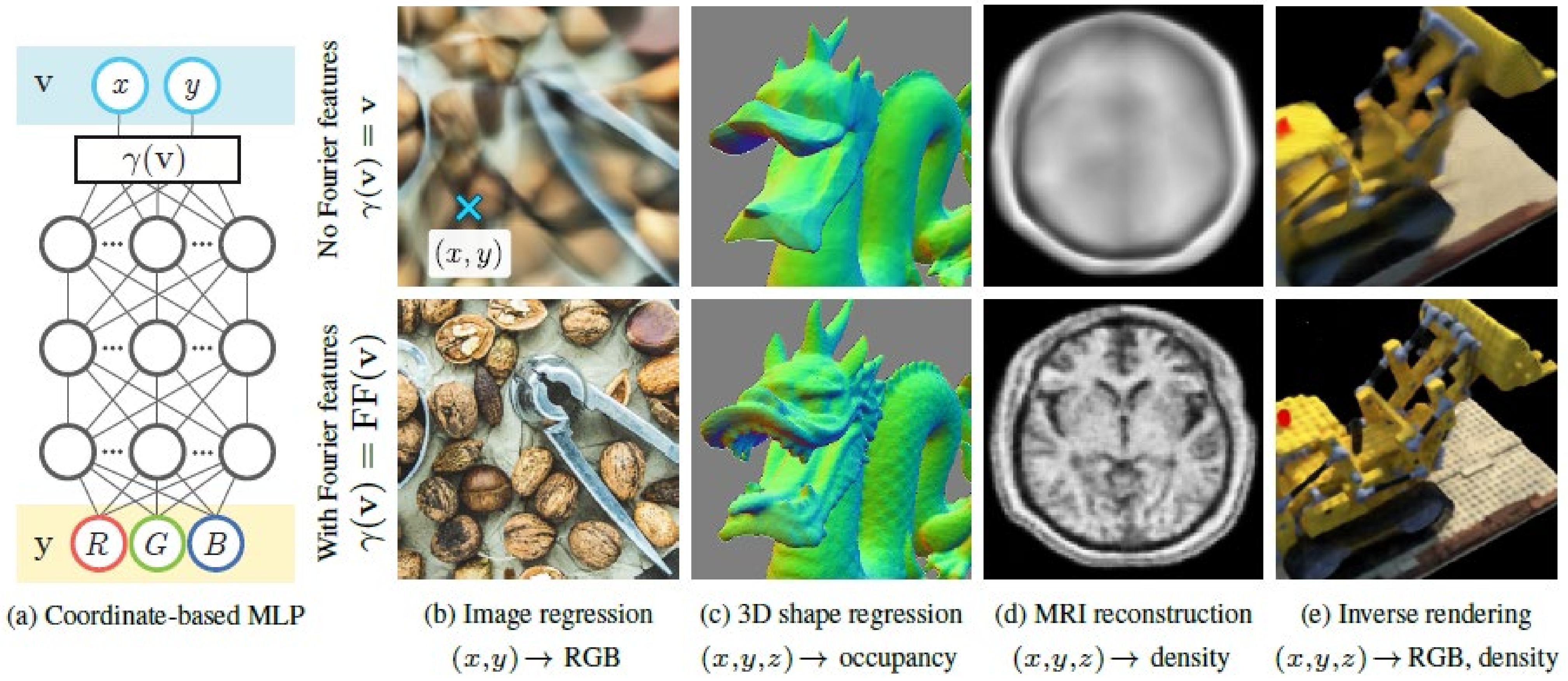


Figure source

Another application example: mapping position/rays to color



- A network can be trained to serve as a query function, for compression and interpolation
  - E.g., $\mathrm{mlp}(x, y) \rightarrow (r, g, b)$ or $\mathrm{mlp}(x, y, z) \rightarrow (r, g, b, density)$
- Fourier features: instead of using $[x, y]$ directly as input, use $[\sin(\omega_0 x), \cos(\omega_0 x), \sin(\omega_1 x), \ldots]$

Fourier Features (Tancik et al. 2020) NeRF (Mildenhall et al. 2020)

Generalized insight from “Fourier Features”

- Input matters – it’s best to represent data in a way that makes it linearly predictive, even if you have a non-linear model

- $f(x, y) \rightarrow R, G, B$ requires a complex network to model because $x_i^T x_j$ is a bad similarity function (maximized when x_j is large, instead of similar to x_i)

- Representing x with a Fourier encoding, e.g. $\gamma(x) = [\sin(x), \cos(x), \sin(2x), \cos(2x), \ldots]$ enables a simpler network because $\gamma(x_i)^T \gamma(x_j)$ falls off smoothly as x_j moves away from x_i
  - This means the initial network layer can model similarity to different positions with each hidden unit

HW 4

2. **MLPs with MNIST** [40 pts]

For this part, you will want to use a GPU to improve runtime. Google Colab provides limited free GPU acceleration to all users. It can be run with CPU, but will be a few times slower. See Tips for detailed guidance on this problem. Note that this problem may require tens of minutes of computation.

First, use **PyTorch** to implement a Multilayer Perceptron network with one hidden layer (size 64) with ReLU activation. Set the network to minimize cross-entropy loss, which is the negative log probability of the training labels given the training features. This objective function takes unnormalized logits as inputs. *Do not use MLP in sklearn for this HW - use Torch.*

a. Using the train/val split provided in the starter code, train your network for 100 epochs with learning rates of 0.01, 0.1, and 1. Use a batch size of 256 and the SGD optimizer. After each epoch, record the mean training and validation loss and compute the validation error of the final model. The mean validation loss should be computed after the epoch is complete. The mean training loss can either be computed after the epoch is complete, or, for efficiency, computed using the losses accumulated during the training of the epoch. Plot the training and validation losses using the `display_error_curves` function.

b. Based on the loss curves, select the learning rate and number of epochs that minimizes the validation loss. Retrain that model (if it's not stored), and *report training loss, validation loss, training error, validation error, and test error.* You should be able to get test error lower than 2.5%.

a. **Improve MNIST Classification Performance using MLPs** [up to 30 pts]

Finally, see if you can improve the model by adjusting the learning rate, the hidden layer size, adding a hidden layer, or trying a different optimizer such as Adam (recommended). Report the train/val/test loss and the train/val/test classification error for the best model. Report your hyperparameters (network layers/size, optimizer type, learning rate, data augmentation, etc.). You can also use an ensemble of networks to achieve lower error for this part. Describe your method and report your val/test error. You must select a model using the validation set and then test your selected model with the test set. Points are awarded as follows: +10 for test error < 2.2%, +10 for test error < 2.0%, +10 for test error < 1.8%.

c. **Positional encoding** [30 pts]

Advanced

Because linear functions are easier to represent in MLPs, it can help to represent features in a way that makes them more useful linearly. An example is the use of positional encoding to represent a pixel position, as described in https://arxiv.org/pdf/2006.10739.pdf.

For this problem, use positional encoding to predict RGB values given pixel coordinate of this image. You can resize the image to a smaller size for speed (e.g. 64 pixels on a side). In this problem, the network is acting as a kind of encoder — you train it on the same pixels that you will use for prediction.

1. Create an MLP that predicts the RGB values of a pixel from its position (x,y). Display the RGB image generated by the network when it receives each pixel position as an input.
2. Write code to extract a sinusoidal positional encoding of (x, y). See this page for details.
3. Create an MLP that predicts a pixel's RGB values from its positional encoding of (x, y). Display the RGB image generated by the network when it receives each pixel position as an input.

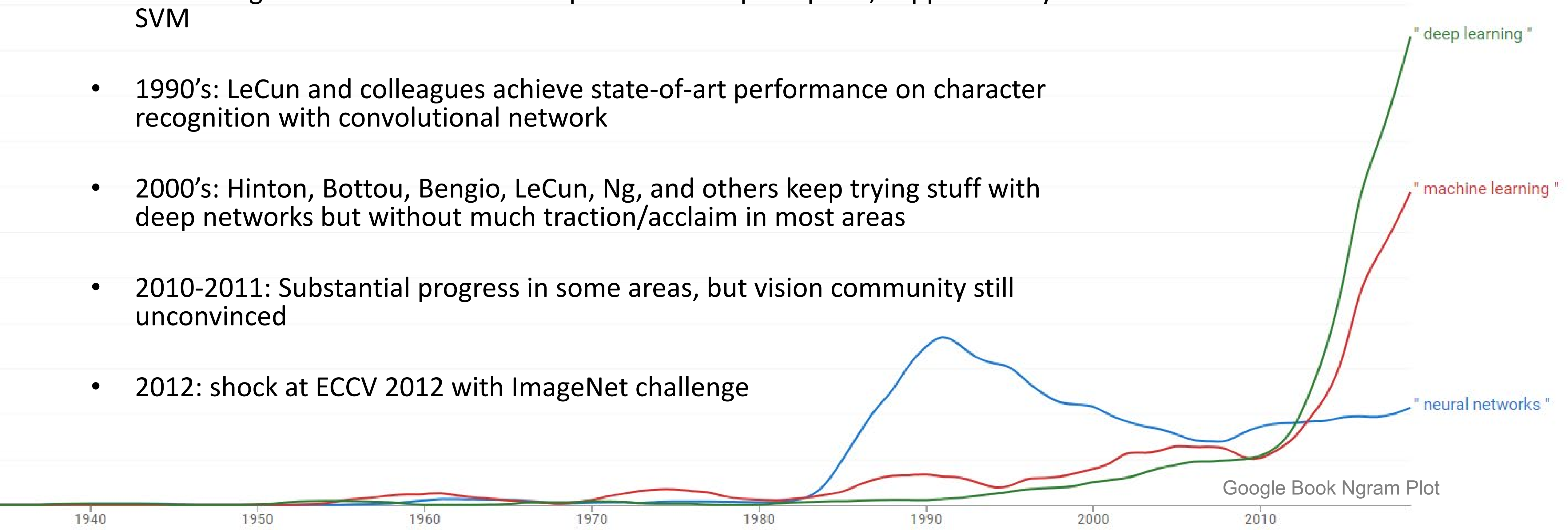
The paper uses these MLP design parameters: L2 loss, ReLU MLP with 4 layers and 256 channels (nodes per layer), sigmoid activation on output, and 256 frequencies.

Today's Lecture

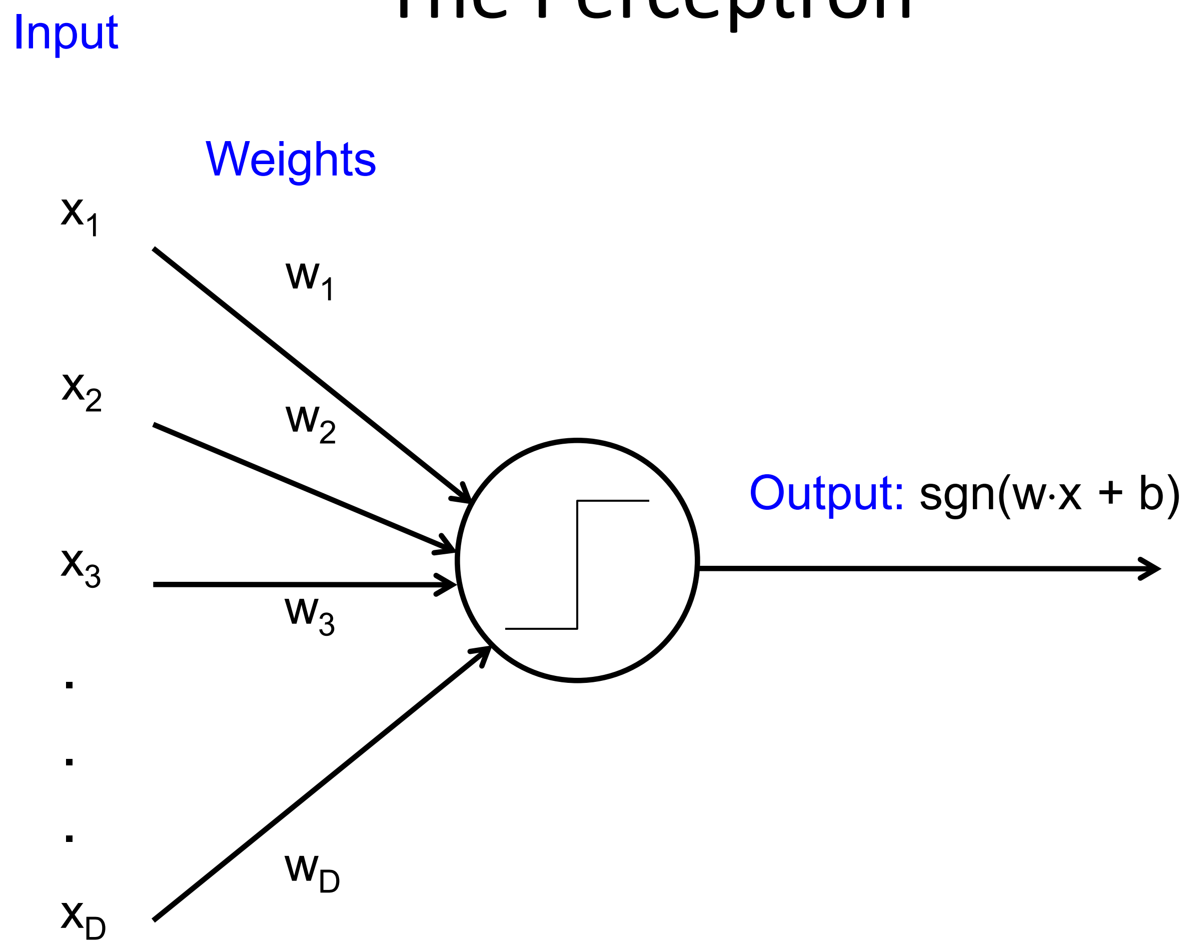
- Deep learning history
- Residual Networks
- SGD++

Brief history of deep learning

- 1958: neural nets (perceptron and MLP) invented by Rosenblatt
- 1967: First use of SGD in deep-learning network (Amari)
- 1980's/1990's: Neural nets are popularized and then abandoned as being interesting idea but too difficult to optimize or "unprincipled", supplanted by SVM
- 1990's: LeCun and colleagues achieve state-of-art performance on character recognition with convolutional network
- 2000's: Hinton, Bottou, Bengio, LeCun, Ng, and others keep trying stuff with deep networks but without much traction/acclaim in most areas
- 2010-2011: Substantial progress in some areas, but vision community still unconvinced
- 2012: shock at ECCV 2012 with ImageNet challenge



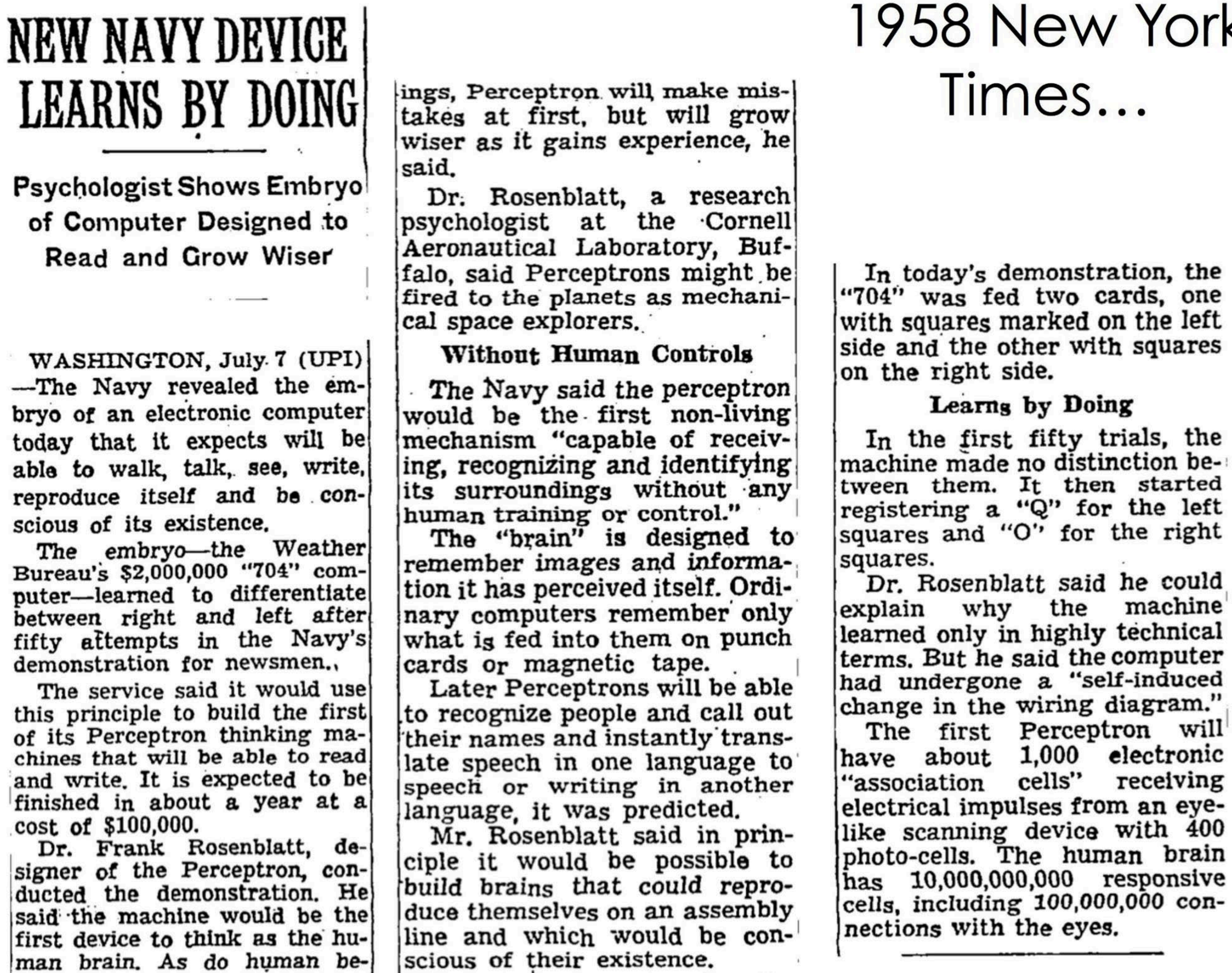
The Perceptron



Rosenblatt, Frank (1958), The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain, Cornell Aeronautical Laboratory, Psychological Review, v65, No. 6, pp. 386–408.

Slide: Lazebnik

1958 New York Times…


NEW NAVY DEVICE LEARNS BY DOING

Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser

WASHINGTON, July 7 (UPI) —The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

The embryo—the Weather Bureau's $2,000,000 "704" computer—learned to differentiate between right and left after fifty attempts in the Navy's demonstration for newsmen.

The service said it would use this principle to build the first of its Perceptron thinking machines that will be able to read and write. It is expected to be finished in about a year at a cost of $100,000.

Dr. Frank Rosenblatt, designer of the Perceptron, conducted the demonstration. He said the machine would be the first device to think as the human brain. As do human beings, Perceptron will make mistakes at first, but will grow wiser as it gains experience, he said.

Dr. Rosenblatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be fired to the planets as mechanical space explorers.

Without Human Controls

The Navy said the perceptron would be the first non-living mechanism "capable of receiving, recognizing and identifying its surroundings without any human training or control."

The "brain" is designed to remember images and information it has perceived itself. Ordinary computers remember only what is fed into them on punch cards or magnetic tape.

Later Perceptrons will be able to recognize people and call out their names and instantly translate speech in one language to speech or writing in another language, it was predicted.

Mr. Rosenblatt said in principle it would be possible to build brains that could reproduce themselves on an assembly line and which would be conscious of their existence.

In today's demonstration, the "704" was fed two cards, one with squares marked on the left side and the other with squares on the right side.

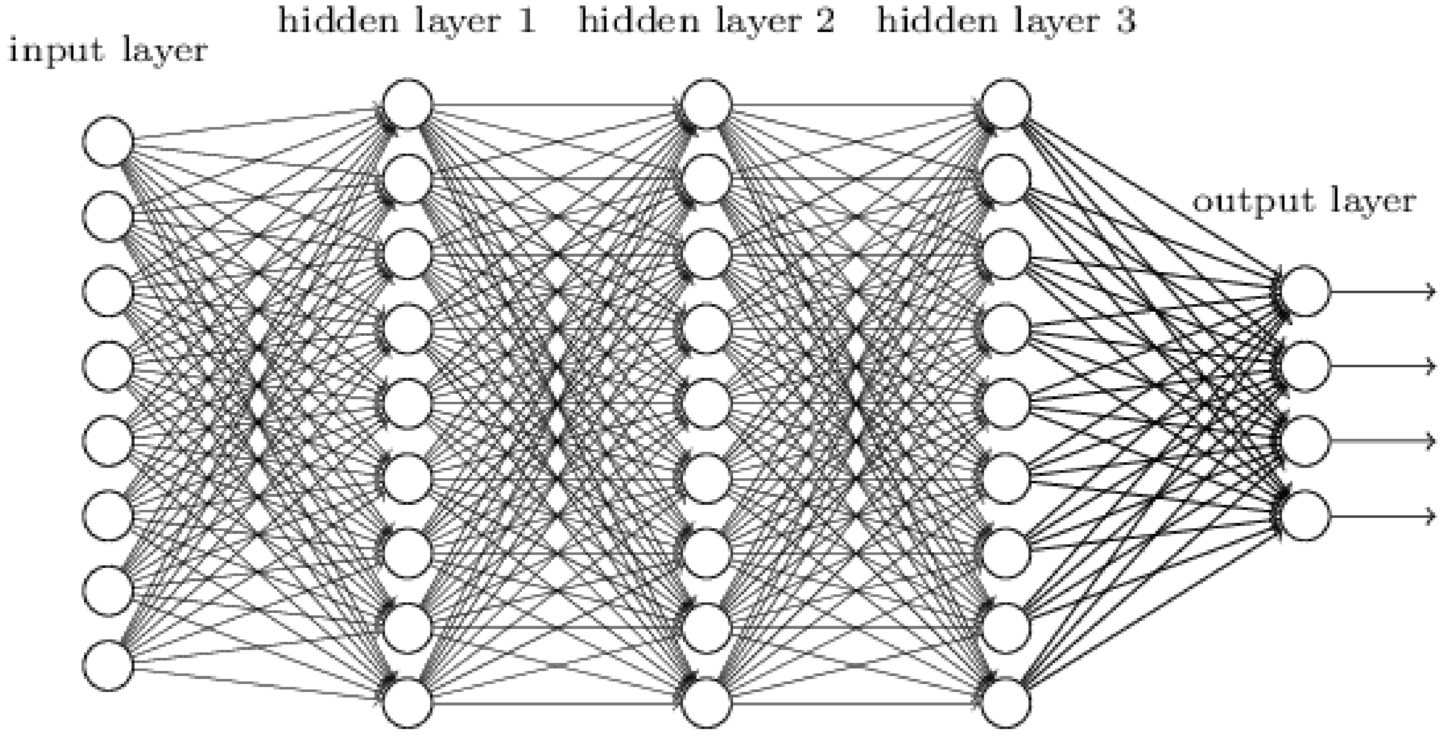
Learns by Doing

In the first fifty trials, the machine made no distinction between them. It then started registering a "Q" for the left squares and "O" for the right squares.

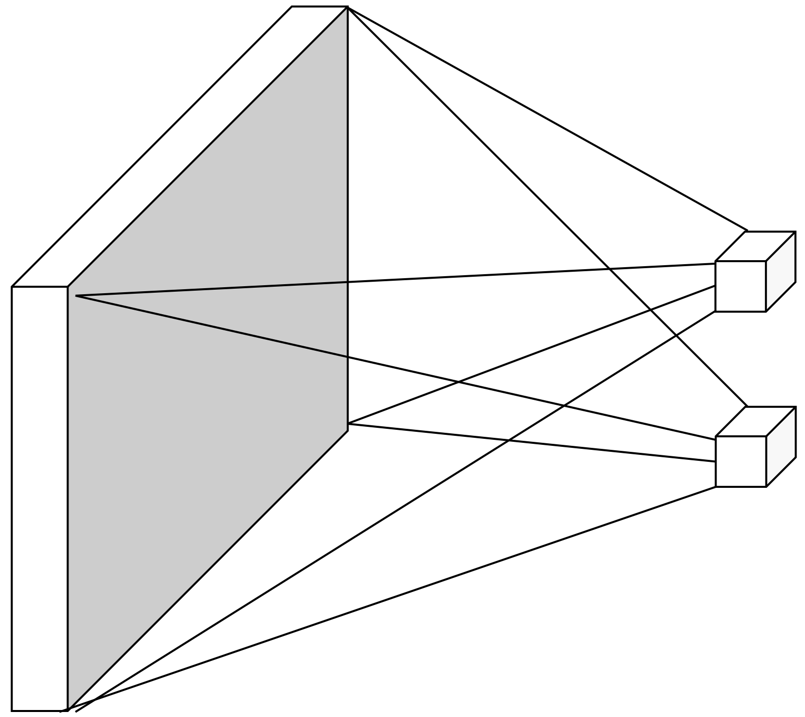
Dr. Rosenblatt said he could explain why the machine learned only in highly technical terms. But he said the computer had undergone a "self-induced change in the wiring diagram."

The first Perceptron will have about 1,000 electronic "association cells" receiving electrical impulses from an eye-like scanning device with 400 photo-cells. The human brain has 10,000,000,000 responsive cells, including 100,000,000 connections with the eyes.

Deeper neural networks could theoretically learn compositional representations of complex functions but were hard to optimize

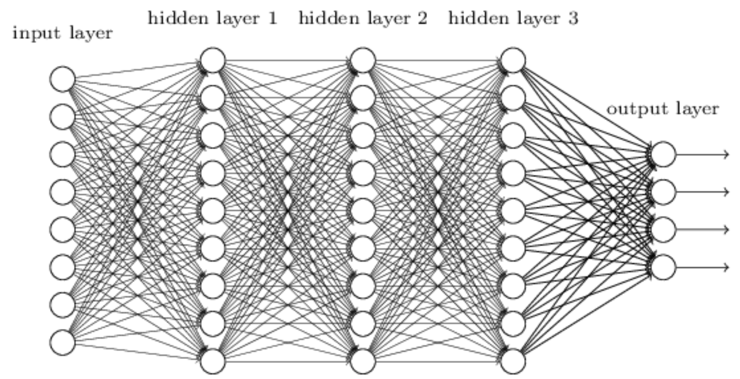


Pure MLPs are not great for images



Image

Fully connected layer

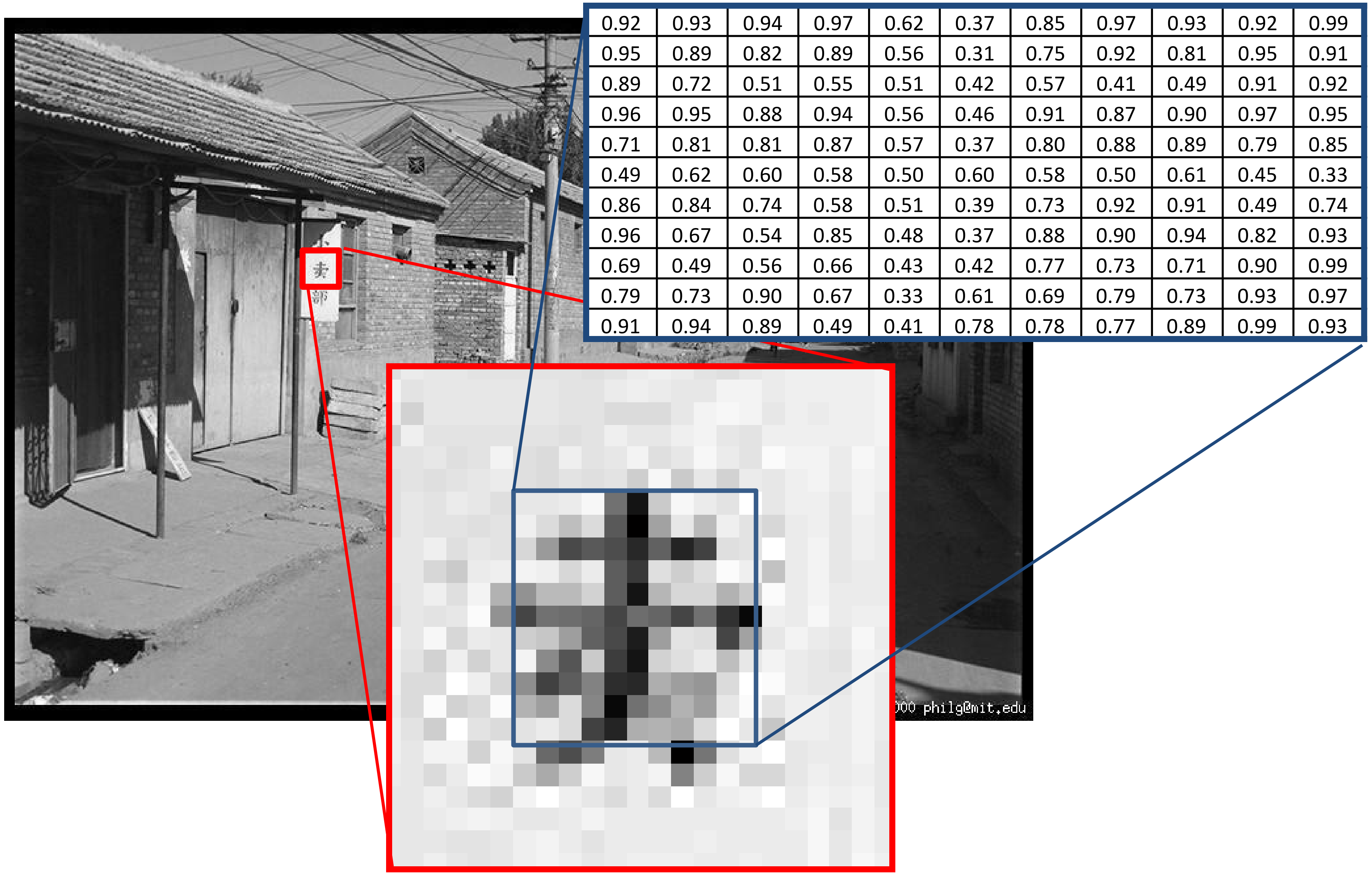


You could treat the image like a vector of values and add fully connected layers (which we do in HW4)

But this doesn't take advantage of the 2D structure of images

Slide: Lazebnik

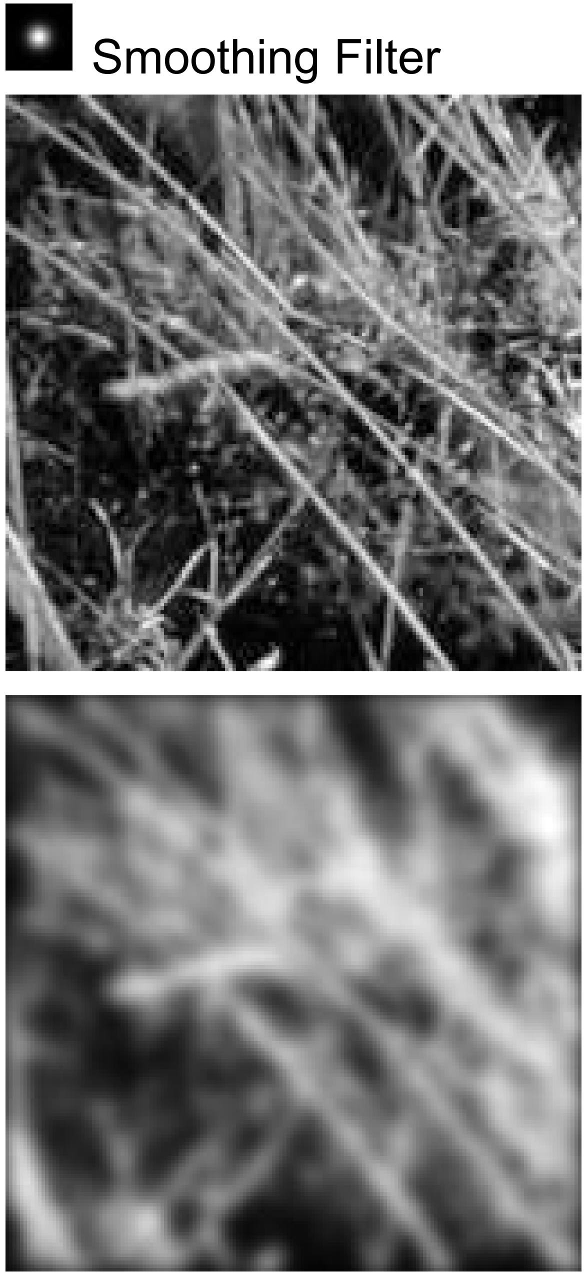
Images have local patterns that can appear at different positions

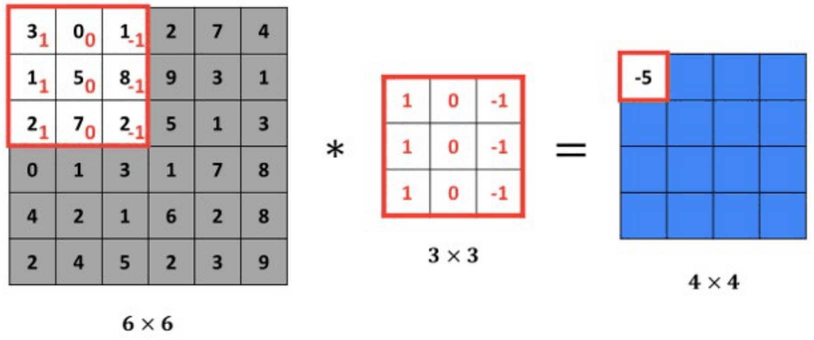


0.92	0.93	0.94	0.97	0.62	0.37	0.85	0.97	0.93	0.92	0.99
0.95	0.89	0.82	0.89	0.56	0.31	0.75	0.92	0.81	0.95	0.91
0.89	0.72	0.51	0.55	0.51	0.42	0.57	0.41	0.49	0.91	0.92
0.96	0.95	0.88	0.94	0.56	0.46	0.91	0.87	0.90	0.97	0.95
0.71	0.81	0.81	0.87	0.57	0.37	0.80	0.88	0.89	0.79	0.85
0.49	0.62	0.60	0.58	0.50	0.60	0.58	0.50	0.61	0.45	0.33
0.86	0.84	0.74	0.58	0.51	0.39	0.73	0.92	0.91	0.49	0.74
0.96	0.67	0.54	0.85	0.48	0.37	0.88	0.90	0.94	0.82	0.93
0.69	0.49	0.56	0.66	0.43	0.42	0.77	0.73	0.71	0.90	0.99
0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97
0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93

Linear filtering is a foundation of image processing

- Linear image filtering: at each pixel, output a weighted sum of pixels in surrounding patch
  - E.g. Gaussian-weighted smoothing filter (right), edge detection (below), local pattern detection

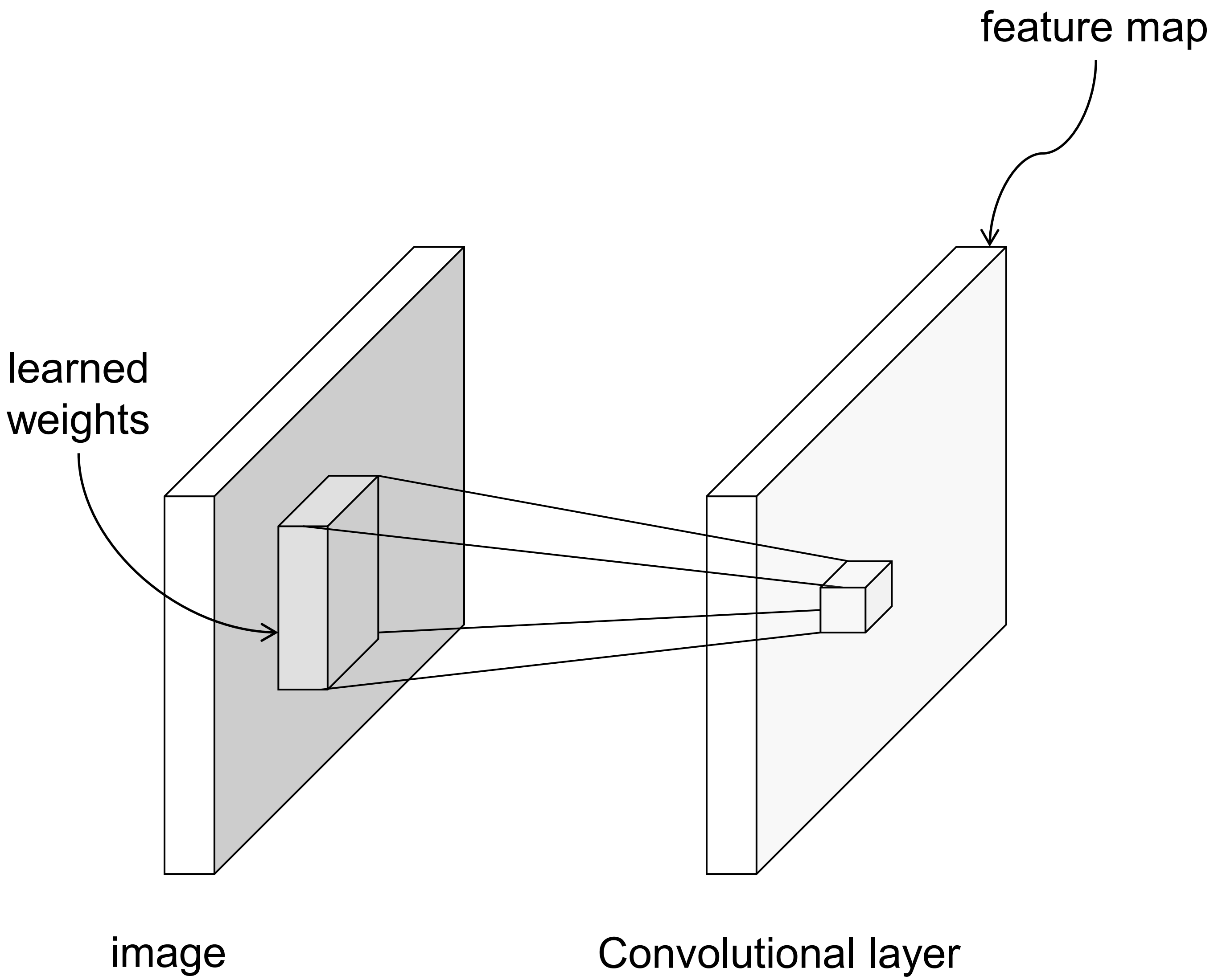




$$3 \times 1 + 1 \times 1 + 2 \times 1 + 0 \times 0 + 5 \times 0 + 7 \times 0 + 1 \times -1 + 8 \times -1 + 2 \times -1 = -5$$

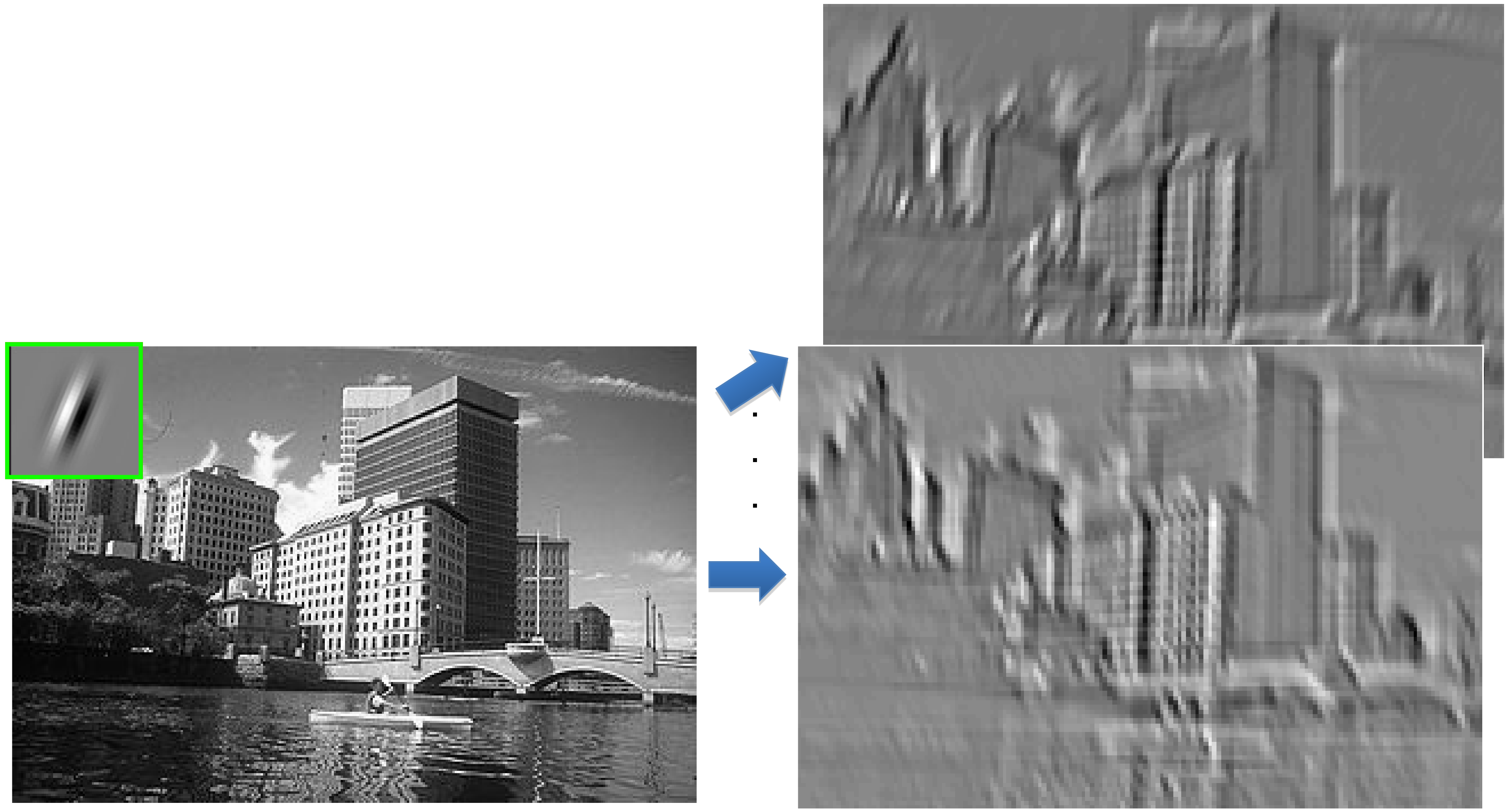
Animation: https://datahacker.rs/004-how-to-smooth-and-sharpen-an-image-in-opencv/

A CNN (convolutional network) learns filter weights to create grids of features ("feature map")



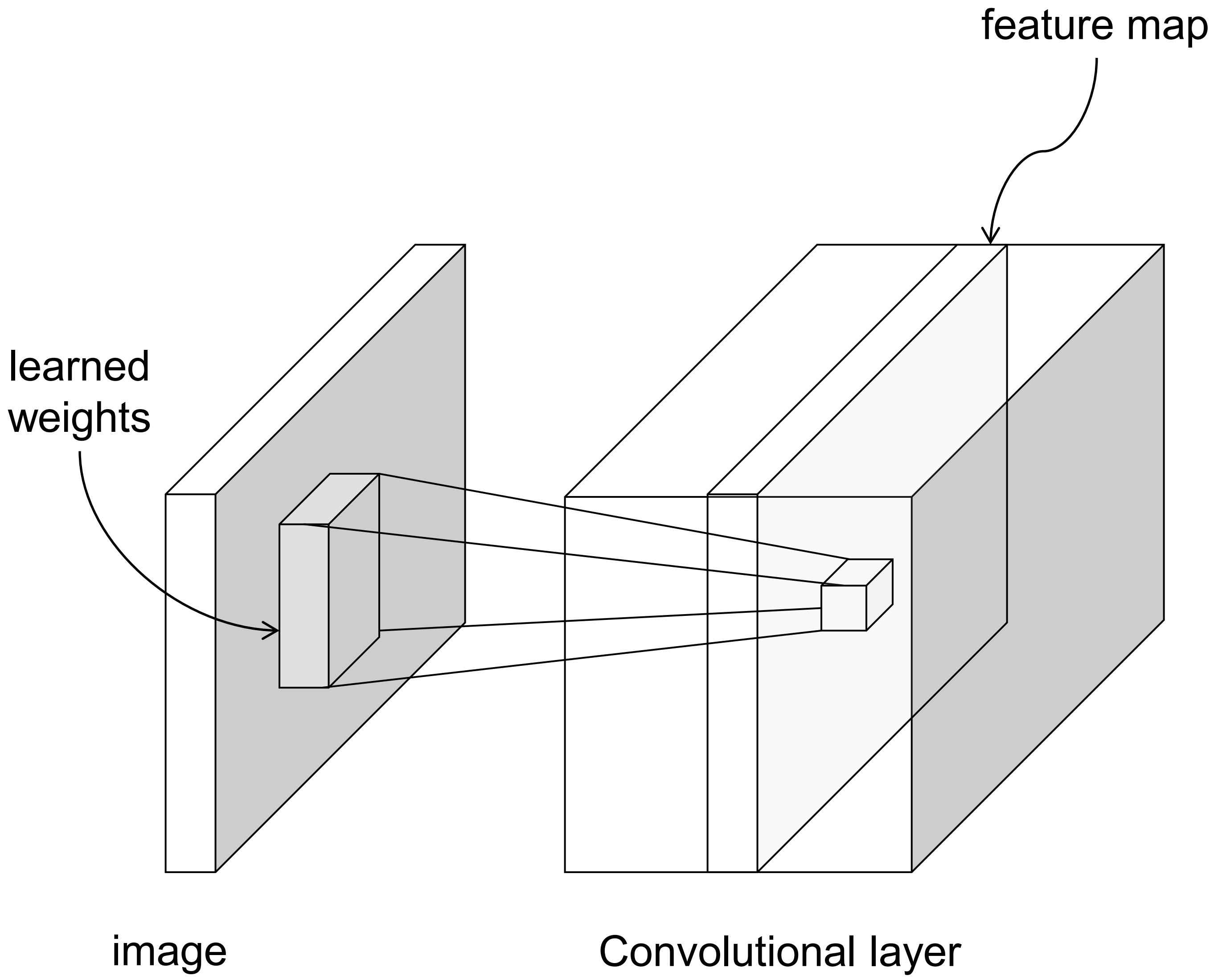
Slide: Lazebnik

Convolution as feature extraction



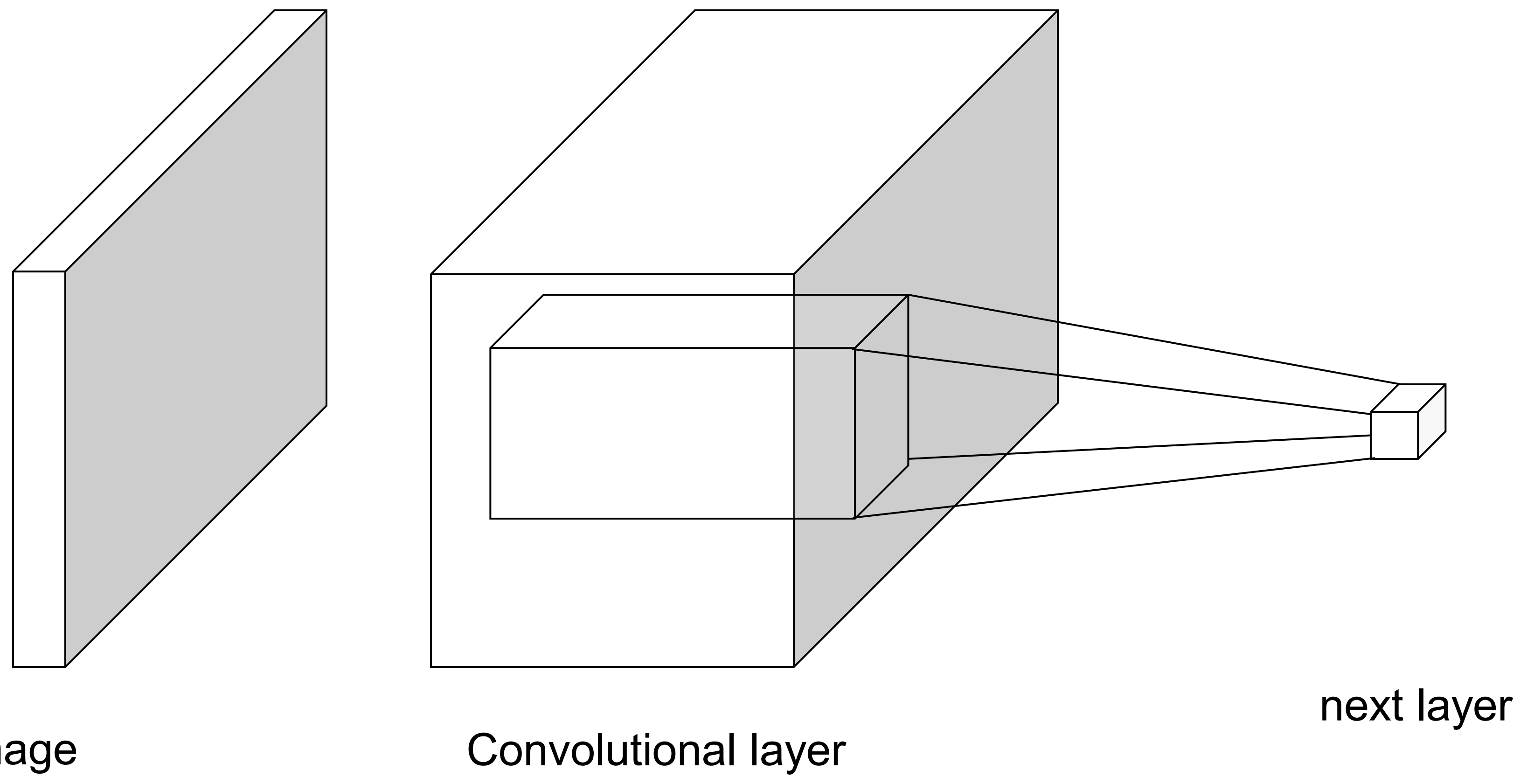
Slide: Lazebnik

Multiple filters are learned, producing a map of feature vectors



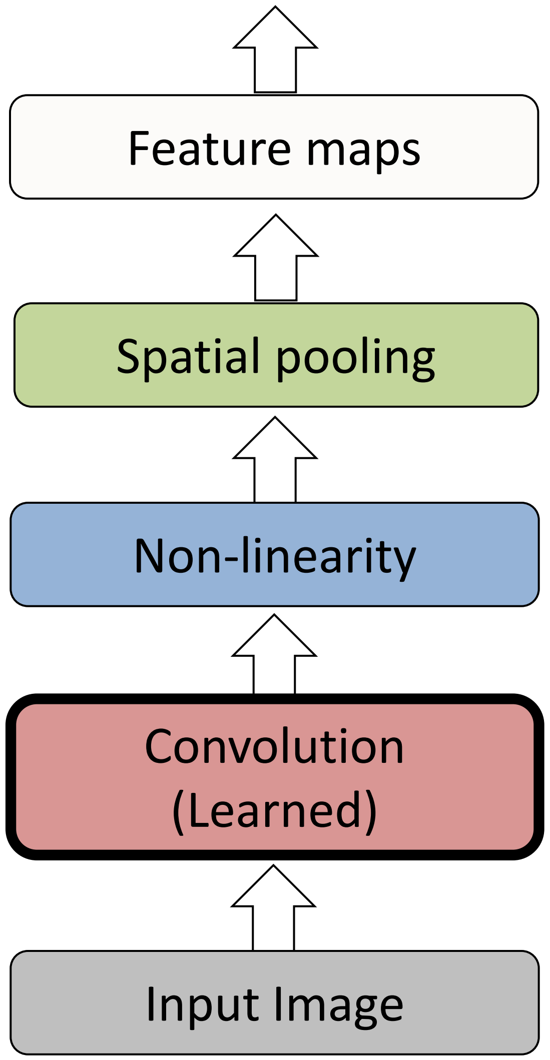
Slide: Lazebnik

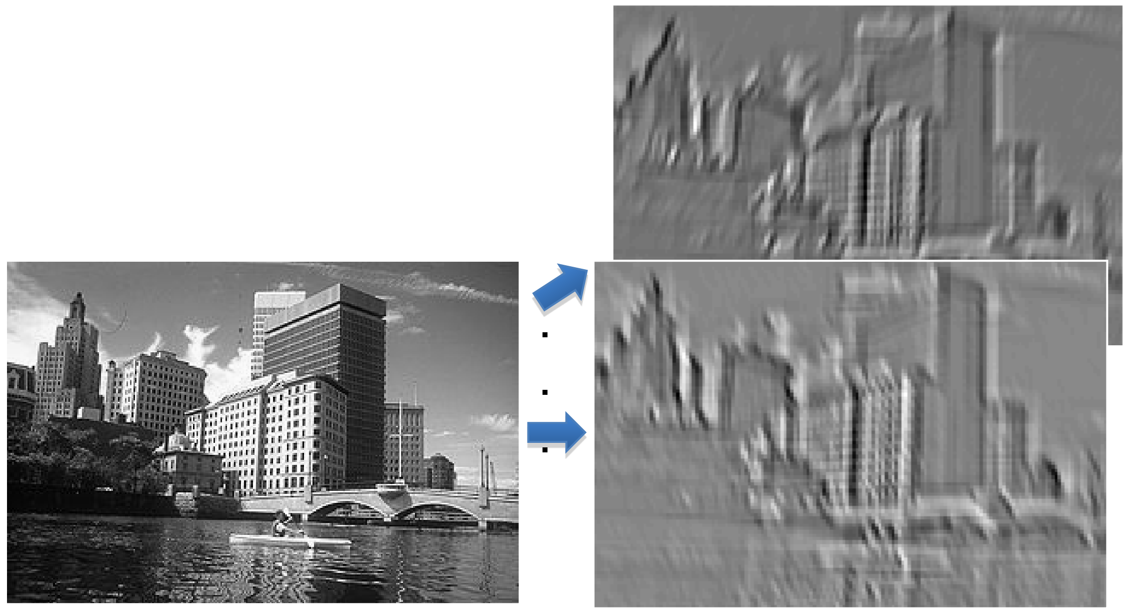
Following layers operate on the feature map from the previous layer



Slide: Lazebnik

Key operations in a CNN





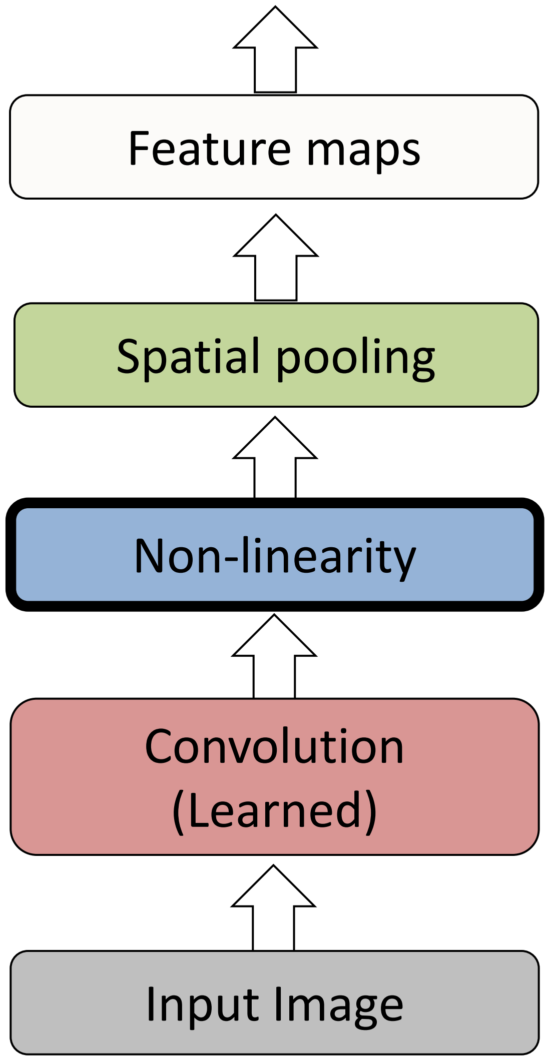
Input

Feature Map

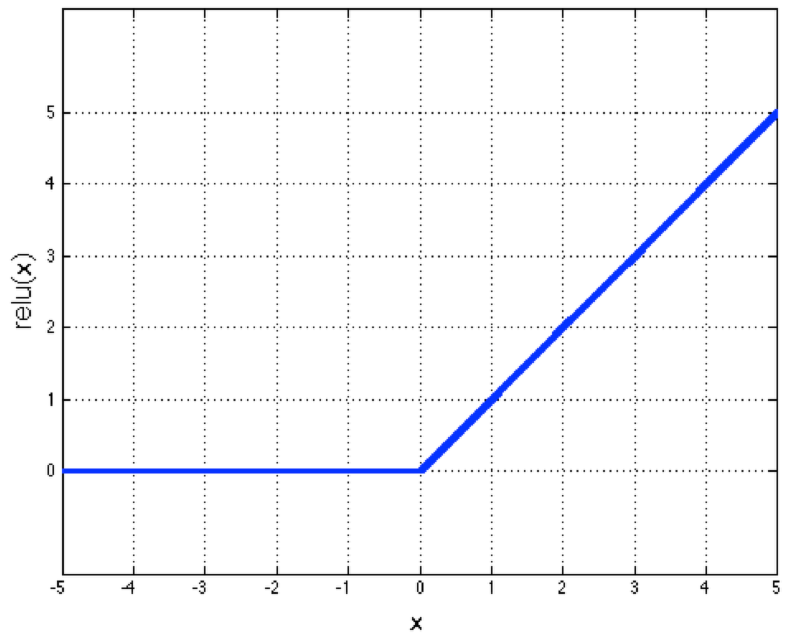
Source: R. Fergus, Y. LeCun

Slide: Lazebnik

Key operations



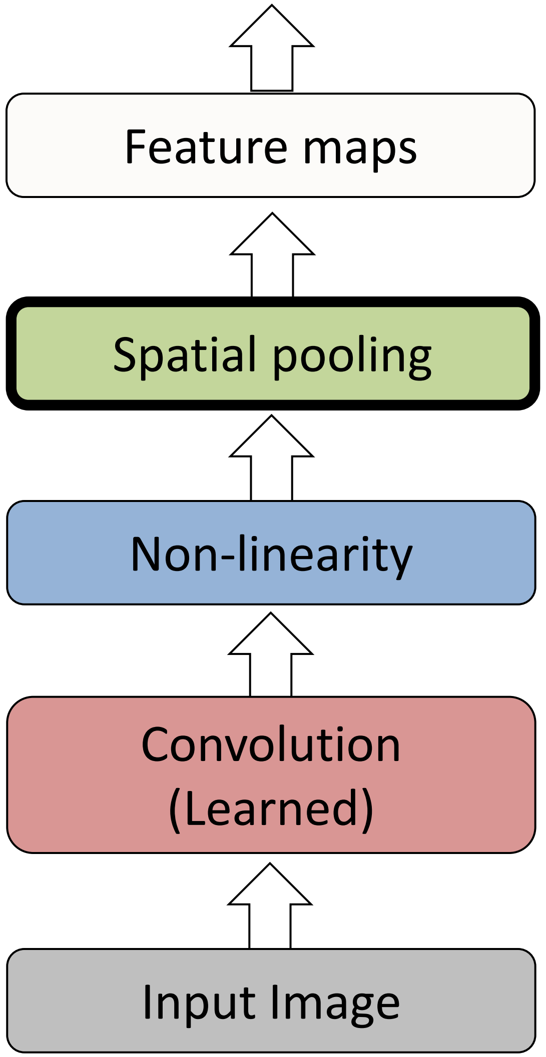
Rectified Linear Unit (ReLU)

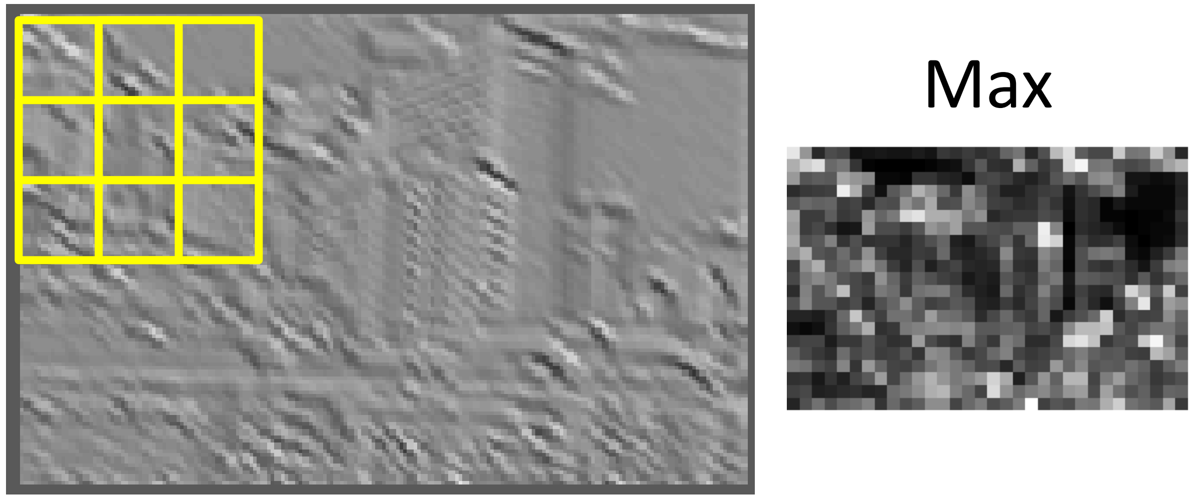


Source: R. Fergus, Y. LeCun

Slide: Lazebnik

Key operations

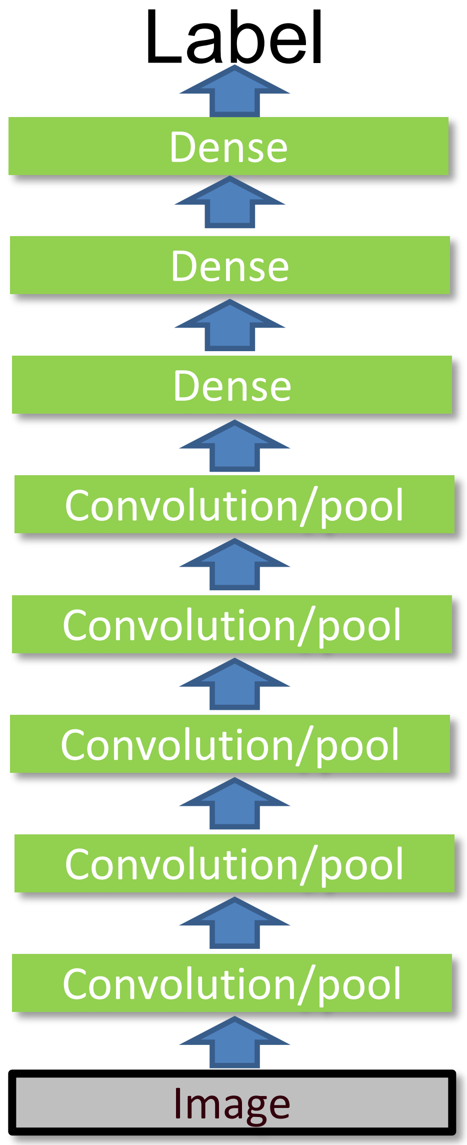




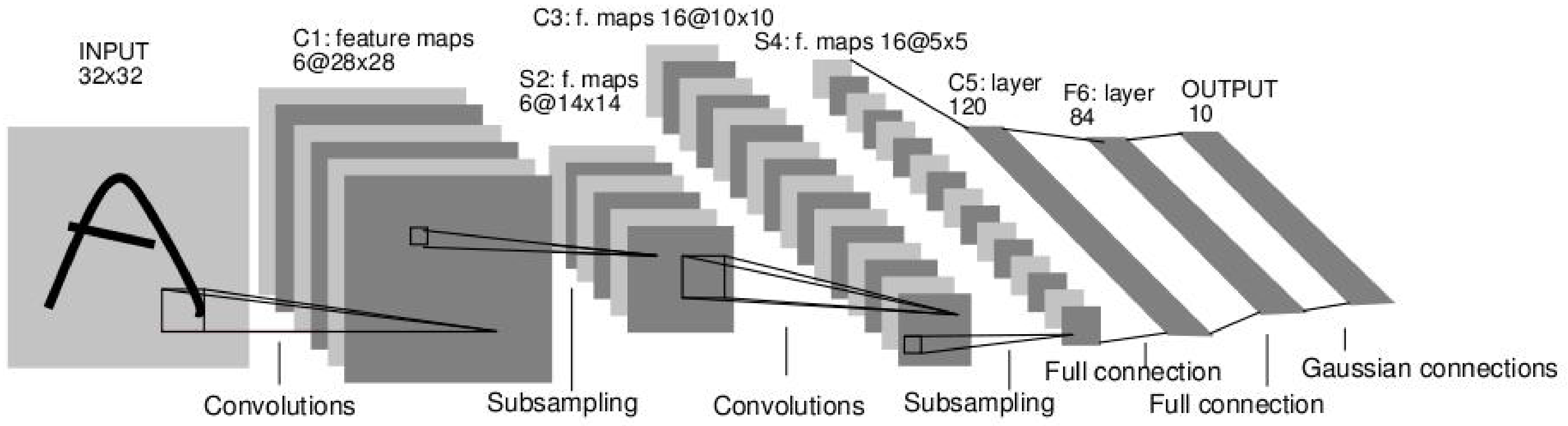
Source: R. Fergus, Y. LeCun

Slide: Lazebnik

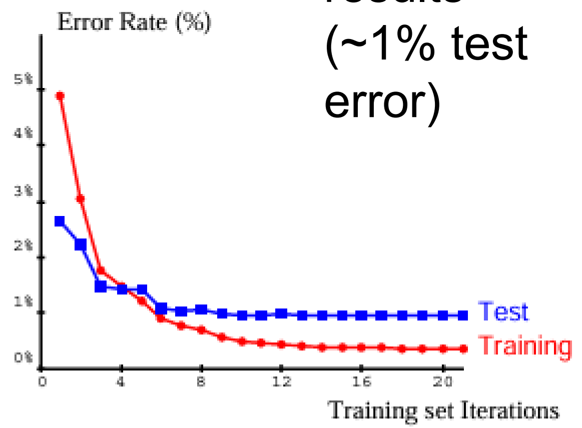
Key idea: learn features and classifier that work well together (“end-to-end training”)



LeNet-5 for character/digit recognition



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

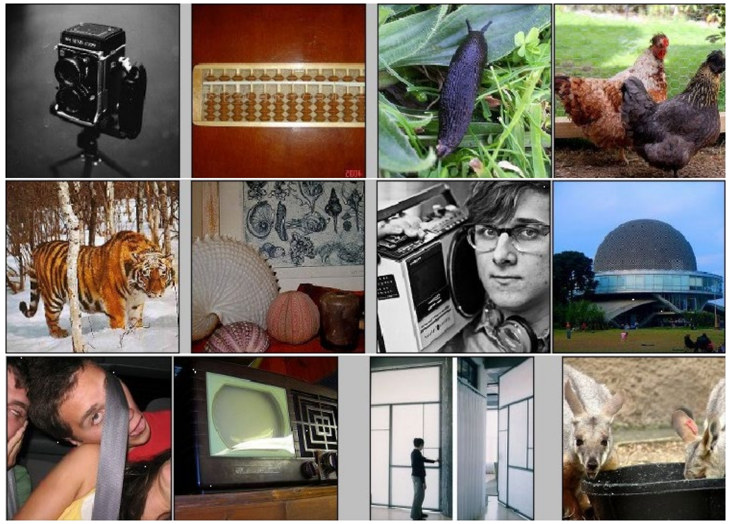


MNIST results (~1% test error)

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE 86(11): 2278–2324, 1998.

Fast forward to the arrival of big visual data…

IMAGENET



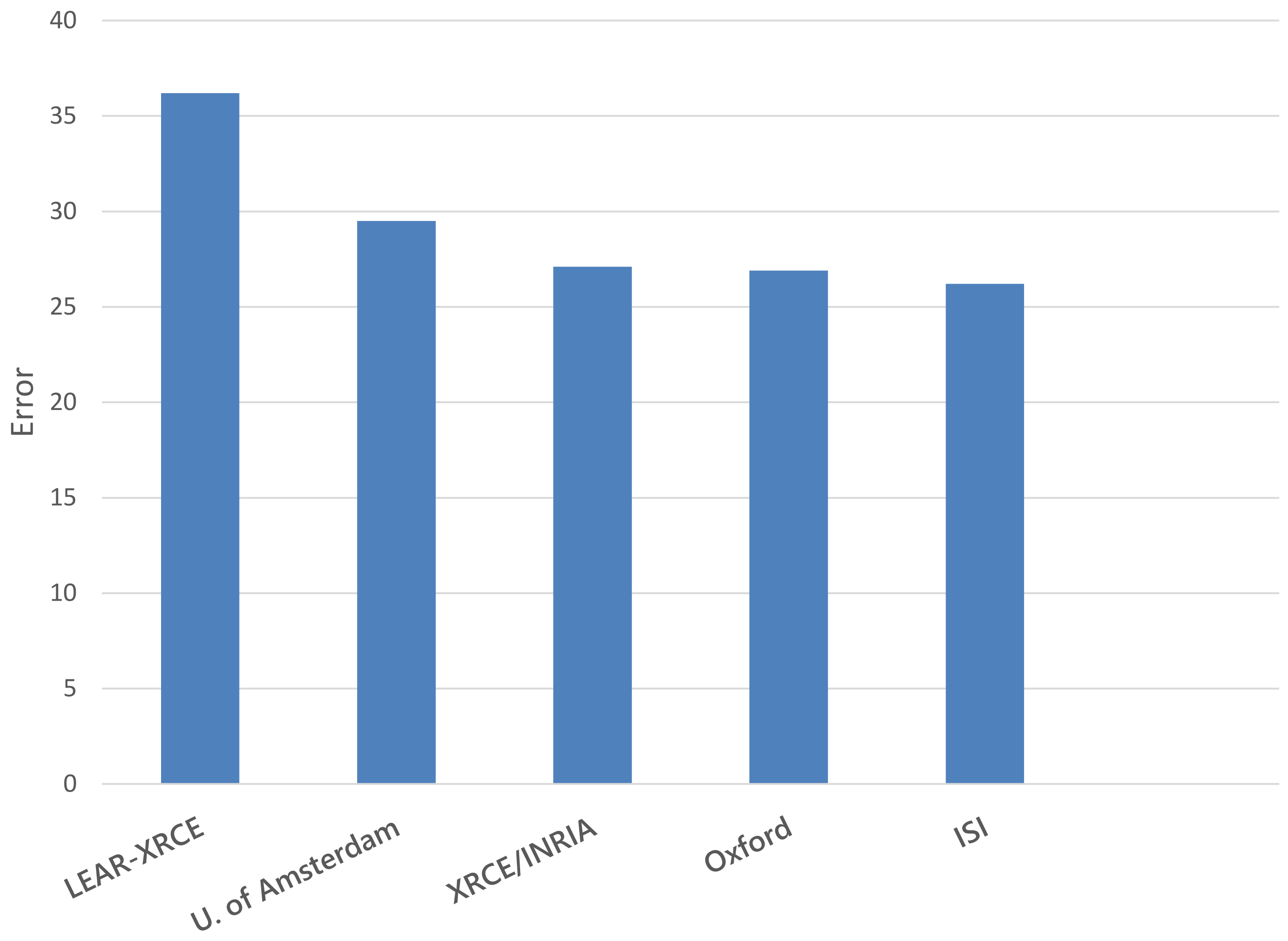
- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- ImageNet Large-Scale Visual Recognition Challenge (ILSVRC):
  1.2 million training images, 1000 classes

www.image-net.org/challenges/LSVRC/

Slide: Lazebnik

2012 ImageNet 1K

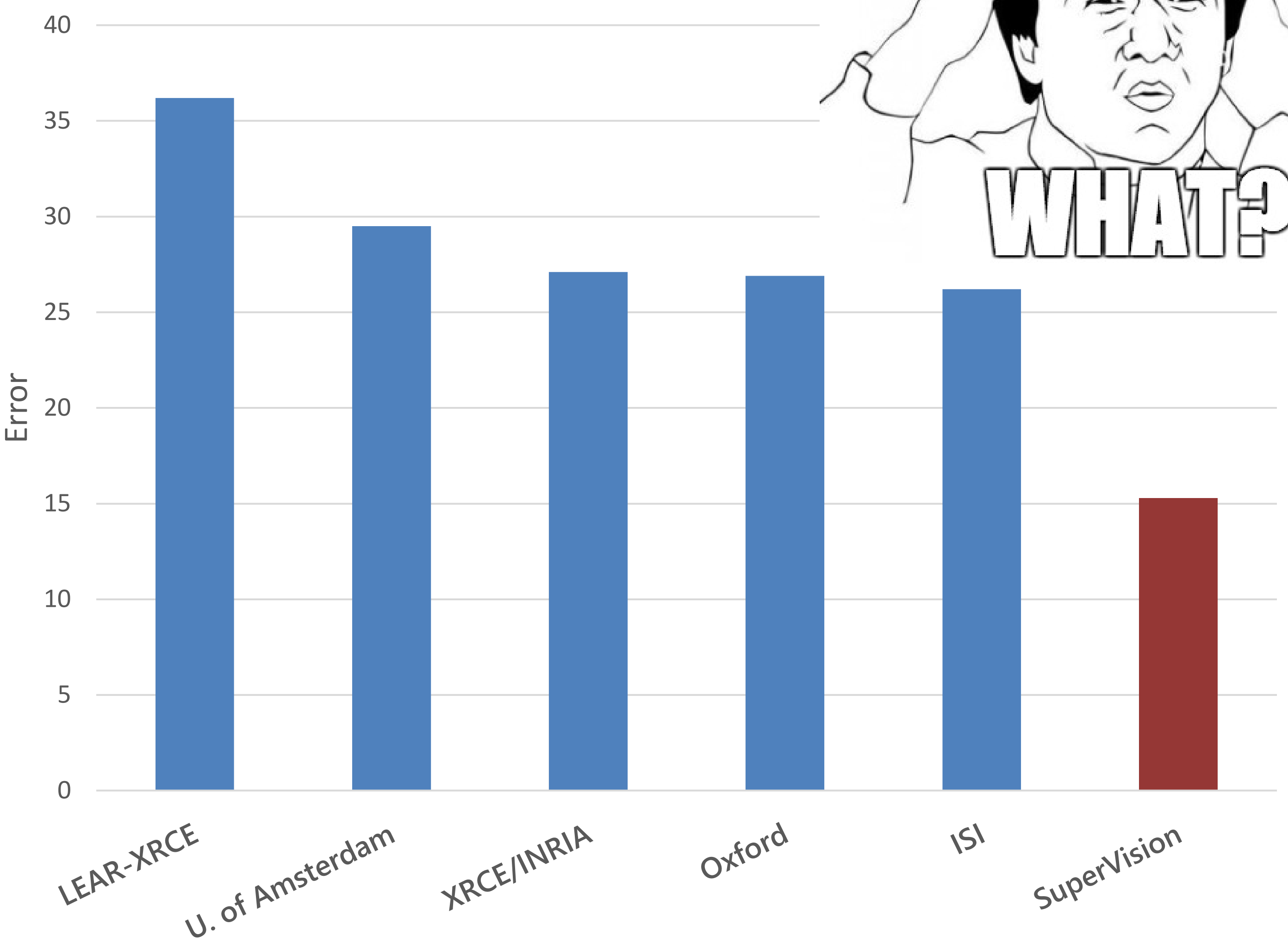
(Fall 2012)

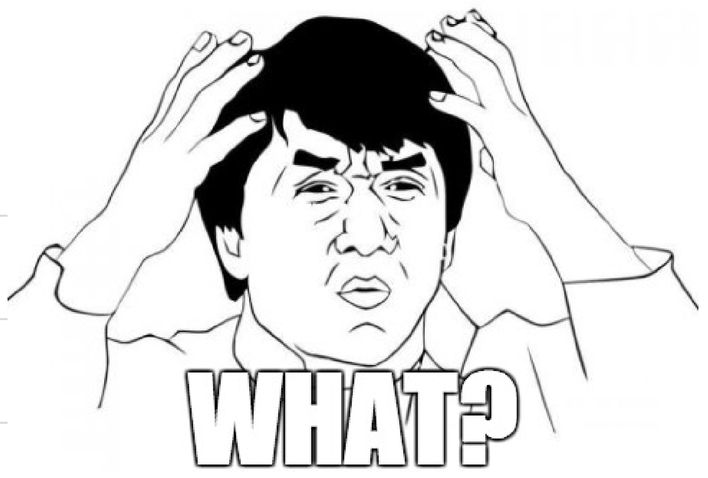


Slide: Jia-bin Huang

2012 ImageNet 1K

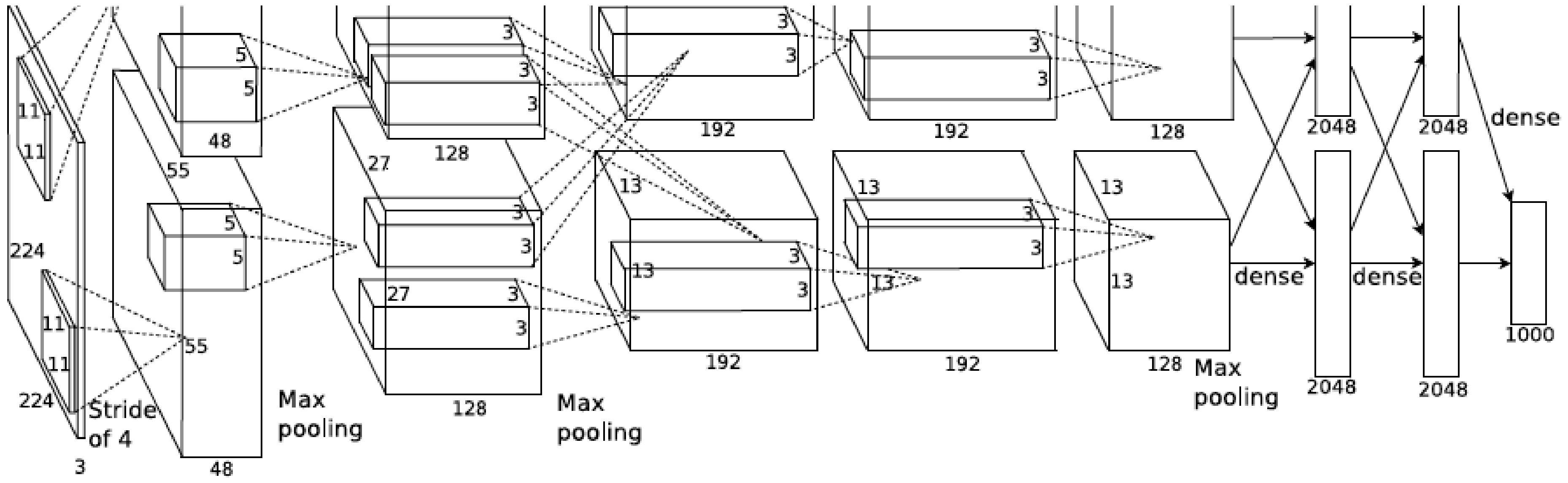
(Fall 2012)





Slide: Jia-bin Huang

AlexNet: ILSVRC 2012 winner



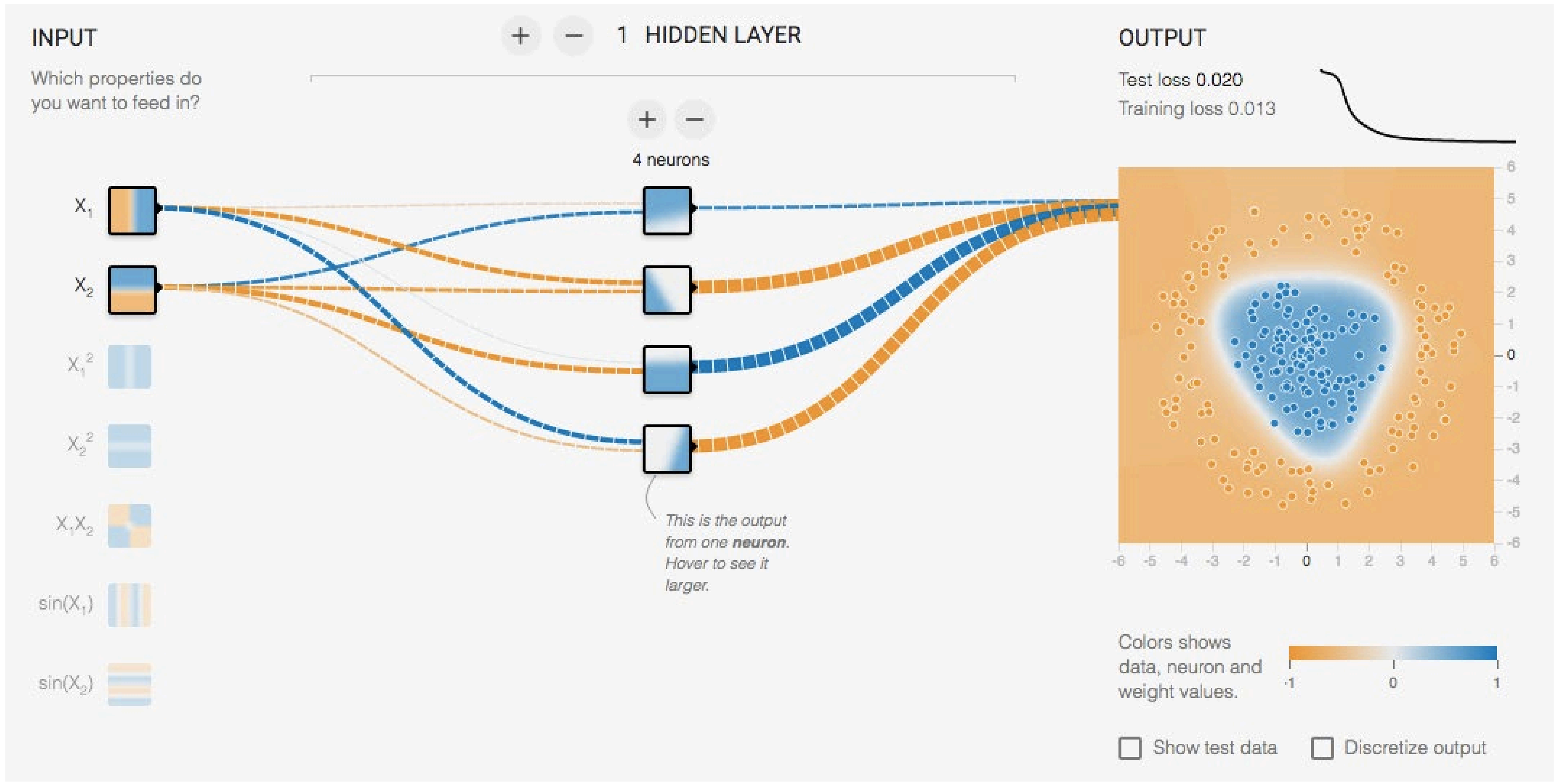
- Similar framework to LeNet but:
    - Max pooling, **ReLU nonlinearity**
    - **More data** and **bigger model** (7 hidden layers, 650K units, 60M params)
    - GPU implementation (**50x speedup** over CPU)
        - Trained on two GPUs for a week
    - Dropout regularization

A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

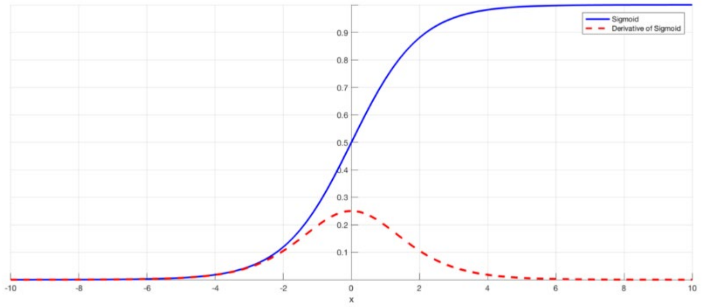
What enabled the breakthrough?

1. ReLU activation enabled large models to be optimized
2. ImageNet provided diverse and massive annotation to take advantage of the models
3. GPU processing made the optimization practicable

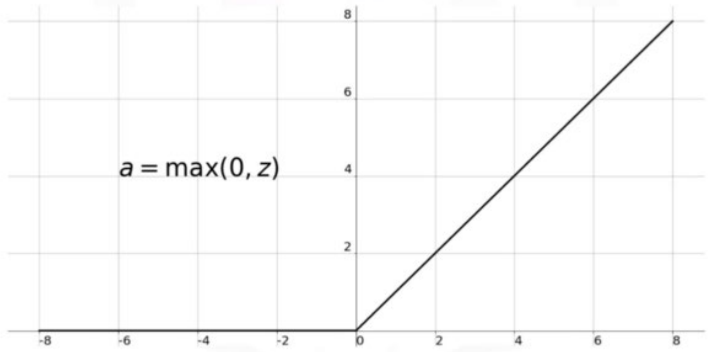
Sigmoid vs. ReLU



Sigmoid



ReLU



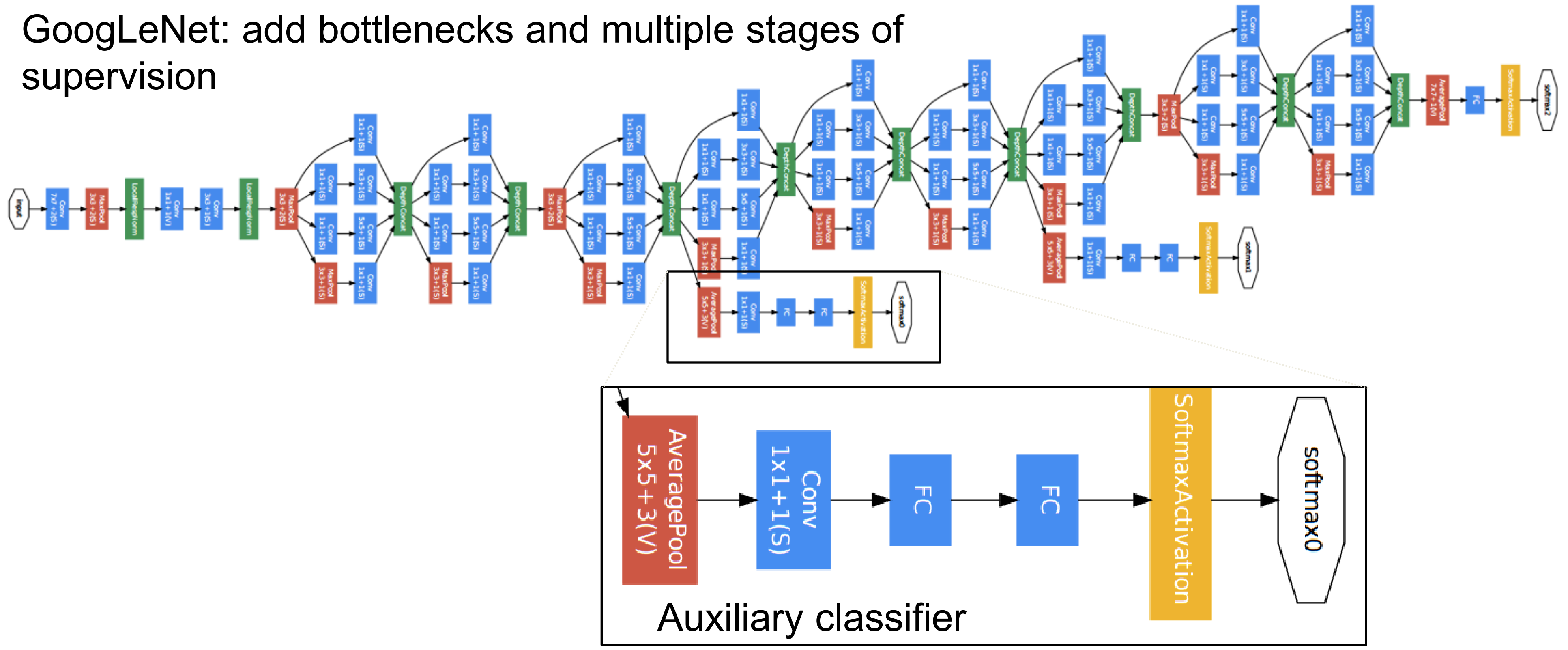
http://playground.tensorflow.org/

Try many layers with sigmoid vs relu

Slide: Lazebnik

Even with ReLU, it was hard to get very deep networks to work well

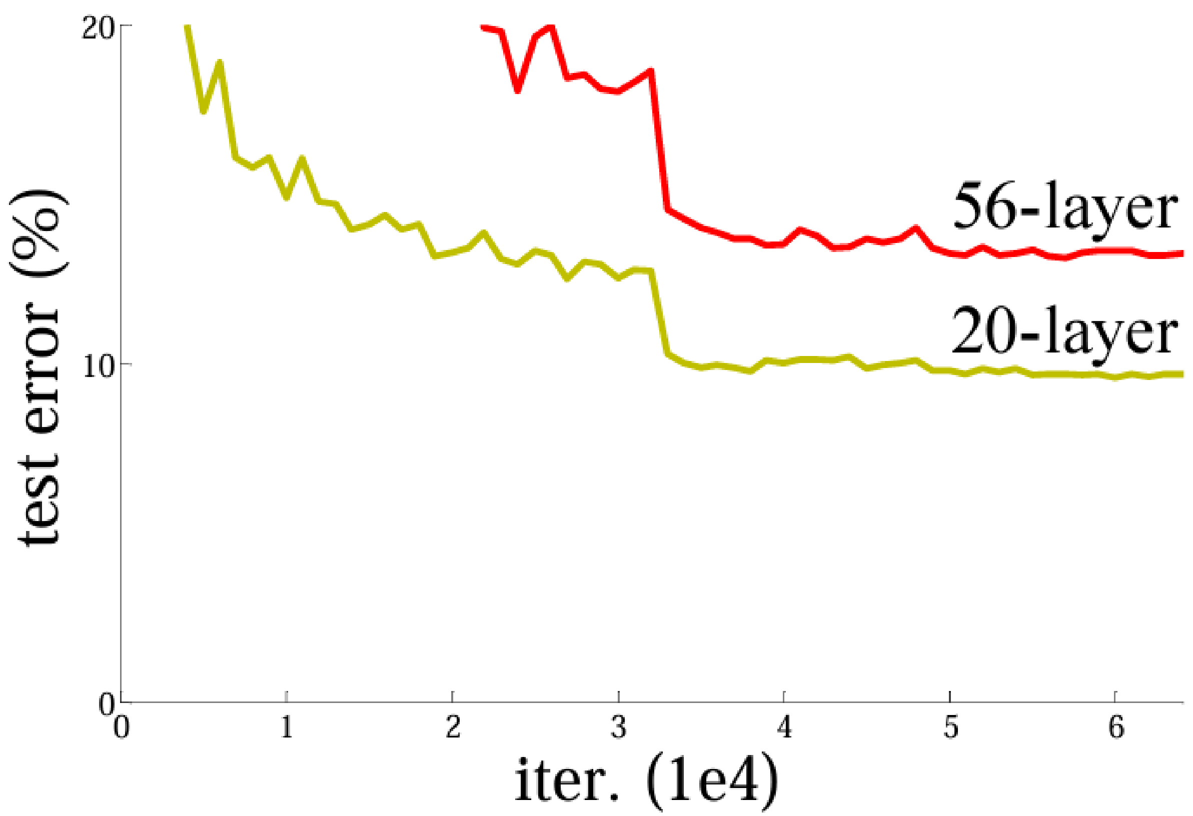
GoogLeNet: add bottlenecks and multiple stages of supervision



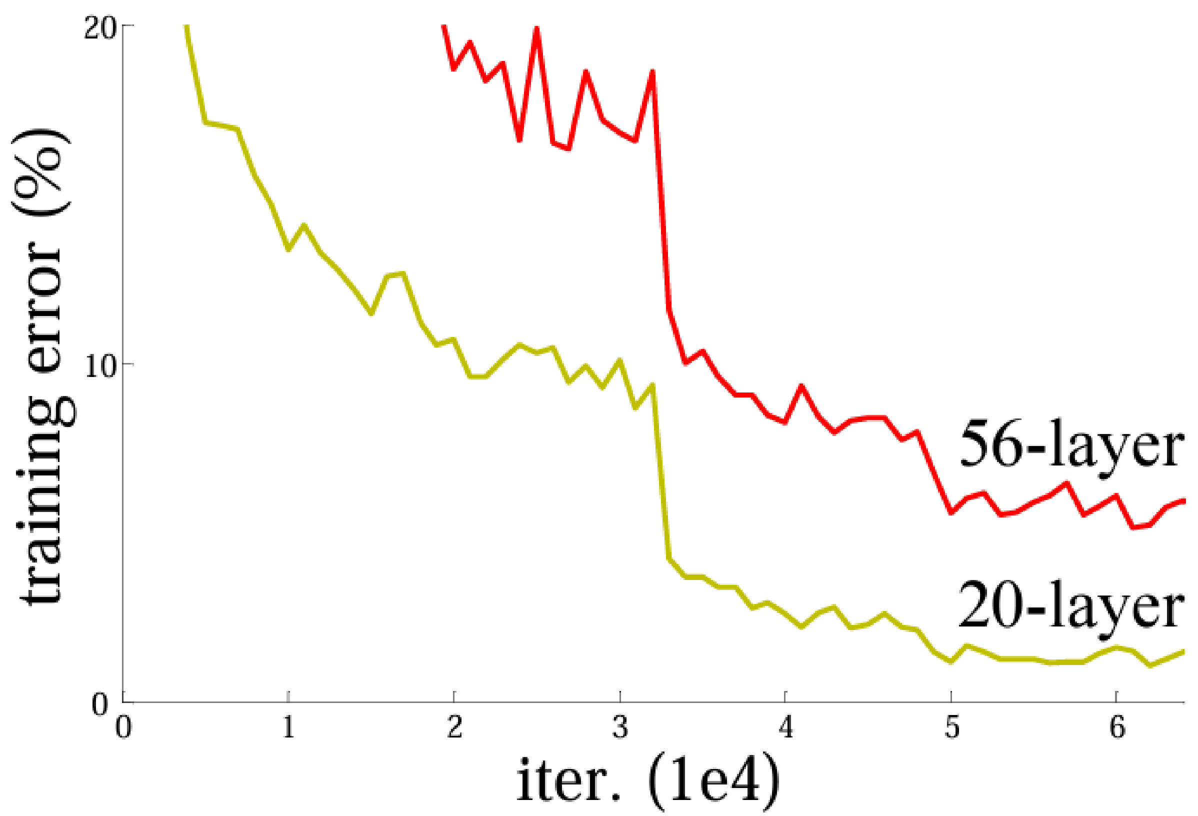
C. Szegedy et al., Going deeper with convolutions, CVPR 2015

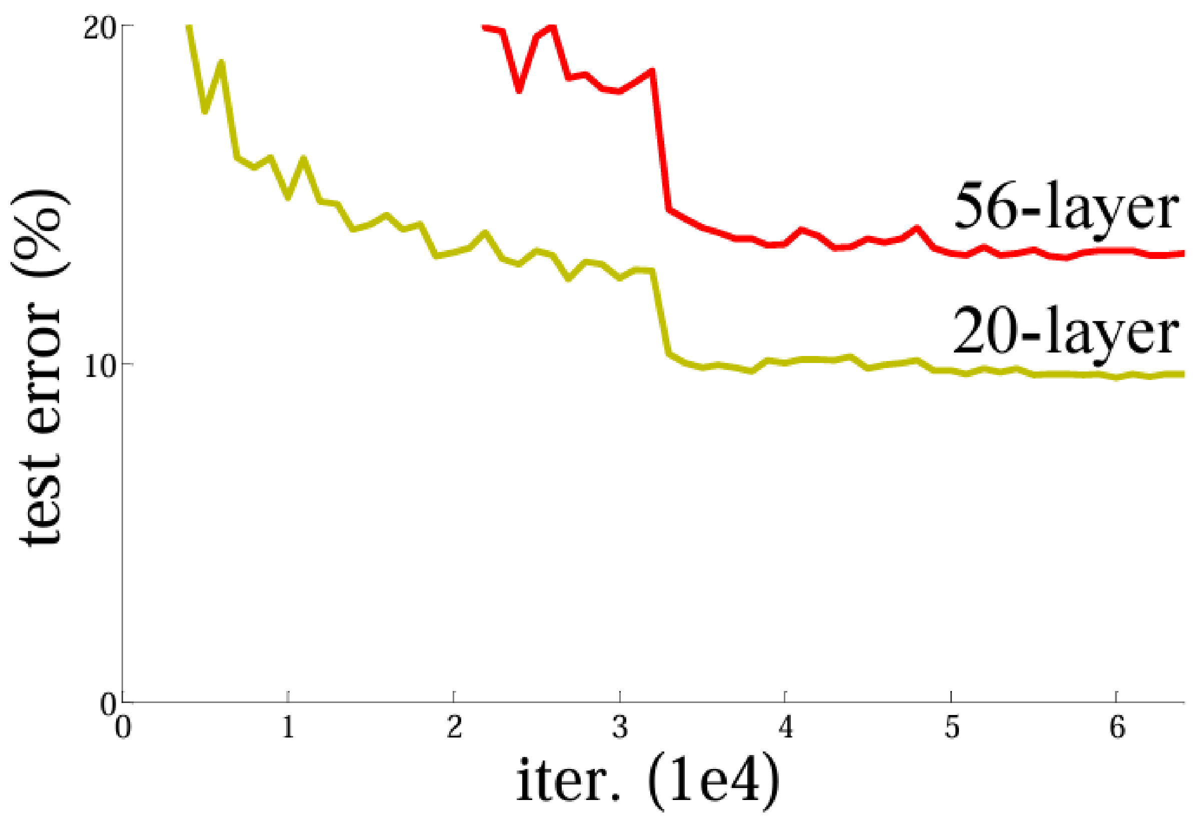
What was the problem?

- Were deeper networks overfitting the training data?
- Or was the problem just that we couldn’t optimize them?
- How could we answer this question?



Look at the training error!





With deeper networks, the training error goes up!?!

Fig: He et al. 2016

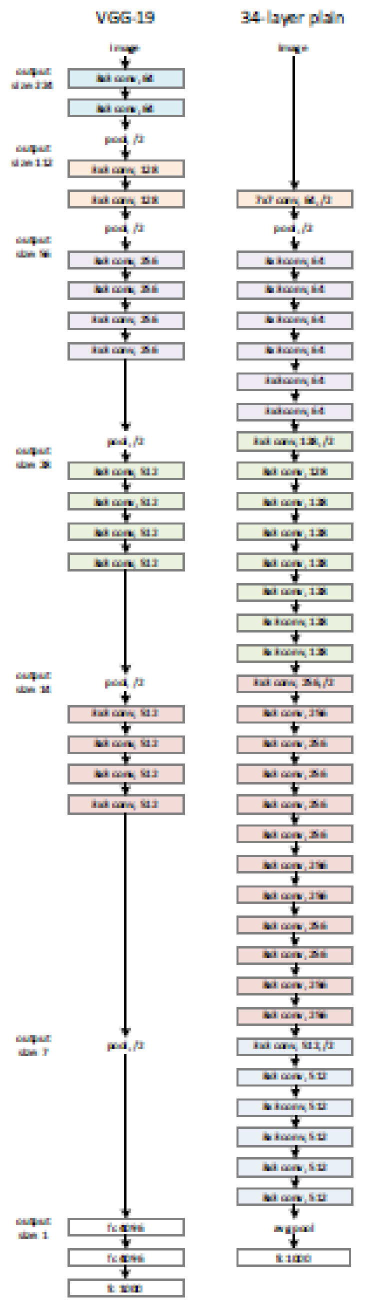
Very deep networks, vanishing gradients, and information propagation

Vanishing gradients

- Early weights have a long path to reach output
- Any zeros along that path kill the gradient
- Early layers cannot be optimized
- Multiple stages of supervision can help, but it’s complicated and time-consuming

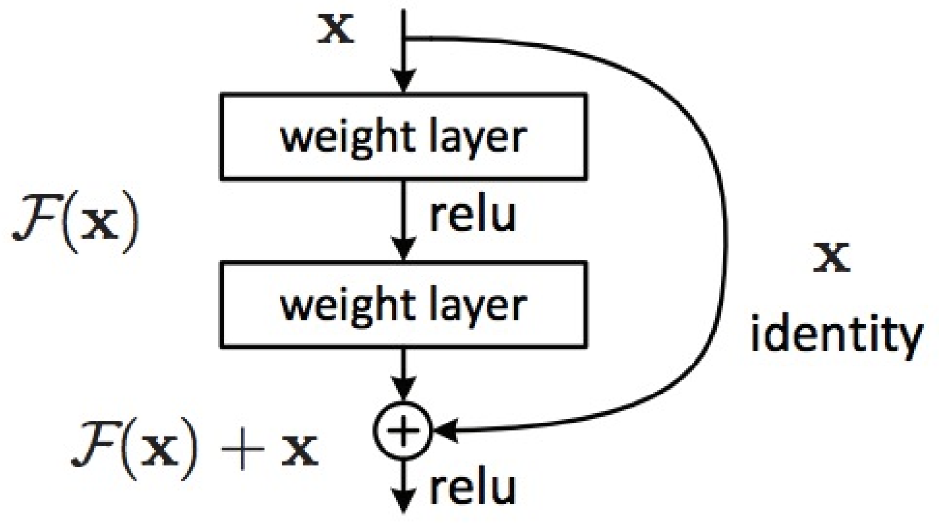
Information propagation

- Networks need to continually maintain and add to information represented in previous layers



ResNet: the residual module

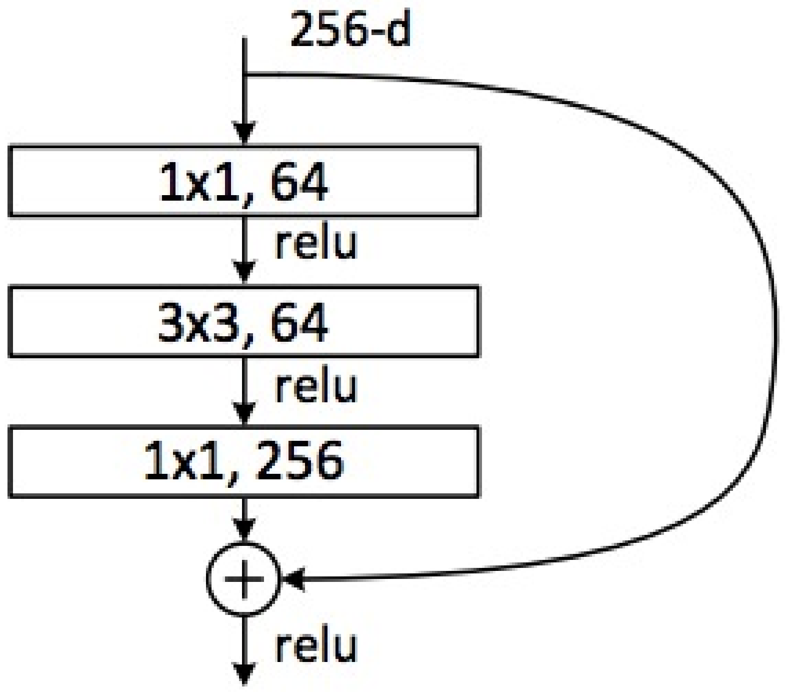
- Use *skip* or *shortcut* connections around 2-3 layer MLPs
- Gradients can flow quickly back through skip connections
- Each module needs only add information to the previous layers



Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, Deep Residual Learning for Image Recognition, CVPR 2016 (Best Paper), 200K+ citations

ResNet: Residual Bottleneck Module

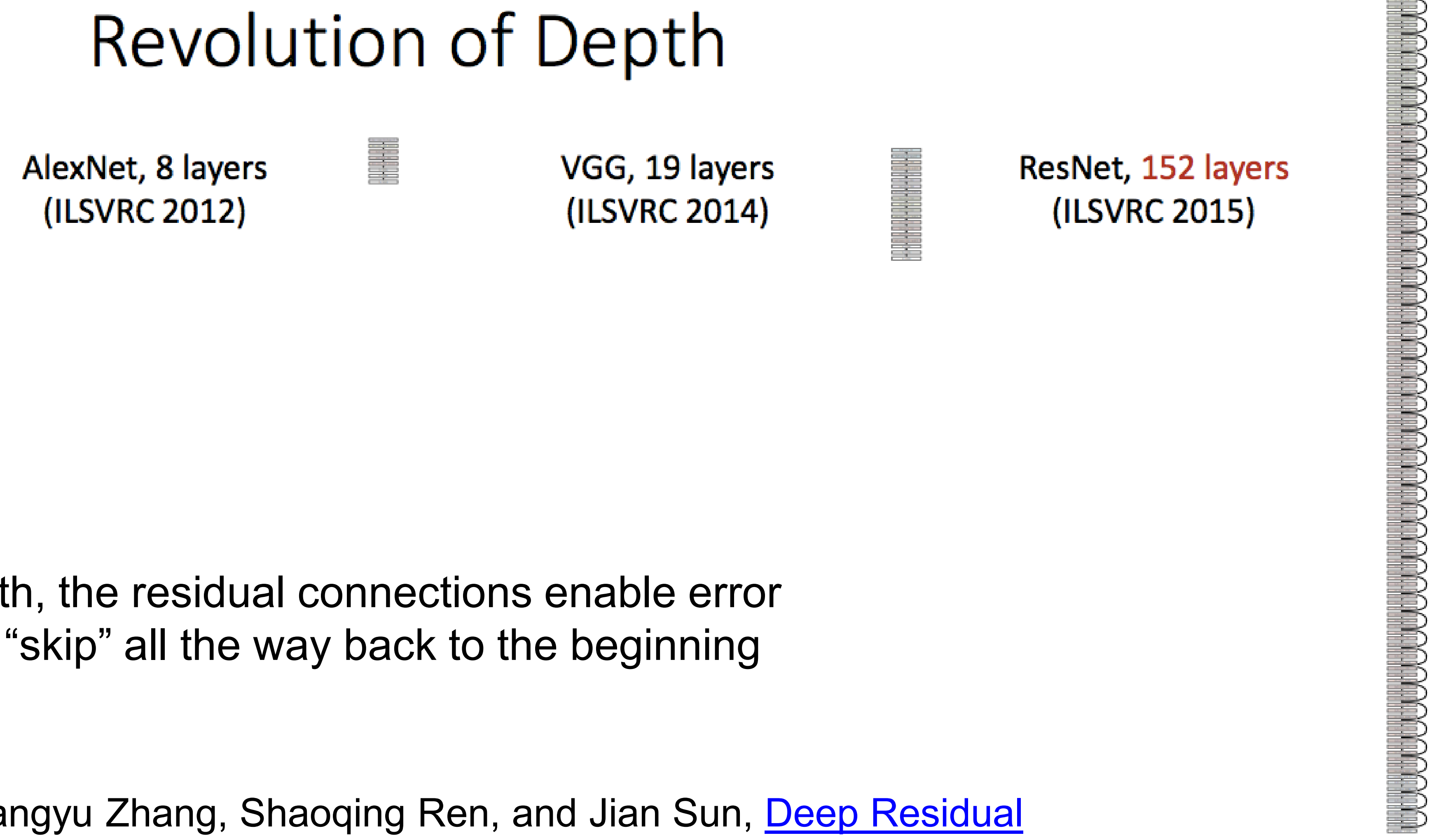
Used in 50+ layer networks



- Directly performing 3x3 convolutions with 256 feature maps at input and output:
  256 x 256 x 3 x 3 ~ 600K
  operations
- Using 1x1 convolutions to reduce 256 to 64 feature maps, followed by 3x3 convolutions, followed by 1x1 convolutions to expand back to 256 maps:
  256 x 64 x 1 x 1 ~ 16K
  64 x 64 x 3 x 3 ~ 36K
  64 x 256 x 1 x 1 ~ 16K
  Total: ~70K

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, Deep Residual Learning for Image Recognition, CVPR 2016

ResNet: going real deep



Despite depth, the residual connections enable error gradients to “skip” all the way back to the beginning

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, [Deep Residual Learning for Image Recognition](), CVPR 2016

Example code: ResBlock

```
class ResBlock(nn.Module):
    def __init__(self, in_channels, out_channels, downsample):
        super().__init__()
        if downsample:
            self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=2, padding=1)
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=2),
                nn.BatchNorm2d(out_channels)
            )
        else:
            self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=1, padding=1)
            self.shortcut = nn.Sequential()

        self.conv2 = nn.Conv2d(out_channels, out_channels, kernel_size=3, stride=1, padding=1)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.bn2 = nn.BatchNorm2d(out_channels)

    def forward(self, input):
        shortcut = self.shortcut(input)
        input = nn.ReLU()(self.bn1(self.conv1(input)))
        input = nn.ReLU()(self.bn2(self.conv2(input)))
        input = input + shortcut
        return nn.ReLU()(input)
```

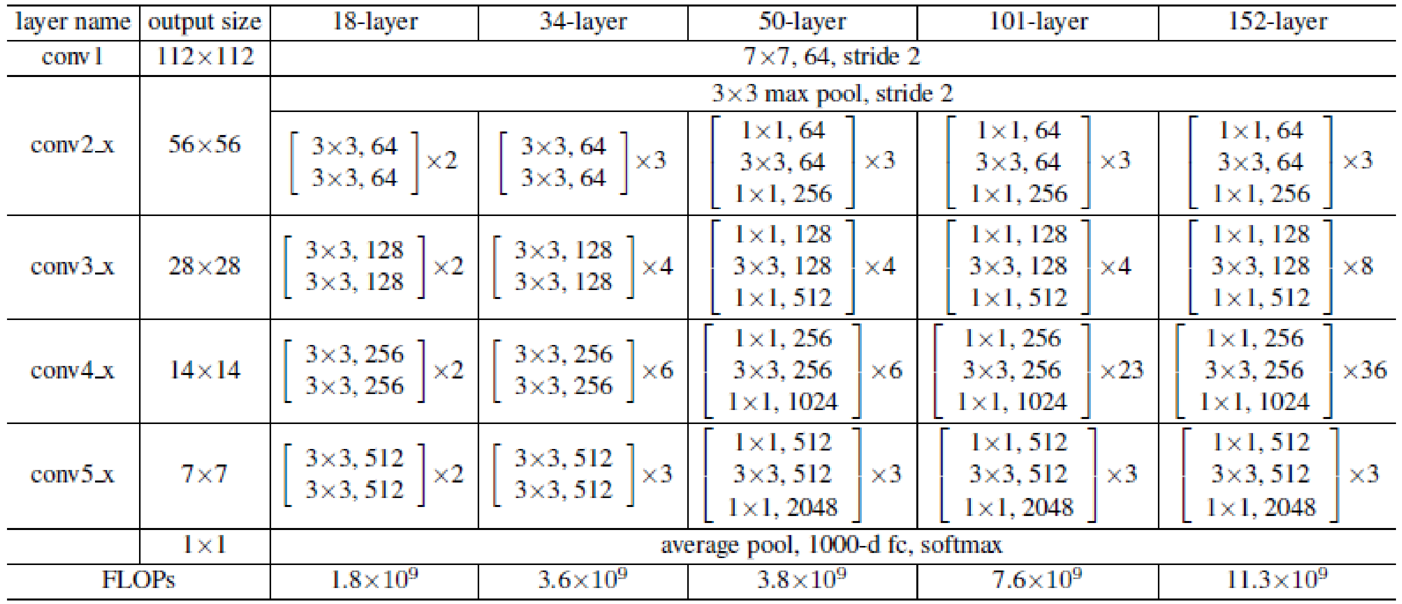
Example code: ResNet-18 architecture for ImageNet

```
class Network(nn.Module):
    def __init__(self, num_classes=37):
        super().__init__()
        resblock = ResBlock
        self.layer0 = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
            nn.MaxPool2d(kernel_size=3, stride=2, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU()
        )
        self.layer1 = nn.Sequential(
            resblock(64, 64, downsample=False),
            resblock(64, 64, downsample=False)
        )
        self.layer2 = nn.Sequential(
            resblock(64, 128, downsample=True),
            resblock(128, 128, downsample=False)
        )
        self.layer3 = nn.Sequential(
            resblock(128, 256, downsample=True),
            resblock(256, 256, downsample=False)
        )
        self.layer4 = nn.Sequential(
            resblock(256, 512, downsample=True),
            resblock(512, 512, downsample=False)
        )
        self.gap = torch.nn.AdaptiveAvgPool2d(1)
        self.fc = torch.nn.Linear(512, num_classes)
```

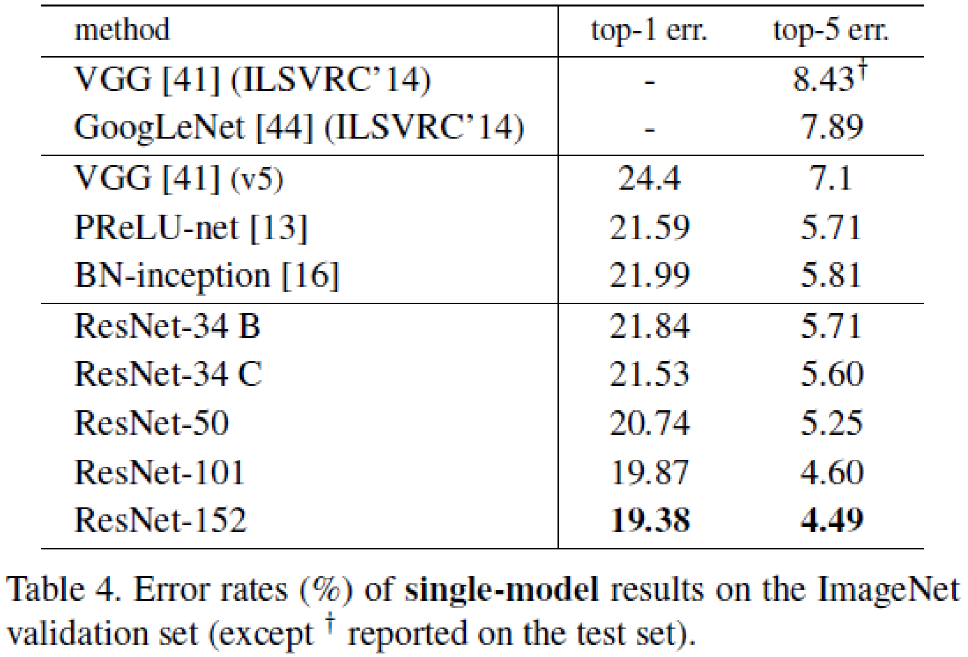
```
def forward(self, input):
    input = self.layer0(input)
    input = self.layer1(input)
    input = self.layer2(input)
    input = self.layer3(input)
    input = self.layer4(input)
    input = self.gap(input)
    input = torch.flatten(input, 1)
    input = self.fc(input)

    return input
```

ResNet Architectures and Results



layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9



method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43[†]
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PReLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except † reported on the test set).

Improvements to SGD

Great site by Lili Jiang

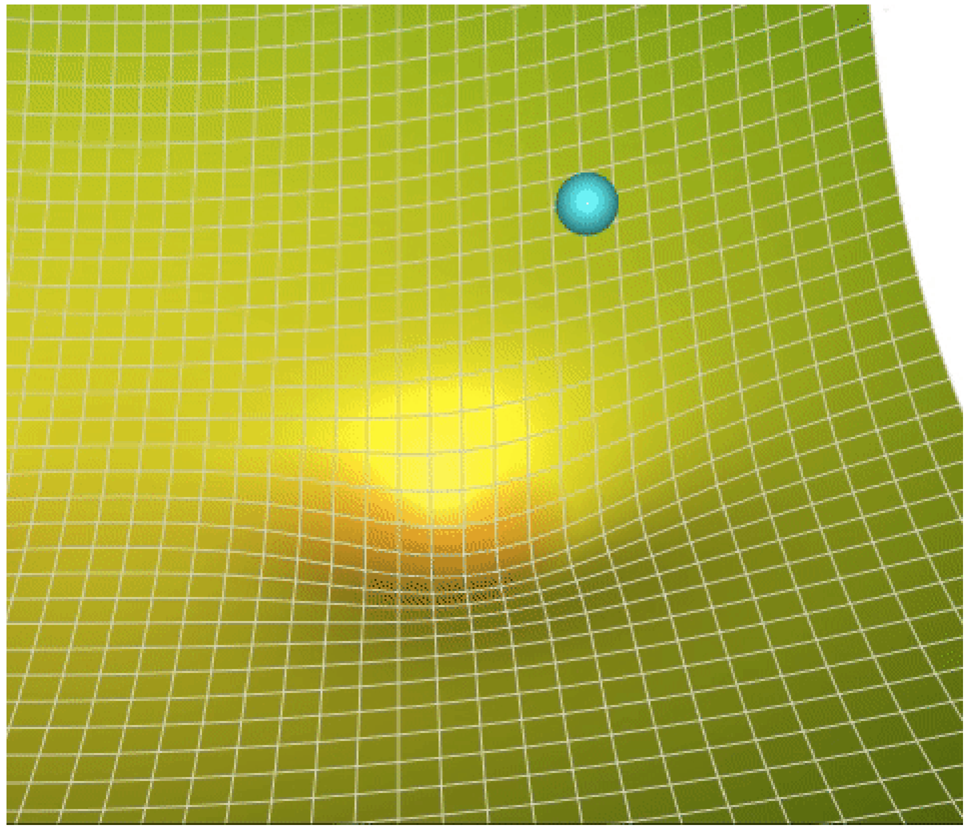
https://towardsdatascience.com/a-visual-explanation-of-gradient-descent-methods-momentum-adagrad-rmsprop-adam-f898b102325c

Gradient of loss wrt weights

Basic SGD:

$$\Delta w_t = -\eta g(w_t)$$

$$w_{t+1} = w_t + \Delta w_t$$



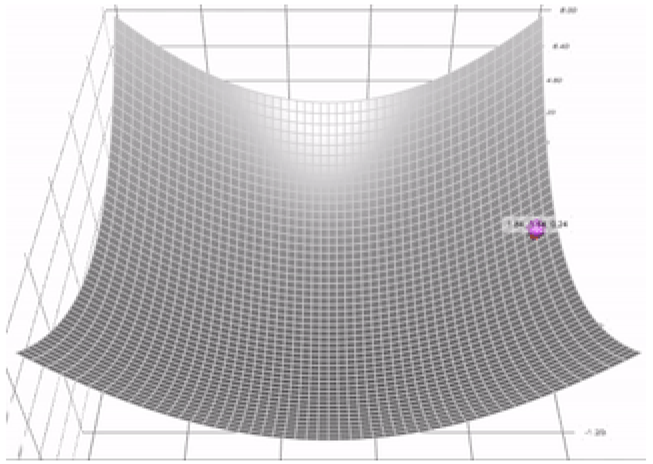
SGD + Momentum

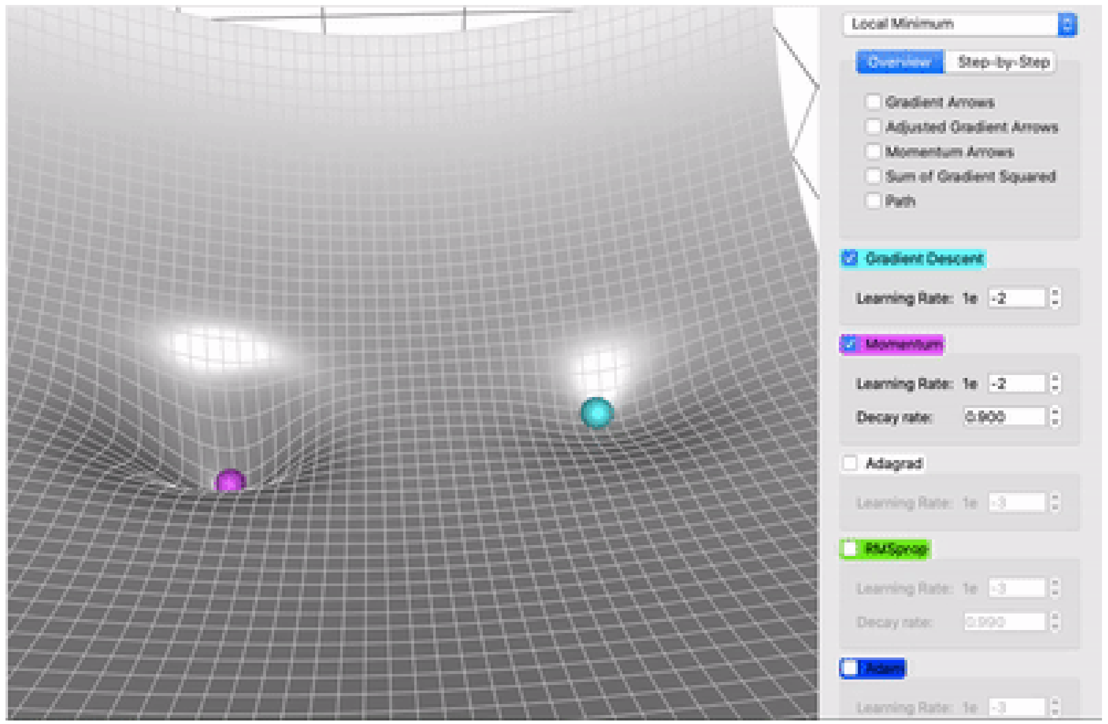
SGD + Momentum:

$$m_t = \beta \cdot m_{t-1} + g(w_t) \quad \text{e.g. } \beta = .9$$

$$\Delta w_t = -\eta \cdot m_t$$

$$w_{t+1} = w_t + \Delta w_t$$





Local Minimum

Overview | Step-by-Step

- [ ] Gradient Arrows
- [ ] Adjusted Gradient Arrows
- [ ] Momentum Arrows
- [ ] Sum of Gradient Squared
- [ ] Path

- [x] Gradient Descent
  Learning Rate: 1e -2
- [x] Momentum
  Learning Rate: 1e -2
  Decay rate: 0.900
- [ ] Adagrad
  Learning Rate: 1e -3
- [ ] RMSprop
  Learning Rate: 1e -3
  Decay rate: 0.990
- [ ] Adam
  Learning Rate: 1e -3

Momentum (magenta) converges faster and carries the ball through a local minimum

Figure source

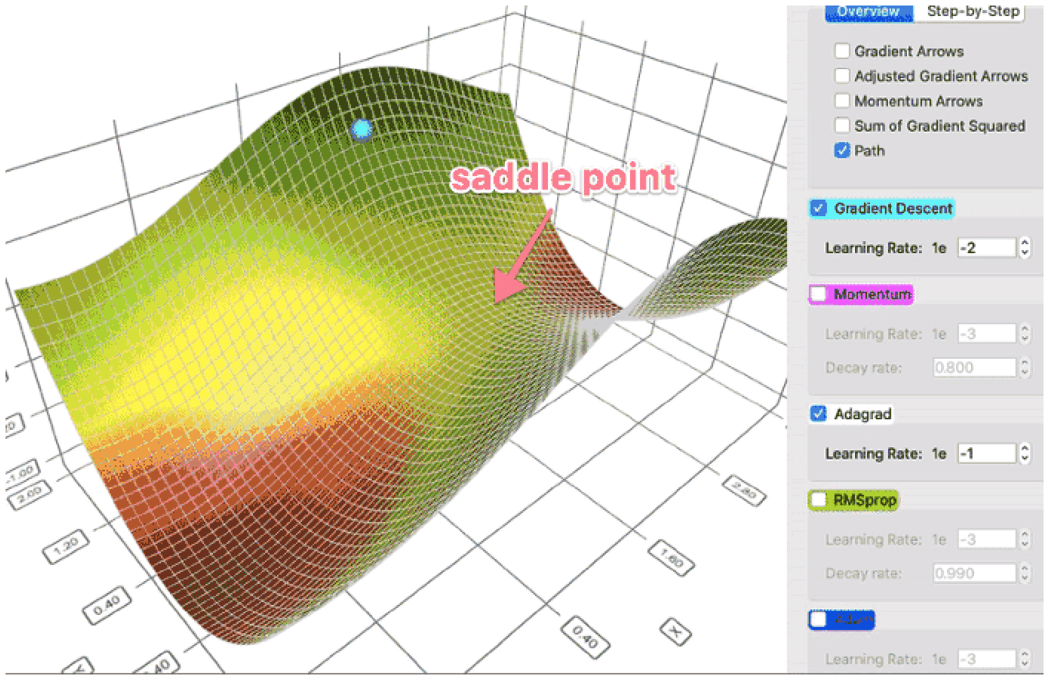
AdaGrad: Adaptive Gradient

AdaGrad:

$$g_{sq}(t) = g_{sq}(t-1) + g(w_t)^2$$

$$\Delta w_t = -\eta g(w_t)/\sqrt{g_{sq}(t)}$$ (normalize by path length of all previous updates)

$$w_{t+1} = w_t + \Delta w_t$$



- [ ] Gradient Arrows
- [ ] Adjusted Gradient Arrows
- [ ] Momentum Arrows
- [ ] Sum of Gradient Squared
- [✓] Path

[✓] Gradient Descent
Learning Rate: 1e -2

[ ] Momentum
Learning Rate: 1e -3
Decay rate: 0.800

[✓] Adagrad
Learning Rate: 1e -1

[ ] RMSprop
Learning Rate: 1e -3
Decay rate: 0.990

[ ] [illegible]
Learning Rate: 1e -3

AdaGrad (white) avoids moving in only one weight direction, and can lead to smoother convergence

Figure source

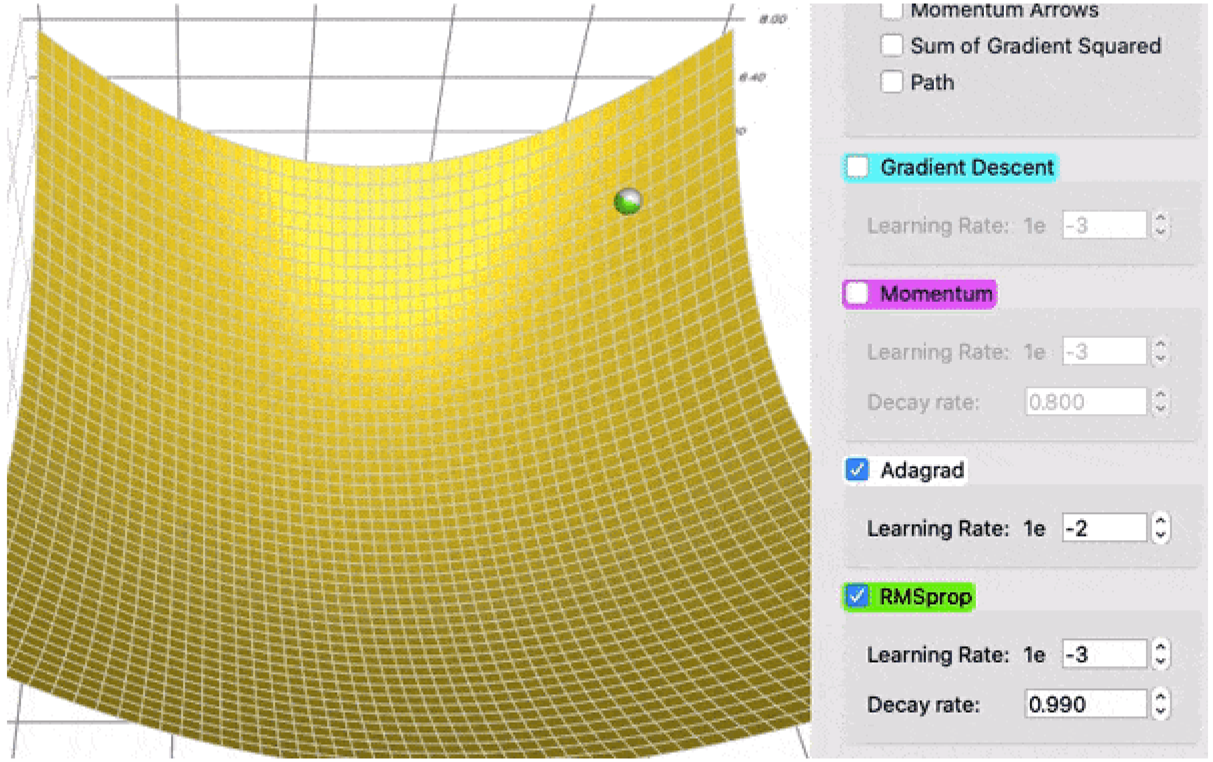
RMSProp: Root Mean Squared Propagation

RMSProp:

$g_{sq}(t) = \epsilon \cdot g_{sq}(t-1) + (1-\epsilon) \cdot g(w_t)^2$ (introducing decay rate turns this into moving avg)

$\Delta w_t = -\eta g(w_t)/\sqrt{g_{sq}(t)}$ (normalize by moving average length of previous updates)

$w_{t+1} = w_t + \Delta w_t$



Momentum Arrows [ ]
Sum of Gradient Squared [ ]
Path [ ]

Gradient Descent [ ]
Learning Rate: 1e -3

Momentum [ ]
Learning Rate: 1e -3
Decay rate: 0.800

Adagrad [✓]
Learning Rate: 1e -2

RMSprop [✓]
Learning Rate: 1e -3
Decay rate: 0.990

RMSProp (green) moves faster than AdaGrad (white)

Figure source

Adam: Adaptive Moment Estimation

Adam:

$m_t = \beta \cdot m_t + (1 - \beta) \cdot g(w_t)$ [momentum, $\beta = 0.9$]

$g_{sq}(t) = \epsilon \cdot g_{sq}(t-1) + (1-\epsilon) \cdot g(w_t)^2$ [RMSProp, $\epsilon = 0.999$]

$\Delta w_t = -\eta \cdot m_t / \sqrt{g_{sq}(w_t)}$

$w_{t+1} = w_t + \Delta w_t$

AdamW is a fix on Adam to correctly update weight decay

Videos

AdamW is widely used and easier to
tune than SGD + momentum

Figure source

What to use?

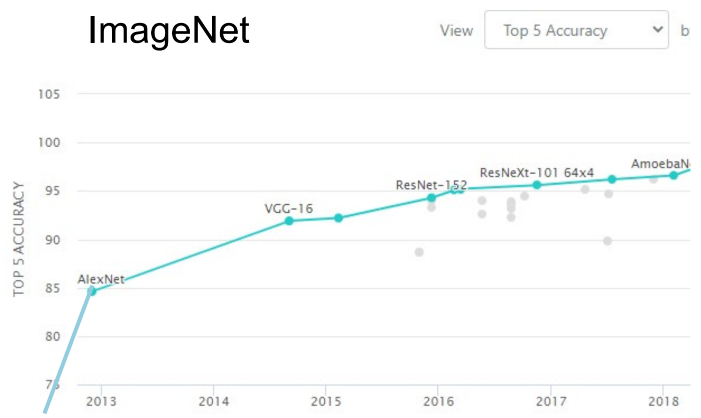
- AdamW is less sensitive to hyperparameters (easier to get a decent solution working)
- Many practitioners say SGD+momentum can achieve the best performance, if you’re able to optimize over hyperparameters
- I commonly see either one used in research papers

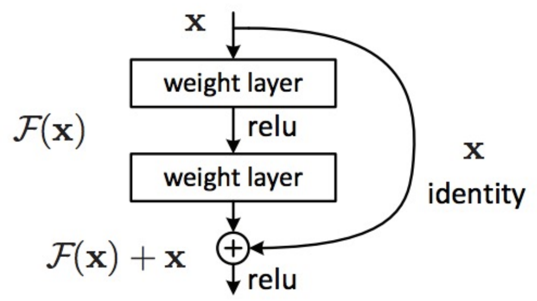
What to remember

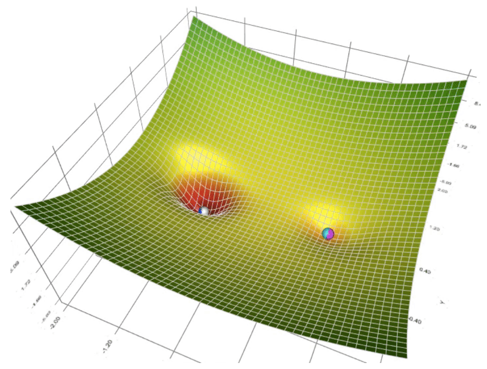
- Deep networks provide huge gains in performance
  - Large capacity, optimizable models
  - Learn from new large datasets

- ReLU and skip connections simplify optimization

- SGD+momentum and AdamW are the most commonly used optimizers







Next lecture

- More deep network optimization
  - Batch Normalization
  - Data Augmentation
- Re-using networks
  - Linear probe
  - Fine-tuning
- Mask RCNN line of work