COMP5212: Machine Learning

Lecture 13

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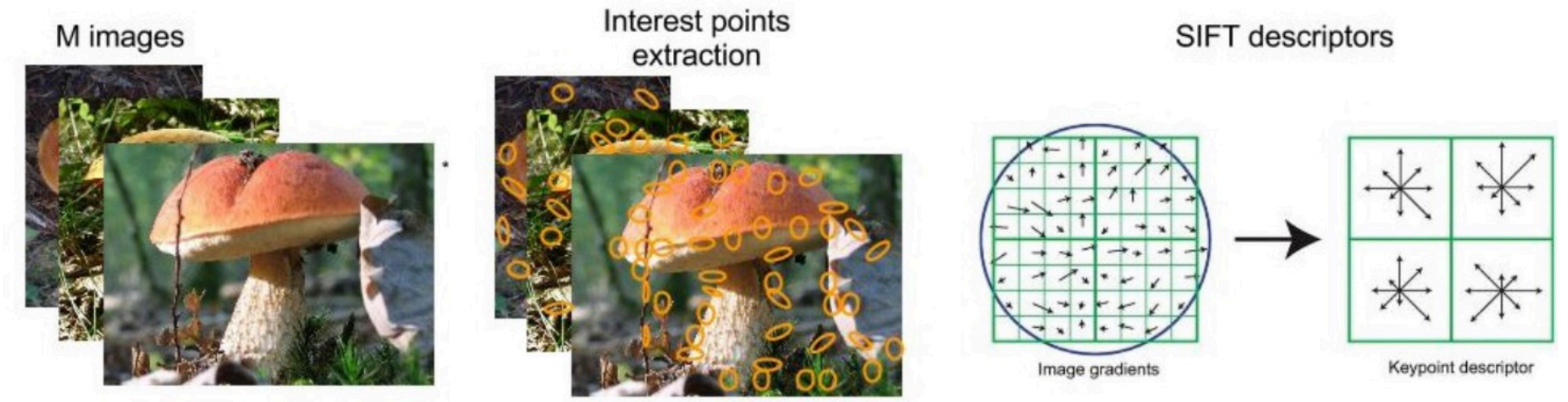
Convolutional Neural Network
Image classification without CNN

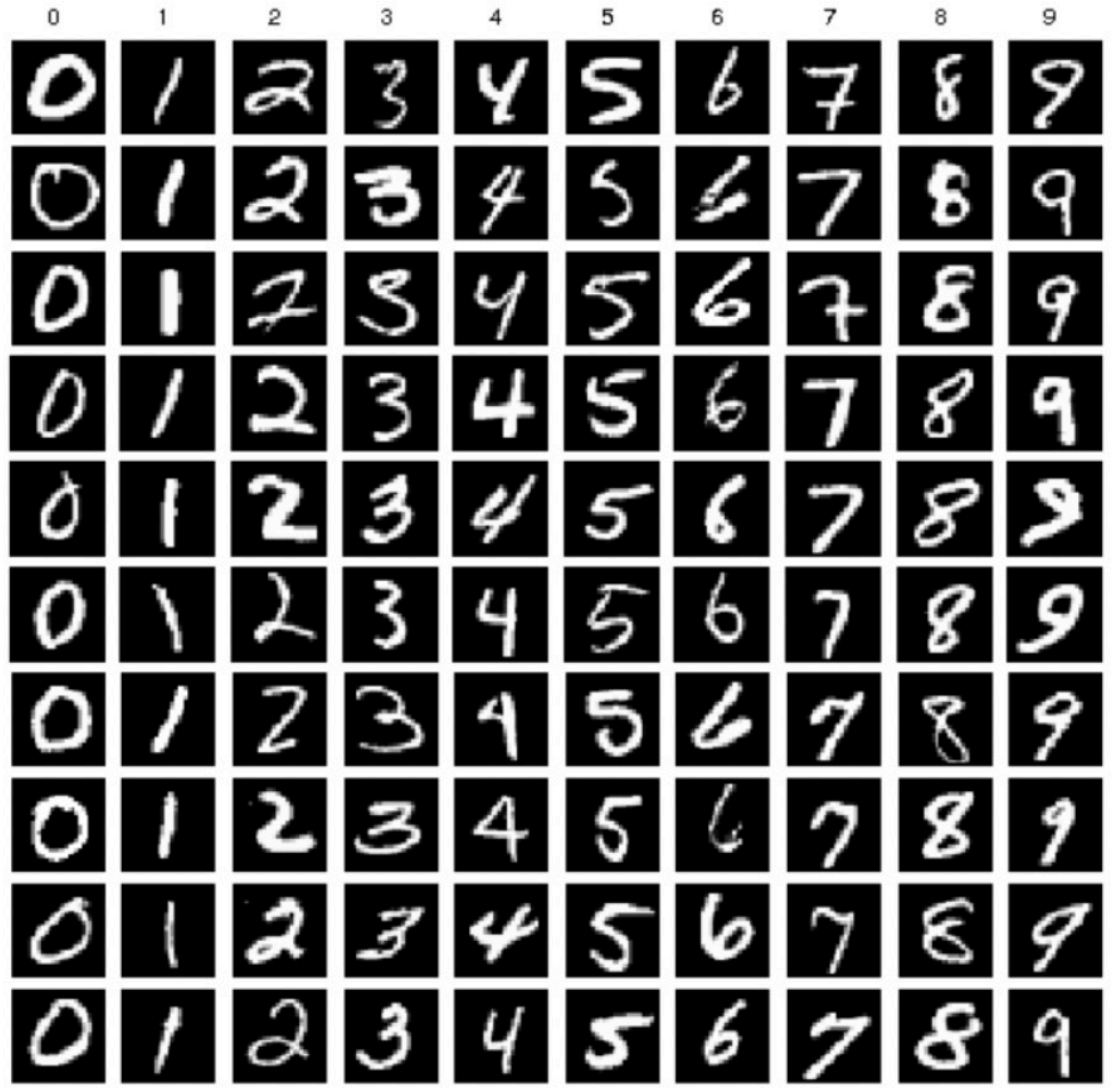
- Input an image
- Extract ``interesting points'' (e.g., corner detector)
- For each interesting point, extract 128-dimensional SIFT descriptor
- Clustering of SIFT descriptor to get ``visual vocabulary''
- Then transform image to a feature vector (bag of visual words)
- Run classification (SVM)



* Mushroom image by Tifred25 (http://commons.wikimedia.org/wiki/File:Bolet_Orange_01.jpg)

Dataset
MNIST

- Hand-written digits (0 to 9)
- Total 60,000 samples, 10-class classification



Dataset

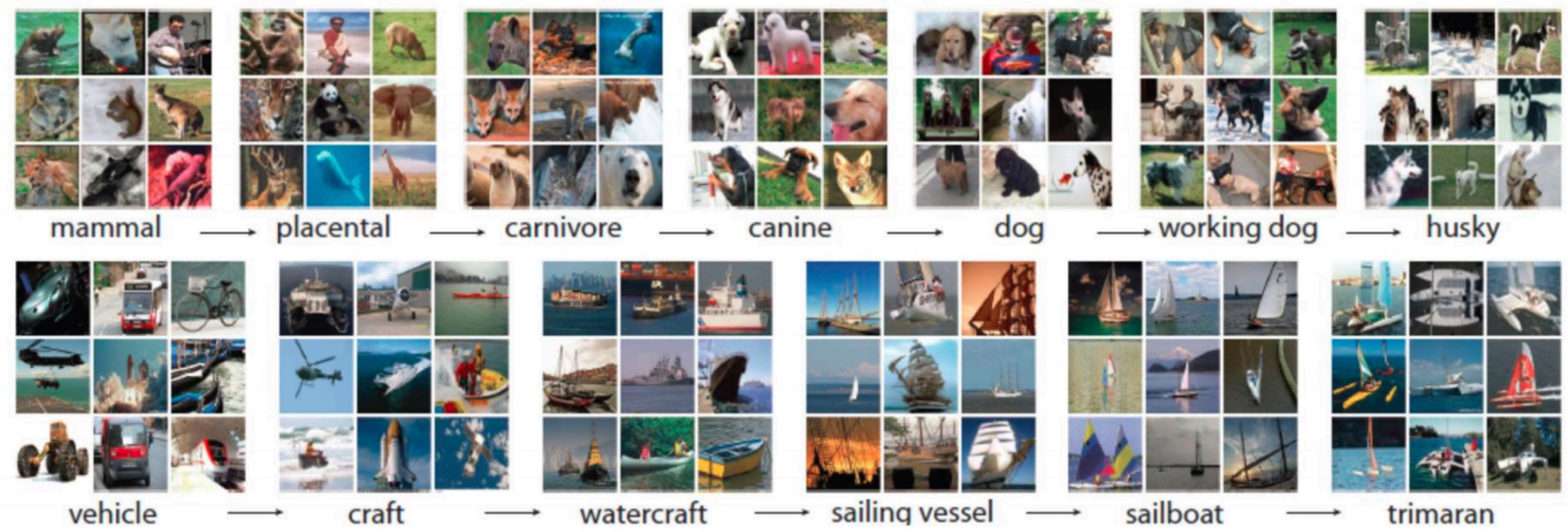
MNIST Classification Accuracy

- See the website by Yann LeCun: http://yann.lecun.com/exdb/mnist/

Classifier	Test Error
Linear classifier	12.0 %
SVM, Gaussian kernel	1.4%
SVM, degree 4 polynomial	1.1%
Best SVM result	0.56%
2-layer NN	$\sim$ 3.0%
3-layer NN	$\sim$ 2.5%
CNN, LeNet-5 (1998)	0.85%
Larger CNN (2011, 2012)	$\sim$ 0.3%

Dataset

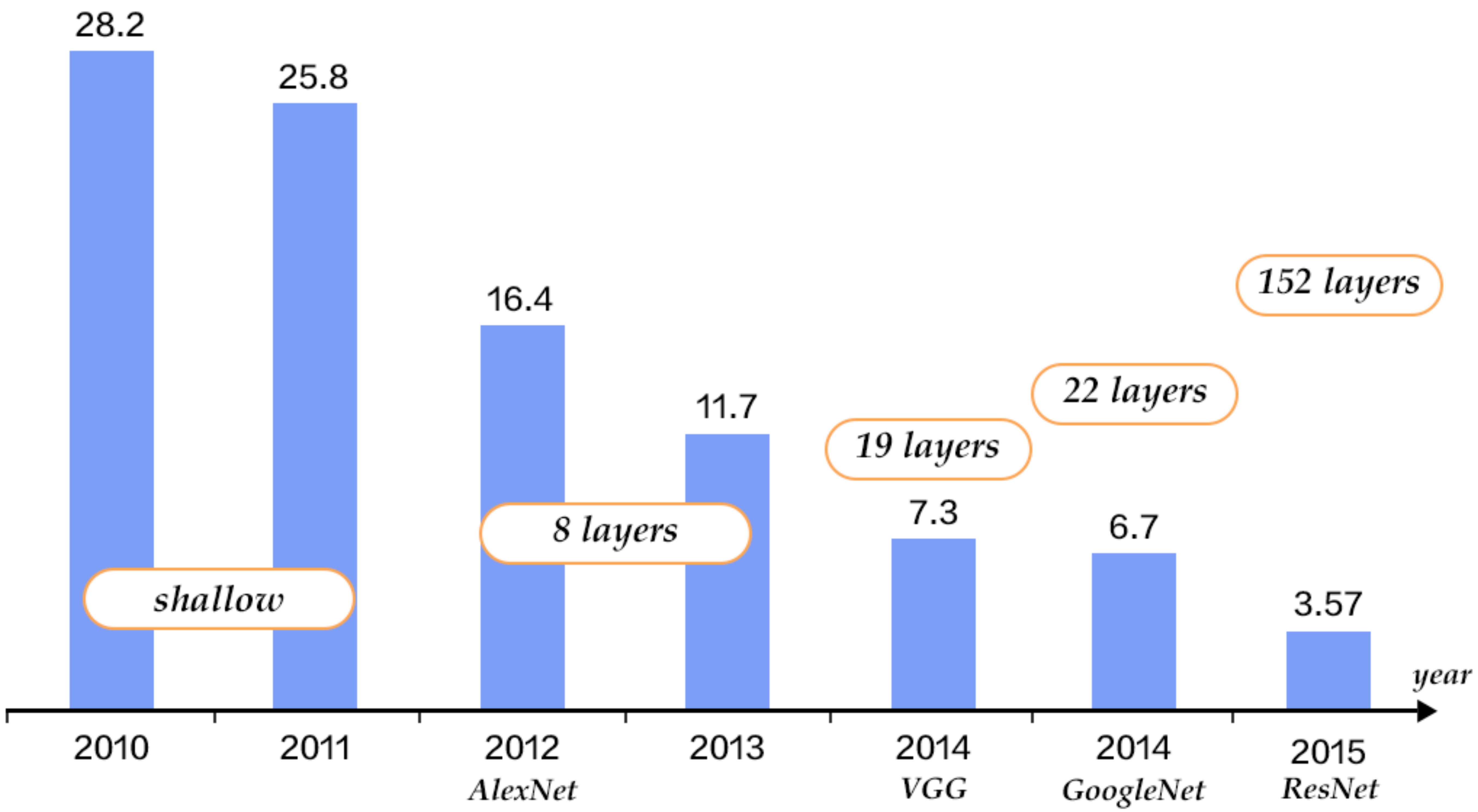
ImageNet Data



- ILSVRC competition: 1000 classes and about 1.2 million images
- Full imagenet: >20,000 categories, each with about a thousand images.

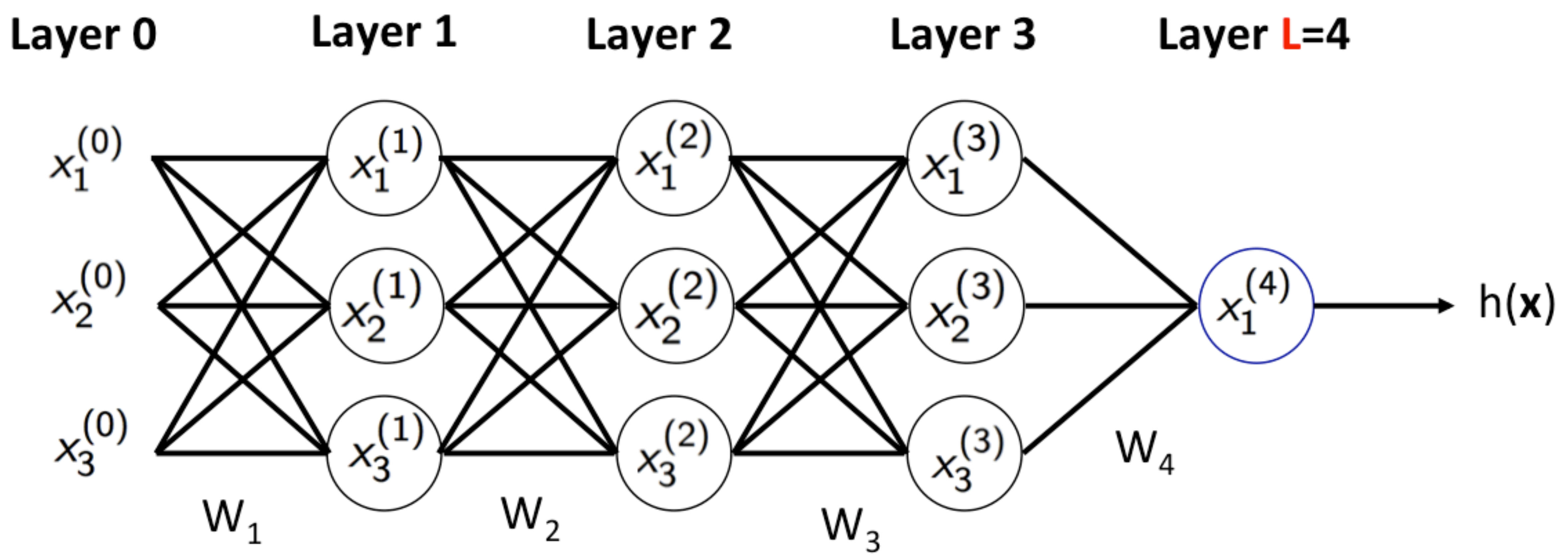
Dataset

ImageNet Results



Convolutional Neural Network

Neural Networks



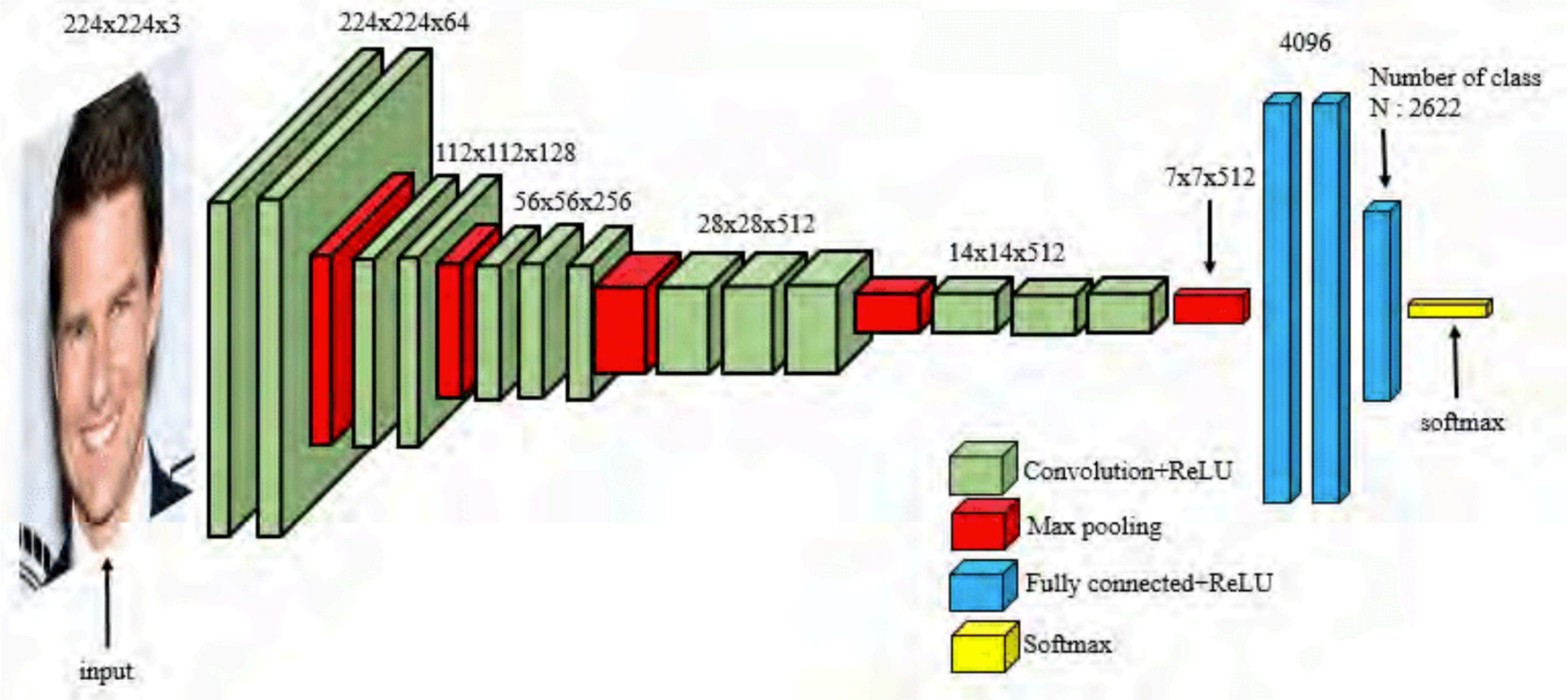
$$h(\boldsymbol{x}) = x_1^{(4)} = \theta(W_4\boldsymbol{x}^{(3)}) = \theta(W_4\theta(W_3\boldsymbol{x}^{(2)}))$$
$$= \cdots = \theta(W_4\theta(W_3\theta(W_2\theta(W_1\boldsymbol{x}))))$$

- Fully connected networks ⇒ doesn't work well for computer vision applications

Convolutional Neural Network

The structure of CNN

- Structure of VGG



- Two important layers:
  - Convolution
  - Pooling

Convolutional Neural Network

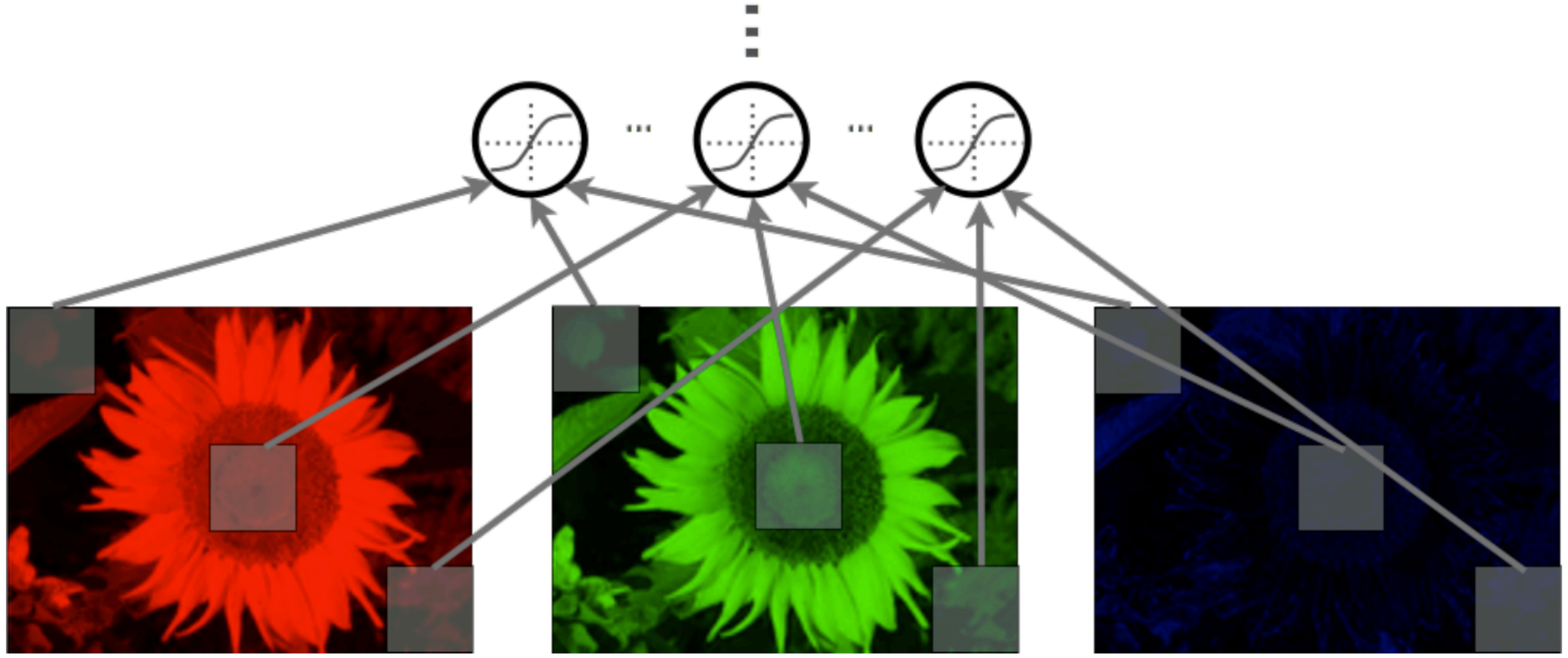
Convolution Layer

- Fully connected layers have too many parameters
  - $\Rightarrow$ poor performance
- Example: VGG first layer
  - Input: $224 \times 224 \times 3$
  - Output: $224 \times 224 \times 64$
  - Number of parameters if we use fully connected net:
    - $(224 \times 224 \times 3) \times (224 \times 224 \times 64) =$ 483 billion
  - Convolution layer leads to:
    - Local connectivity
    - Parameter sharing

Convolutional Neural Network

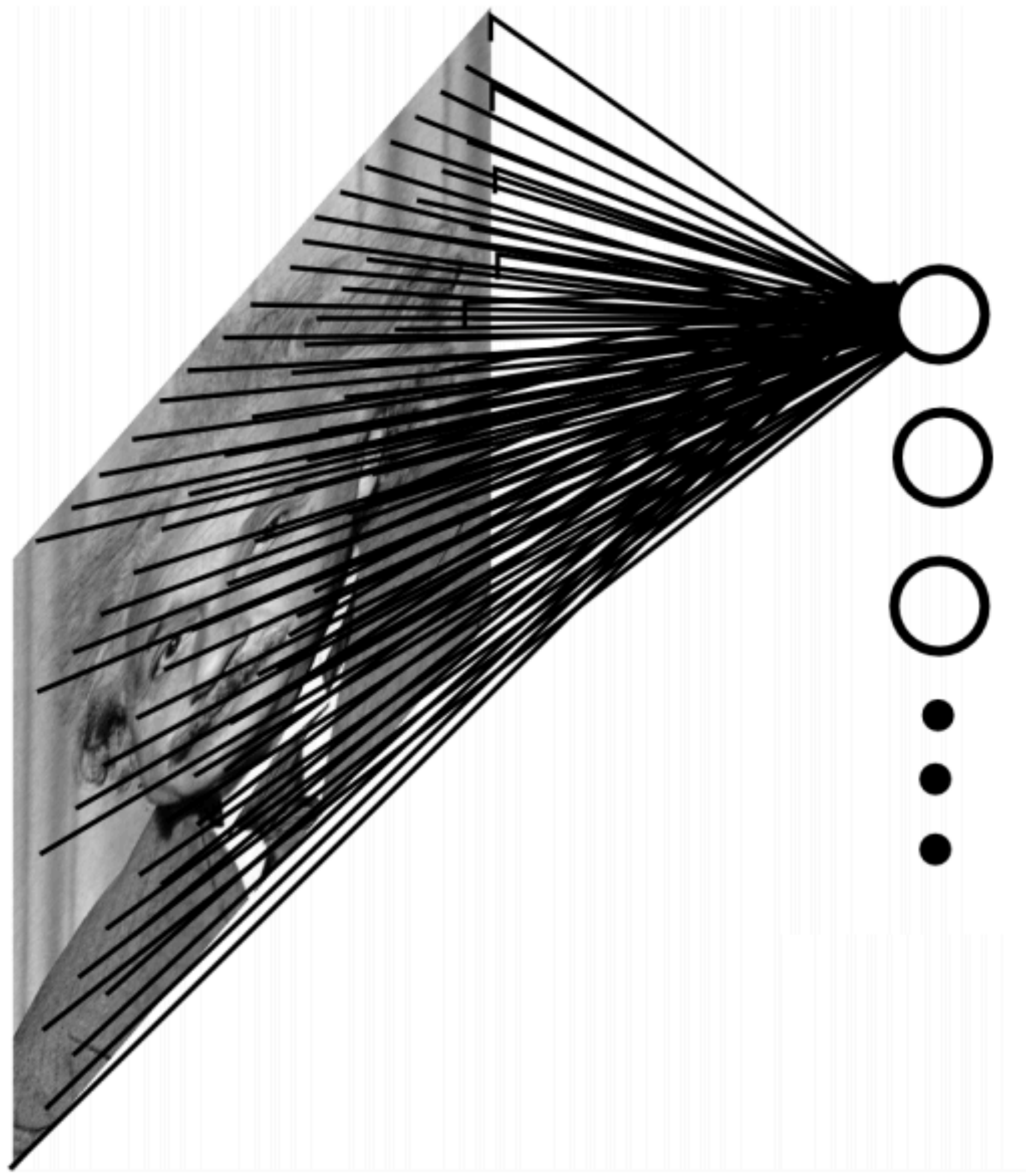
Local connectivity

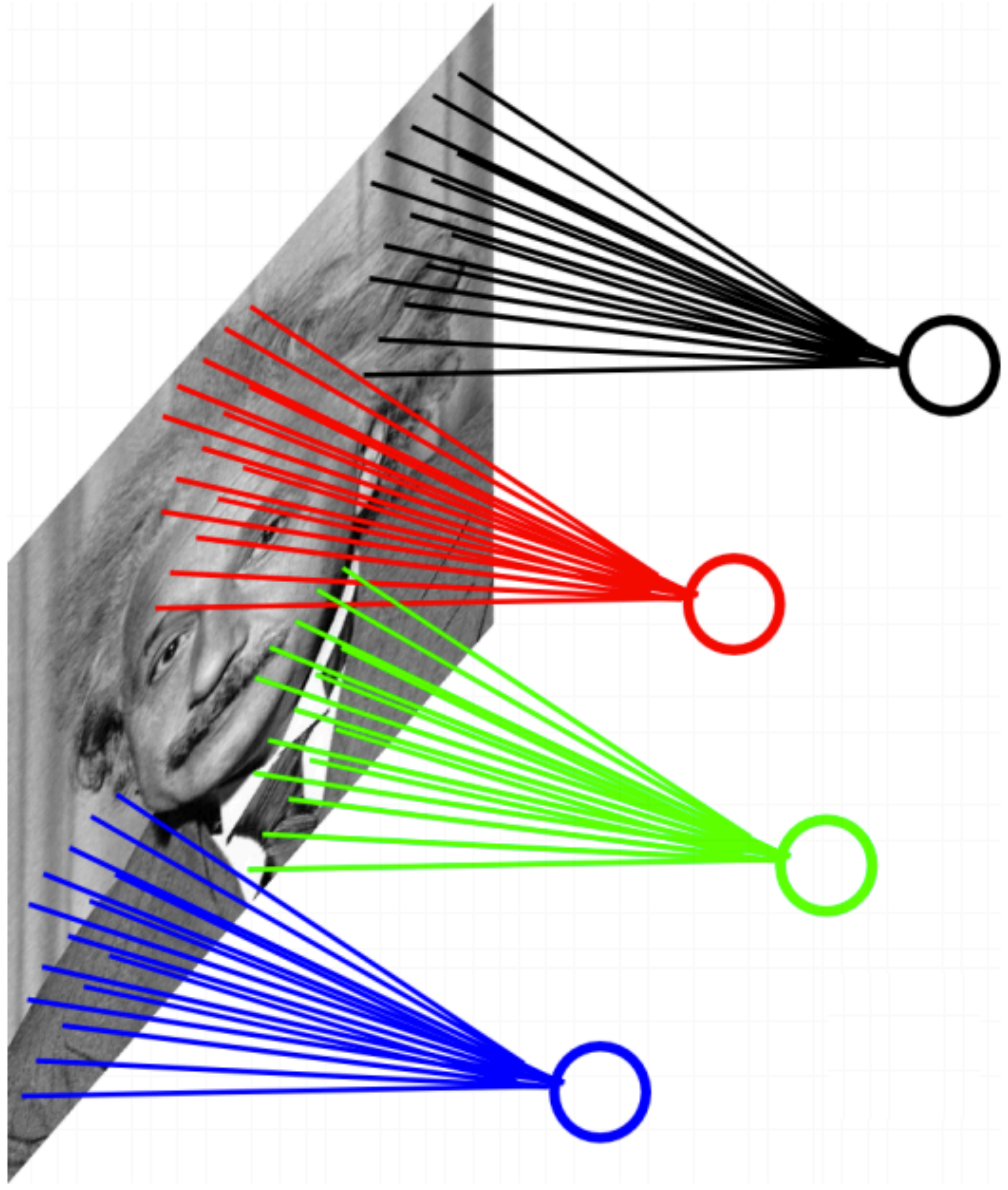
- Each hidden unit is connected only to a sub-region of input
- It is connected to all channels (R, G, B)



Convolutional Neural Network

Local connectivity





Convolutional Neural Network

Parameter Sharing

- Making a reasonable assumption:
  - If one feature is useful to compute at some spatial position (x, y),
  - then it should also be useful to compute at a different position (x_2, y_2)
- Using the convolution operator

Convolutional Neural Network

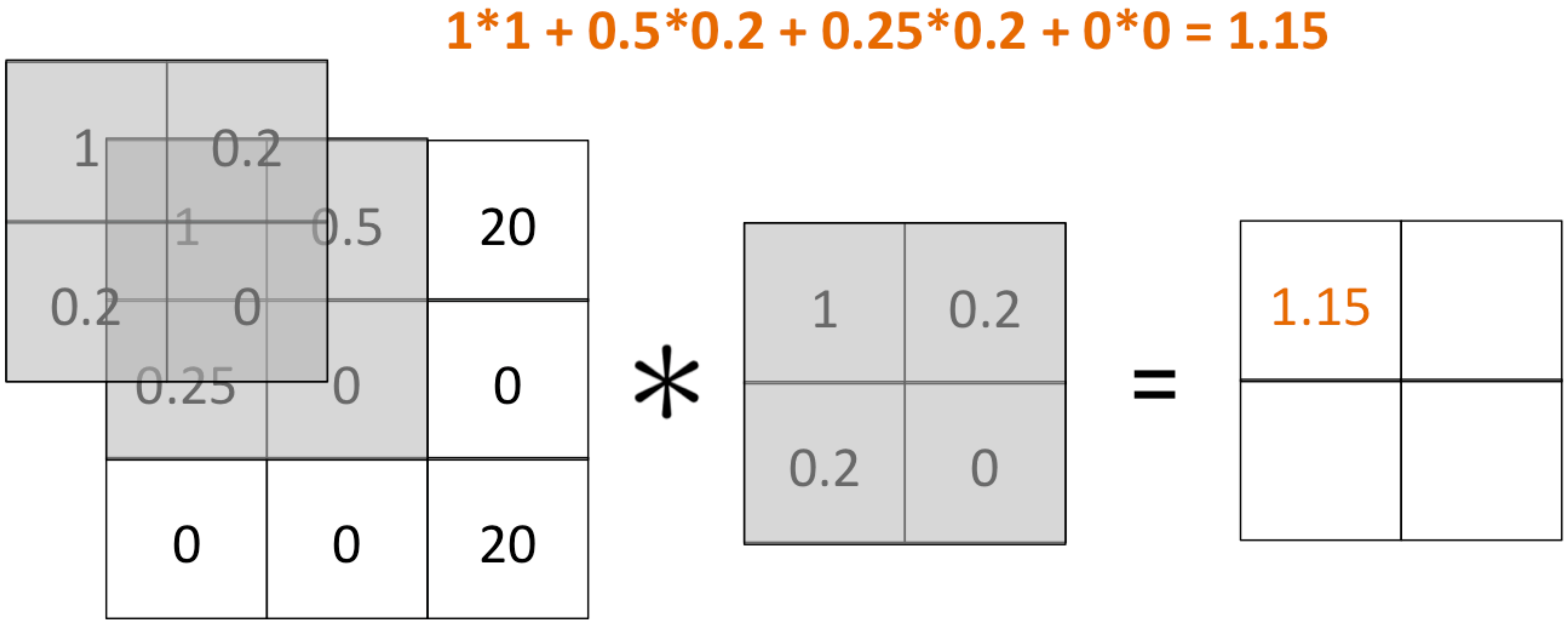
Convolution

- The convolution of an image x with a kernel k is computed as
  - $(x * k)_{ij} = \sum_{pq} x_{i+p,j+q} k_{p,q}$

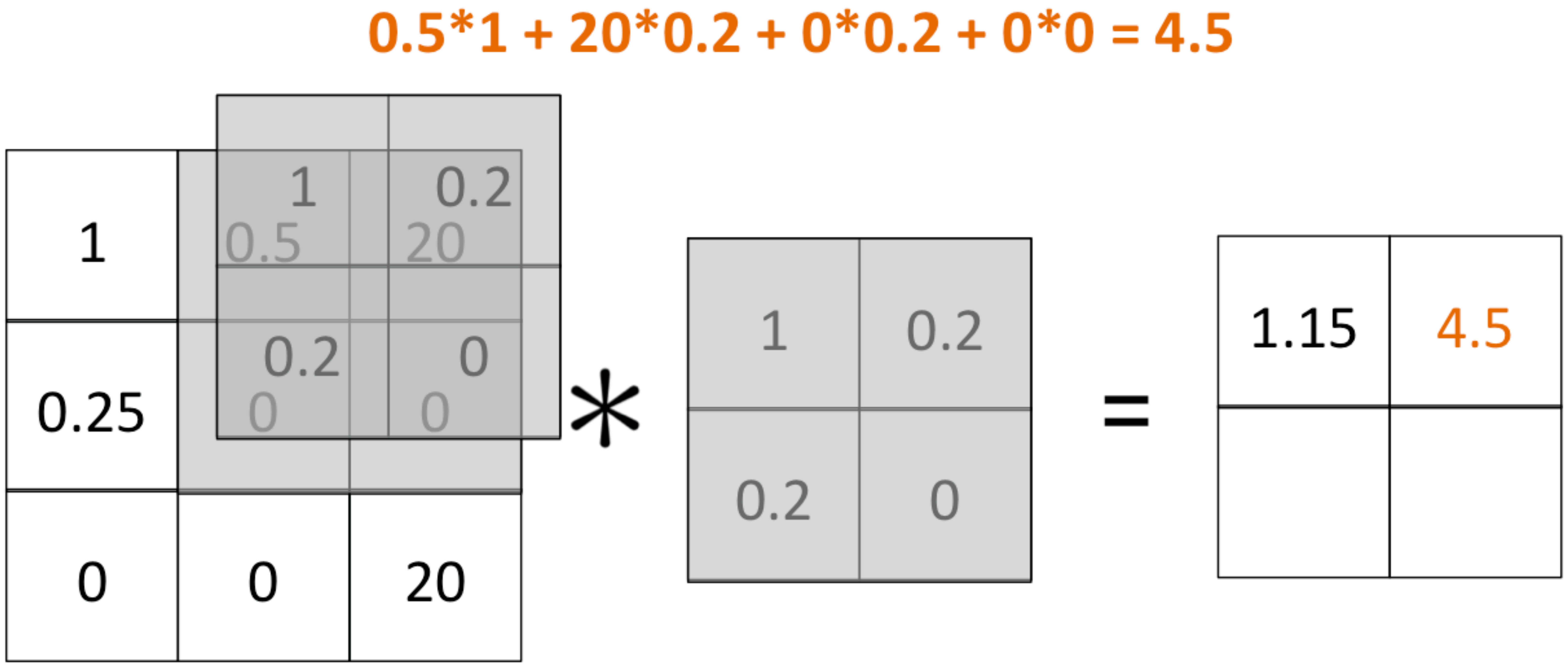
$$\begin{bmatrix} 1 & 0.5 & 20 \\ 0.25 & 0 & 0 \\ 0 & 0 & 20 \end{bmatrix} * \begin{bmatrix} 1 & 0.5 \\ 0.25 & 0 \end{bmatrix} = \begin{bmatrix} & \\ & \end{bmatrix}$$

Convolutional Neural Network

Convolution



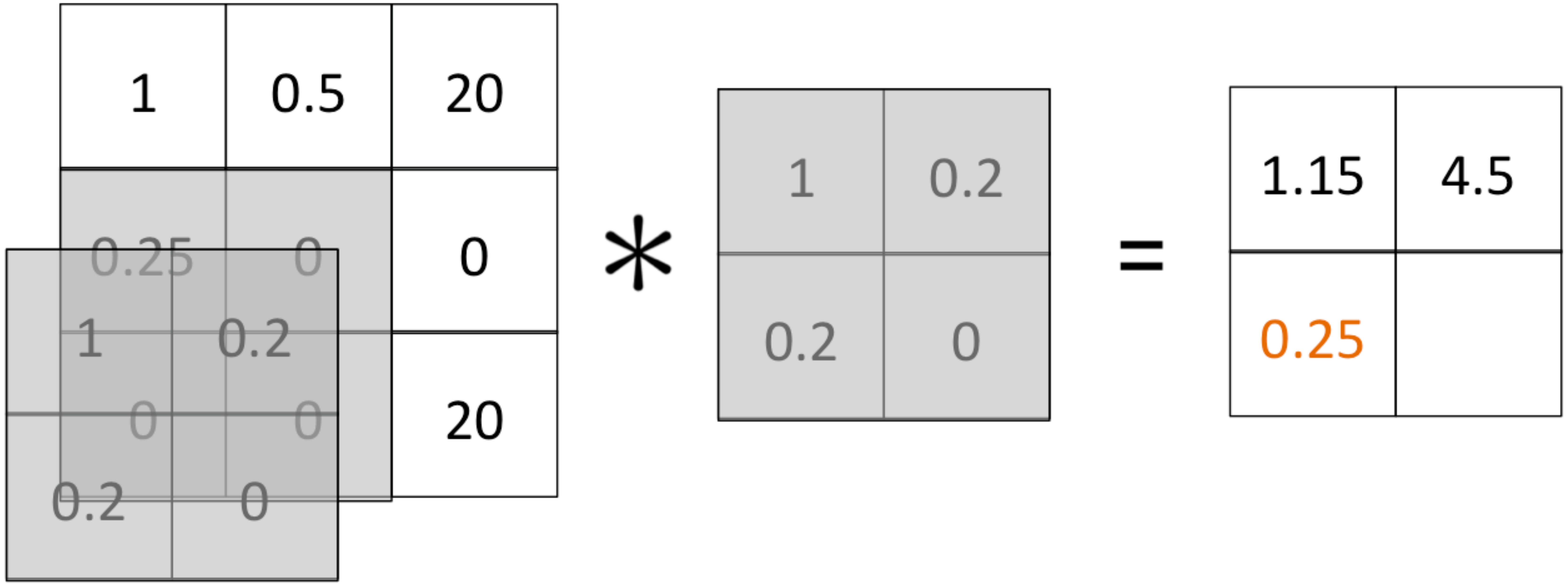
Convolutional Neural Network
Convolution



Convolutional Neural Network

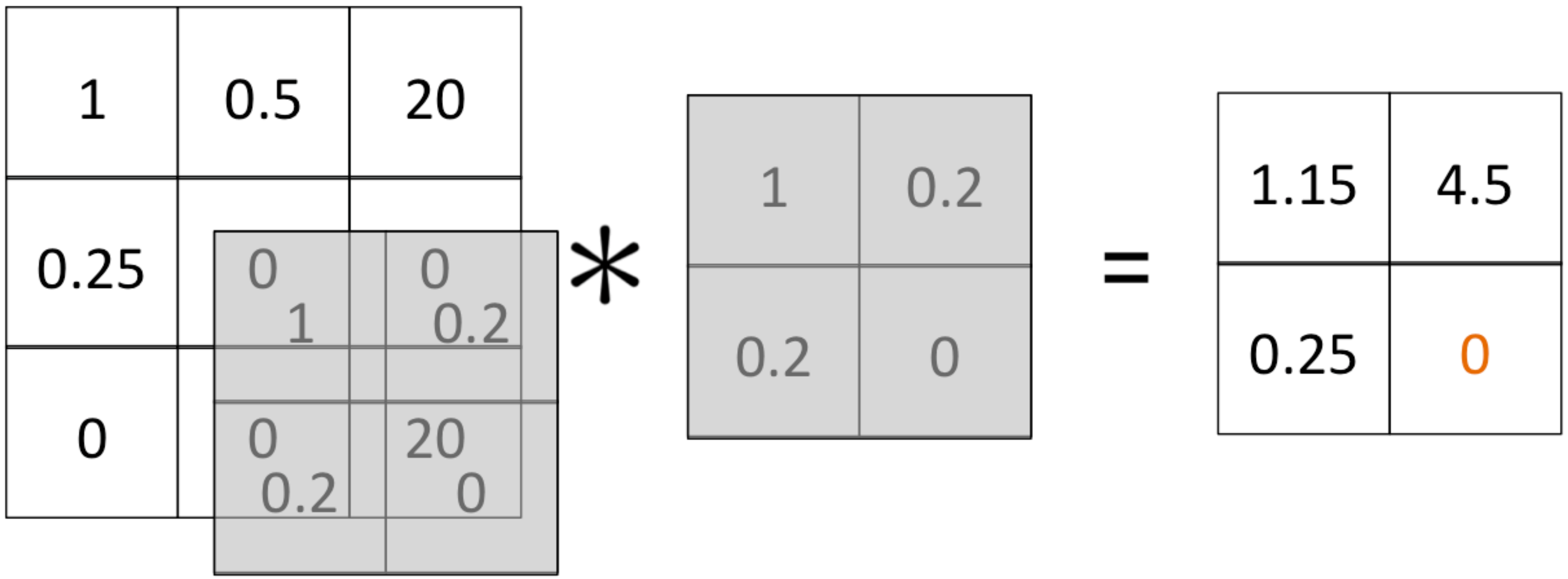
Convolution

0.25*1 + 0*0.2 + 0*0.2 + 0*0 = 0.25



Convolutional Neural Network
Convolution

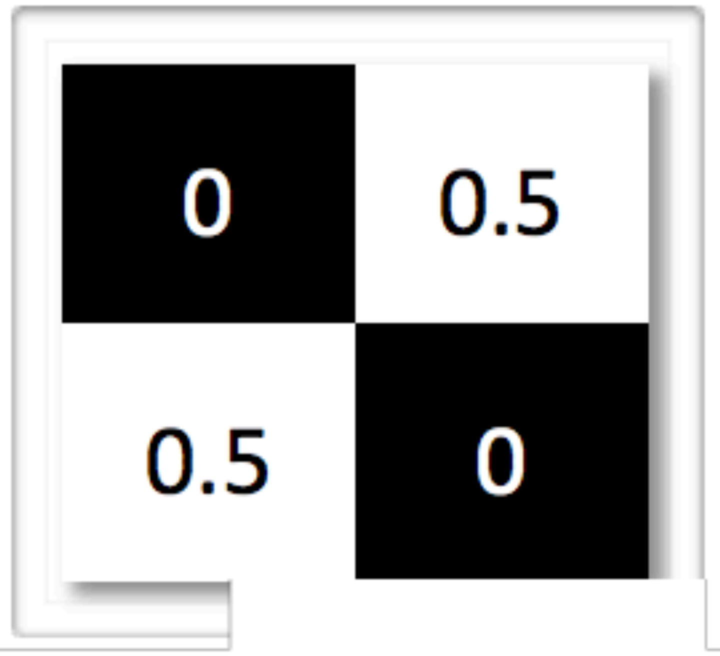
0*1 + 0*0.2 + 0*0.2 + 20*0 = 0

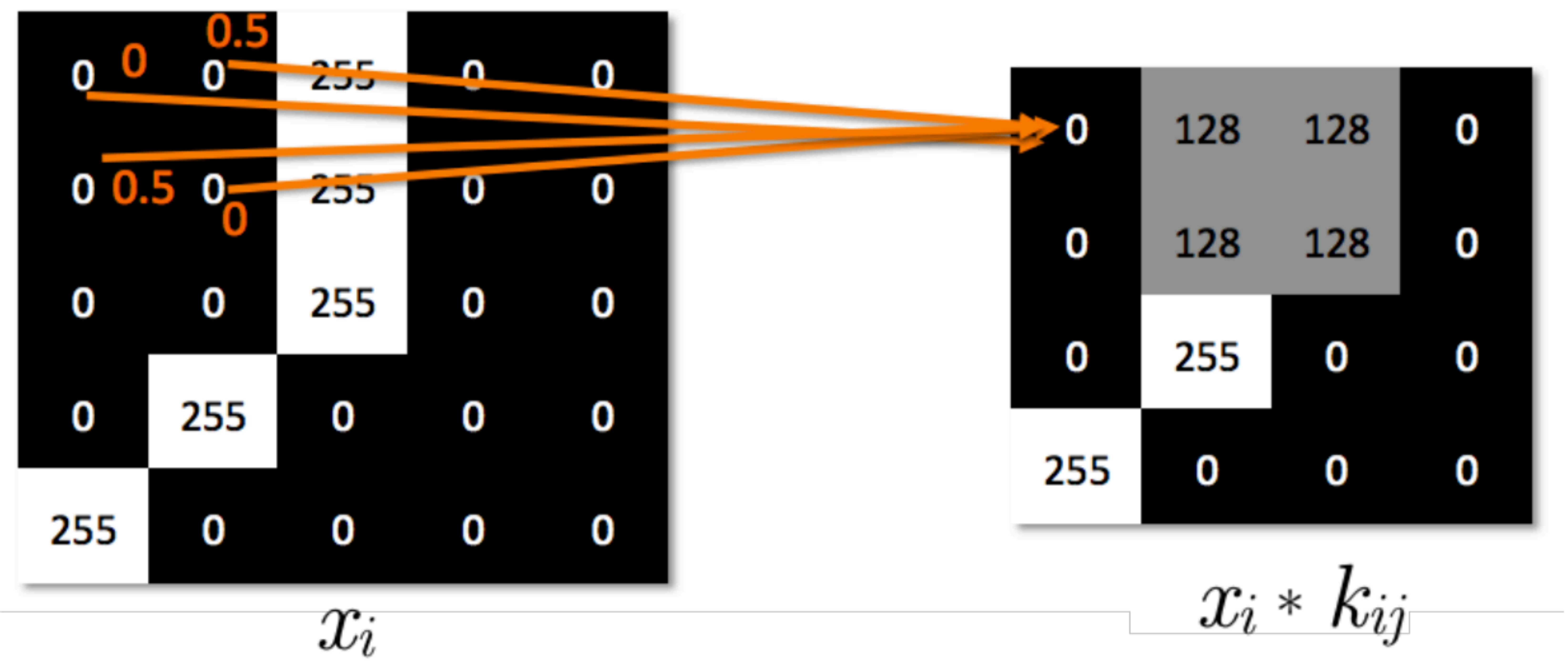


Convolutional Neural Network

Convolution

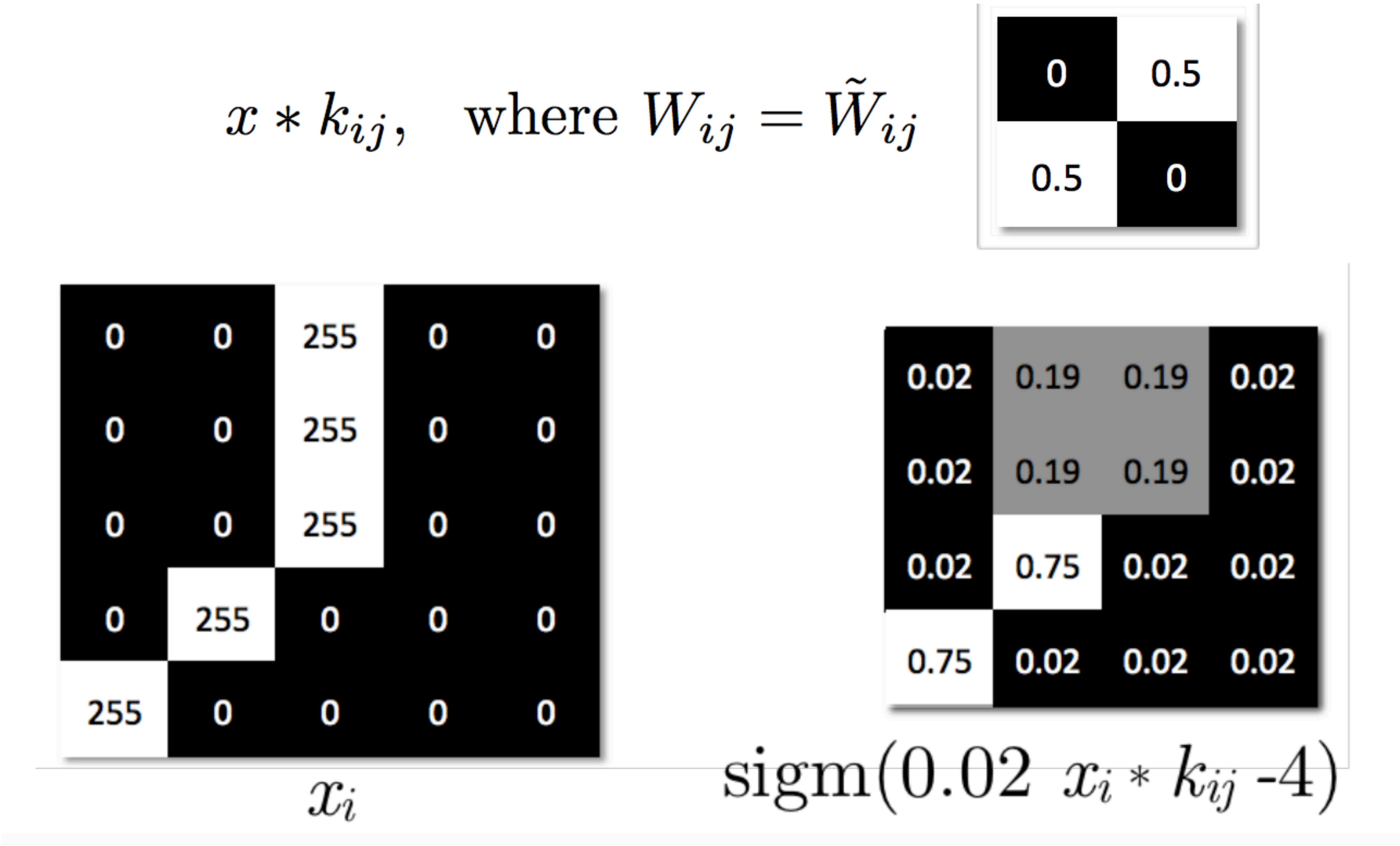
$$x * k_{ij}, \quad \text{where } W_{ij} = \tilde{W}_{ij}$$





Convolutional Neural Network
Convolution

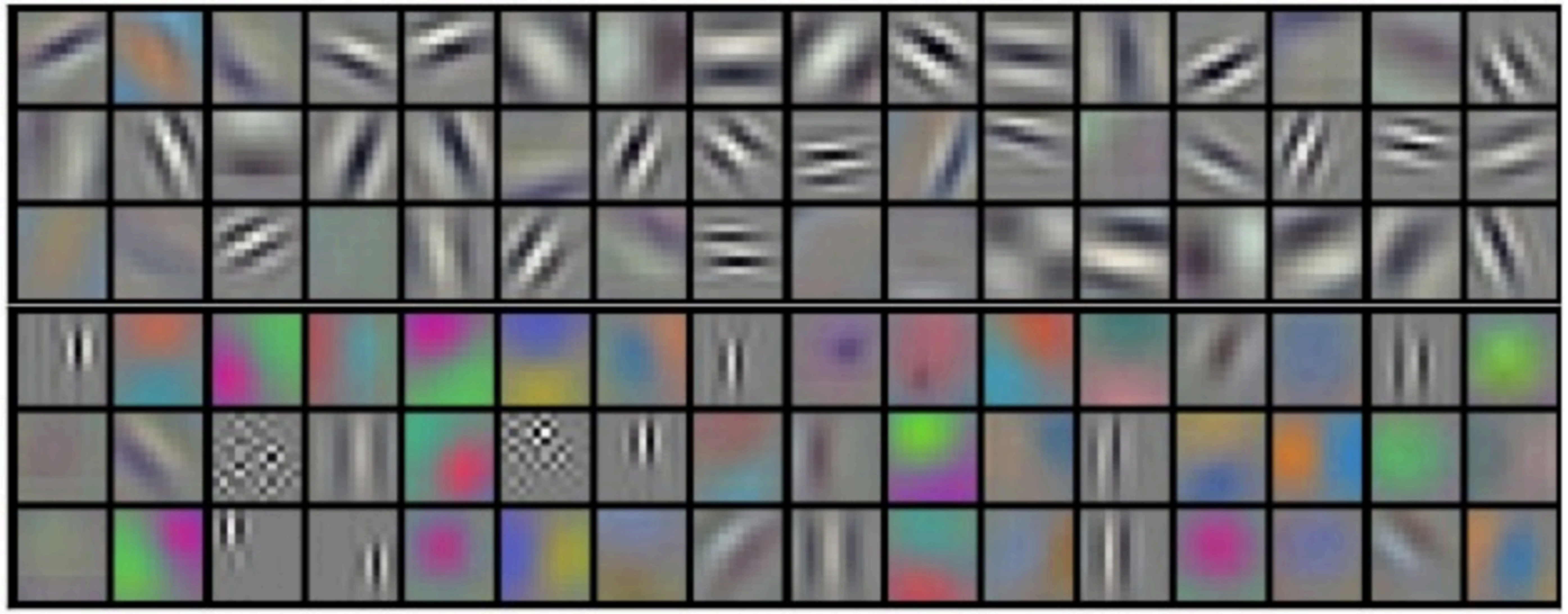
- Element-wise activation function after convolution
  - $\Rightarrow$ detector of a feature at any position in the image



Convolutional Neural Network

Learned Kernels

- Example kernels learned by AlexNet

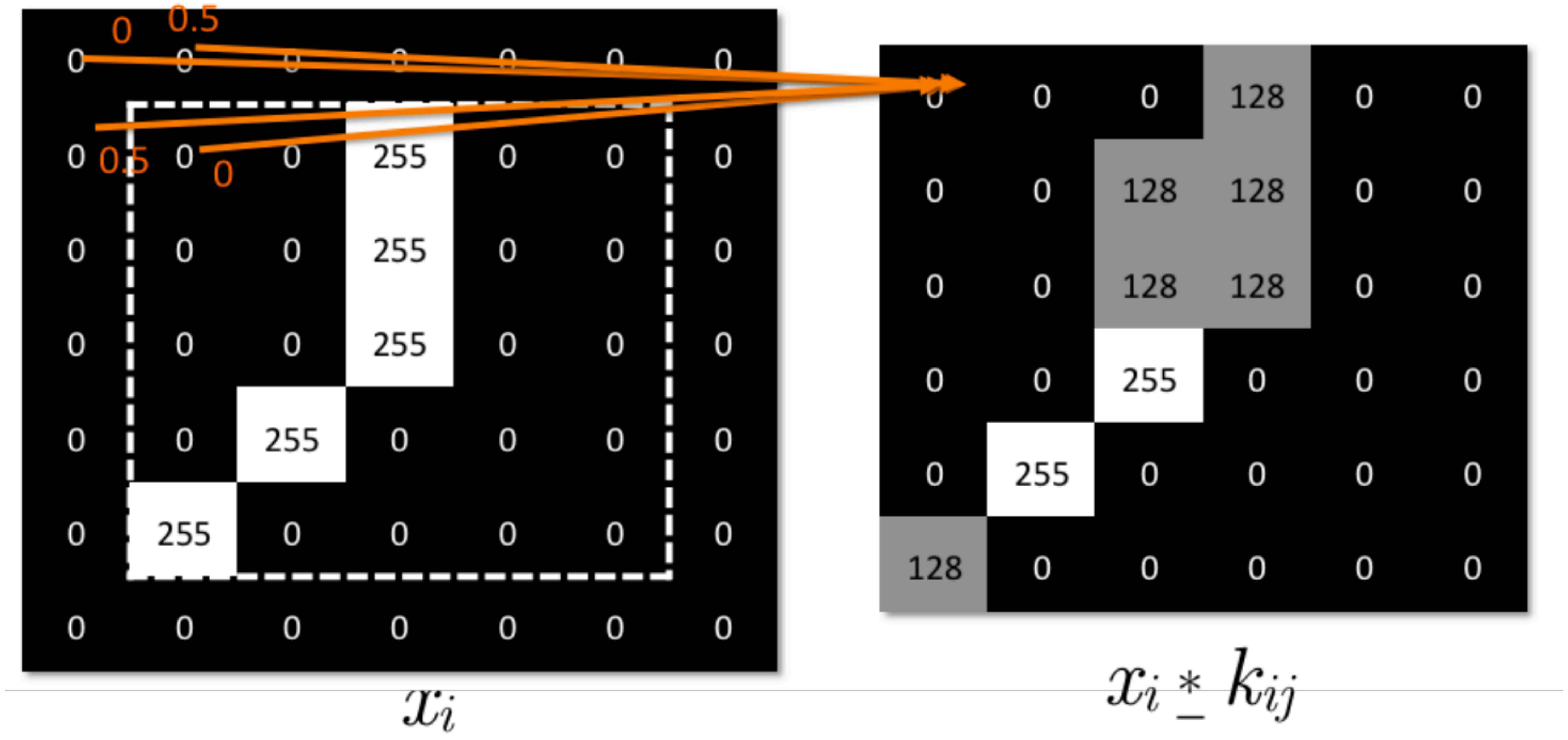


- Number of parameters:
  - Example: 200×200 image, 100 kernels, kernel size 10×10
  - $\Rightarrow 10 \times 10 \times 100$ = 10K parameters

Convolutional Neural Network

Padding

- Use zero padding to allow going over the boundary
  - Easier to control the size of output layer

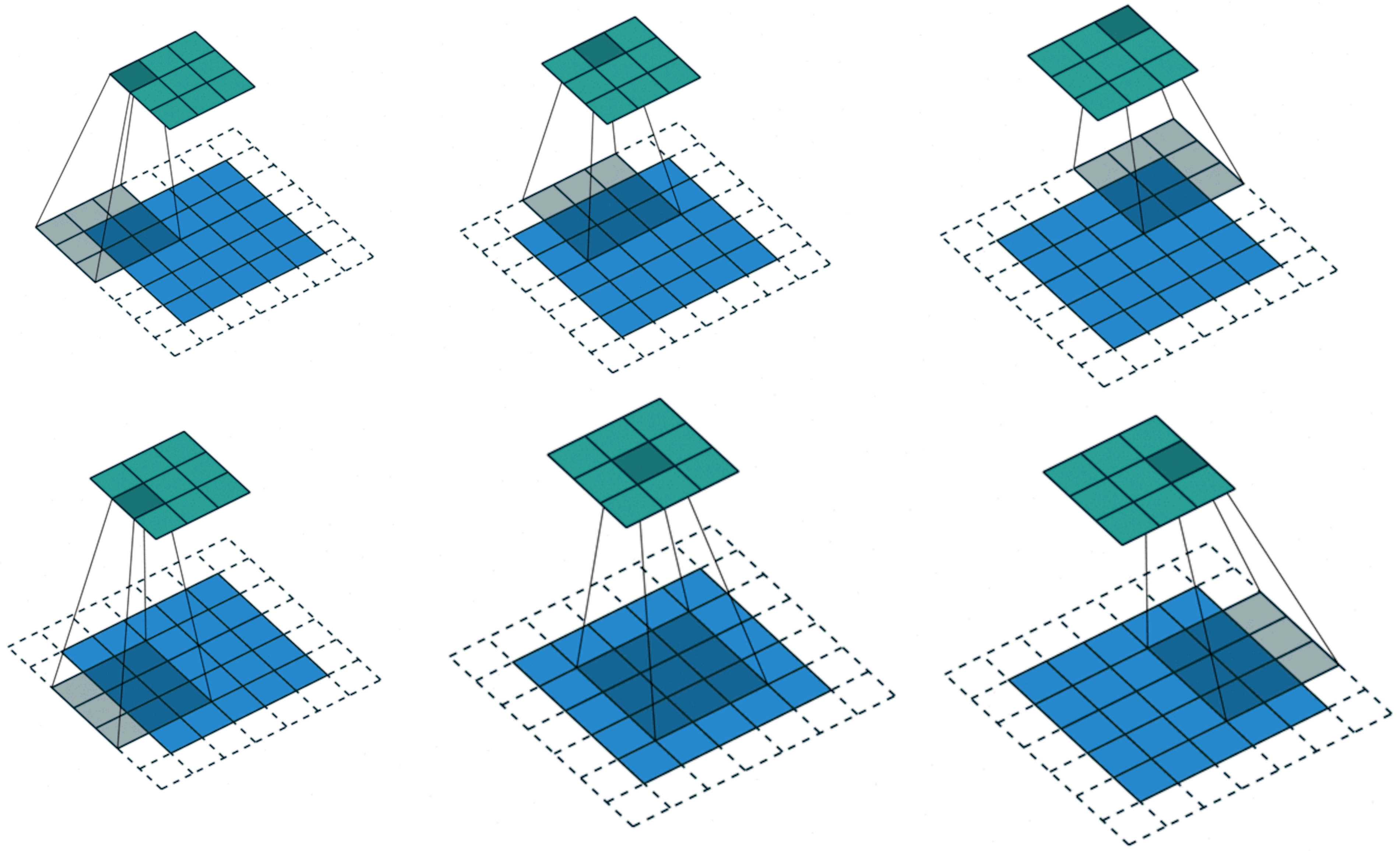


Convolutional Neural Network

Strides

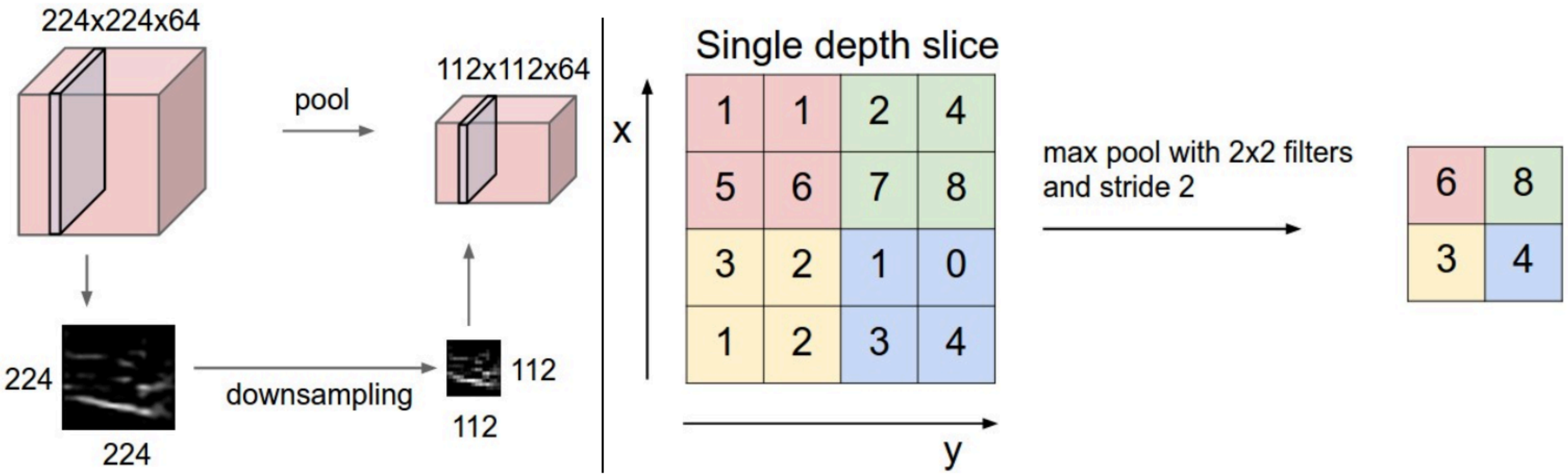
- Stride: The amount of movement between applications of the filter to the input image

- Stride $(1,1)$: no stride



Convolutional Neural Network
Pooling

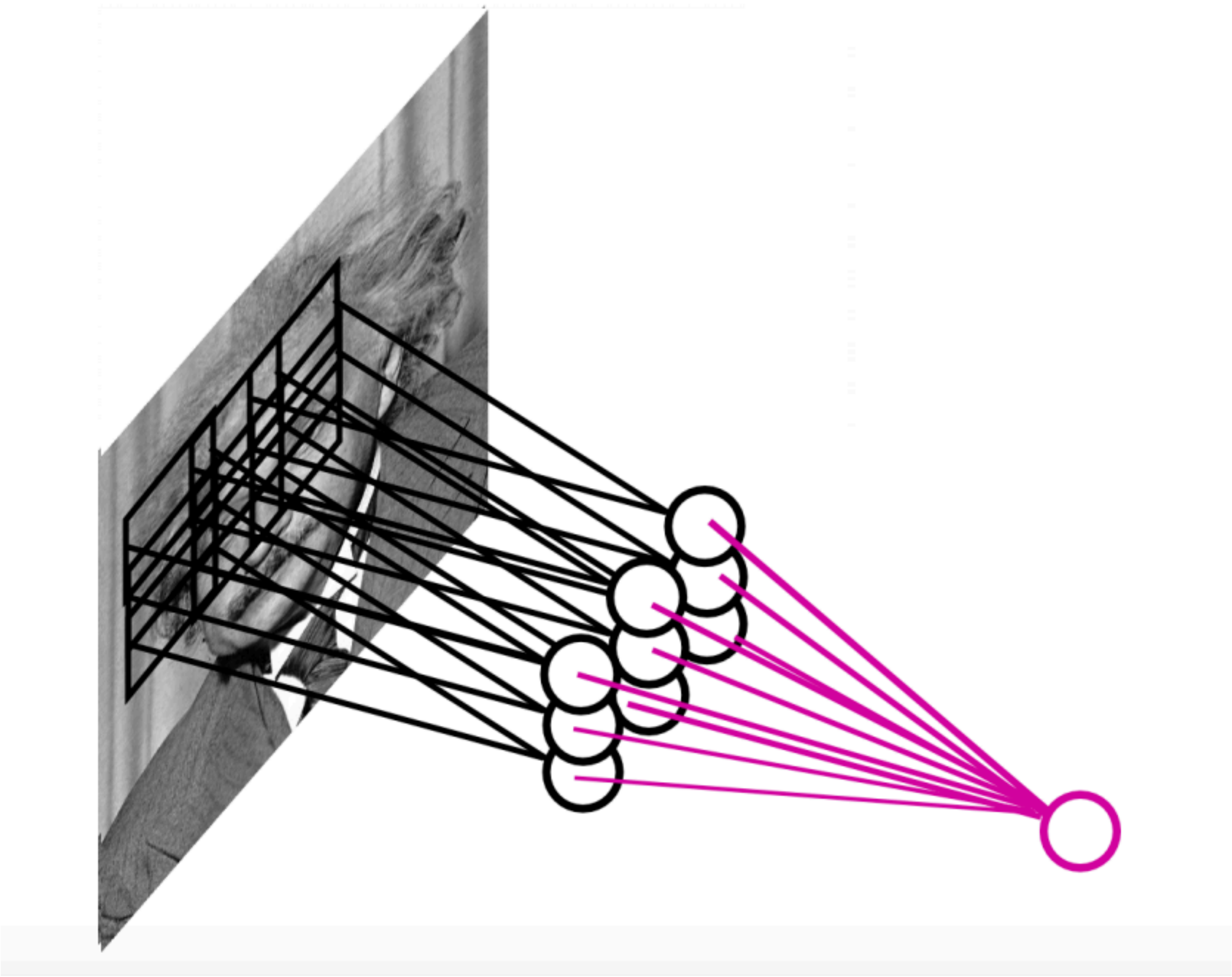
- It’s common to insert a pooling layer in-between successive convolutional layers
- Reduce the size of presentation, down-sampling
- Example: Max pooling



Convolutional Neural Network

Pooling

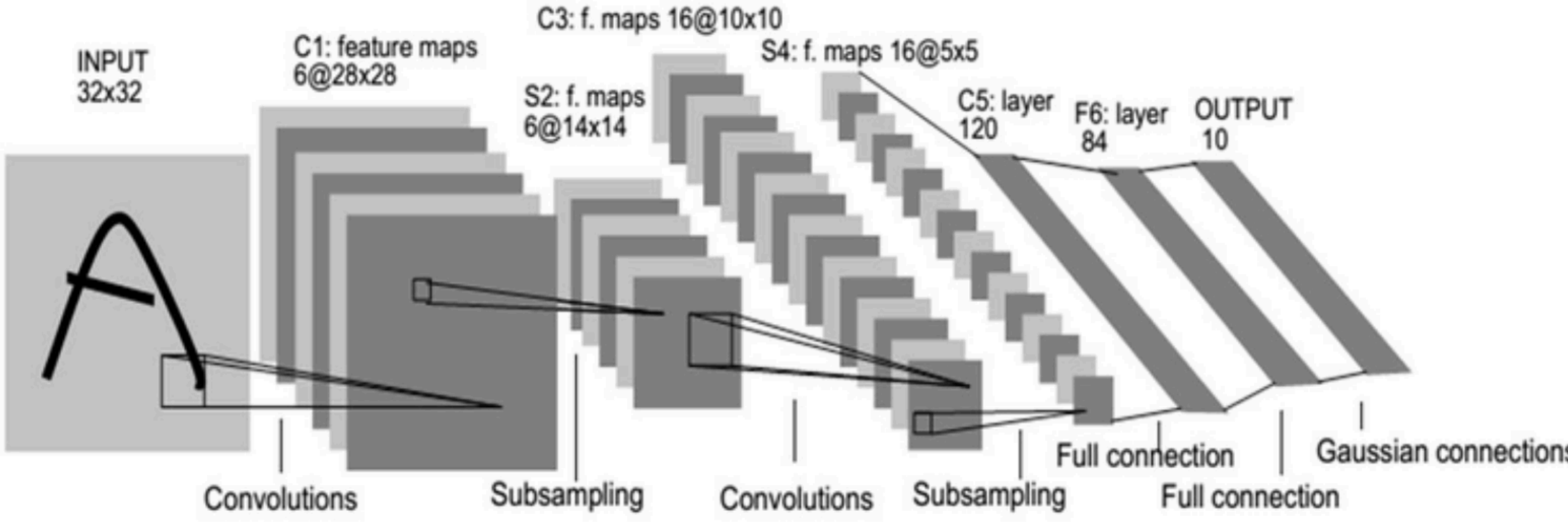
- By pooling, we gain robustness to the exact spatial location of features



Convolutional Neural Network

Example: LeNet5

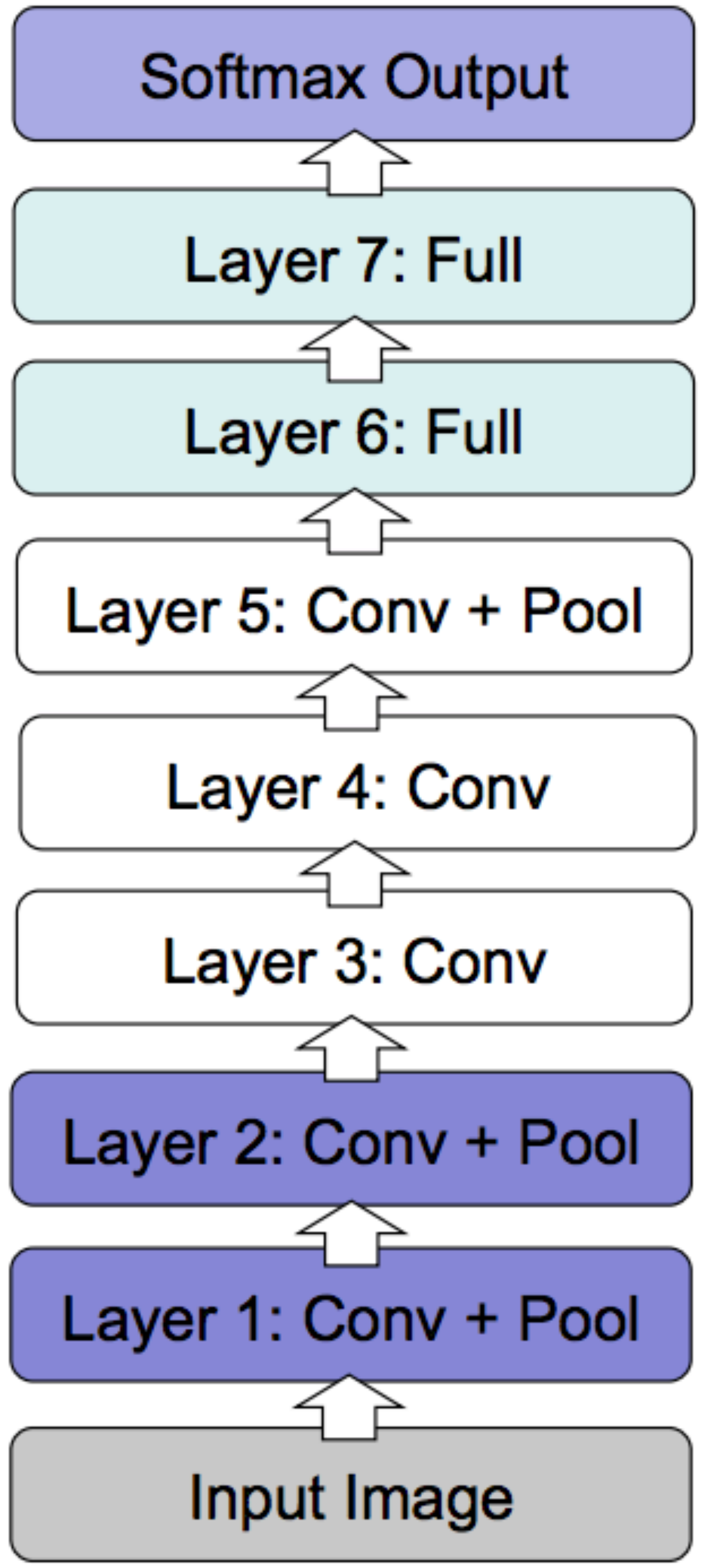
- Input: 32×32 images (MNIST)
- Convolution 1: 6 5×5filters, stride 1
    - Output: 6 28×28 maps
- Pooling 1: 2×2 max pooling, stride 2
    - Output: 6 14×14 maps
- Convolution 2: 16 5×5 filters, stride 1
    - Output: 16 10×10 maps
- Pooling 2: 2×2 max pooling with stride 2
    - Output: 16 5×5 maps (total 400 values)
- 3 fully connected layers: $120 \Rightarrow 84 \Rightarrow 10$ neurons



Convolutional Neural Network

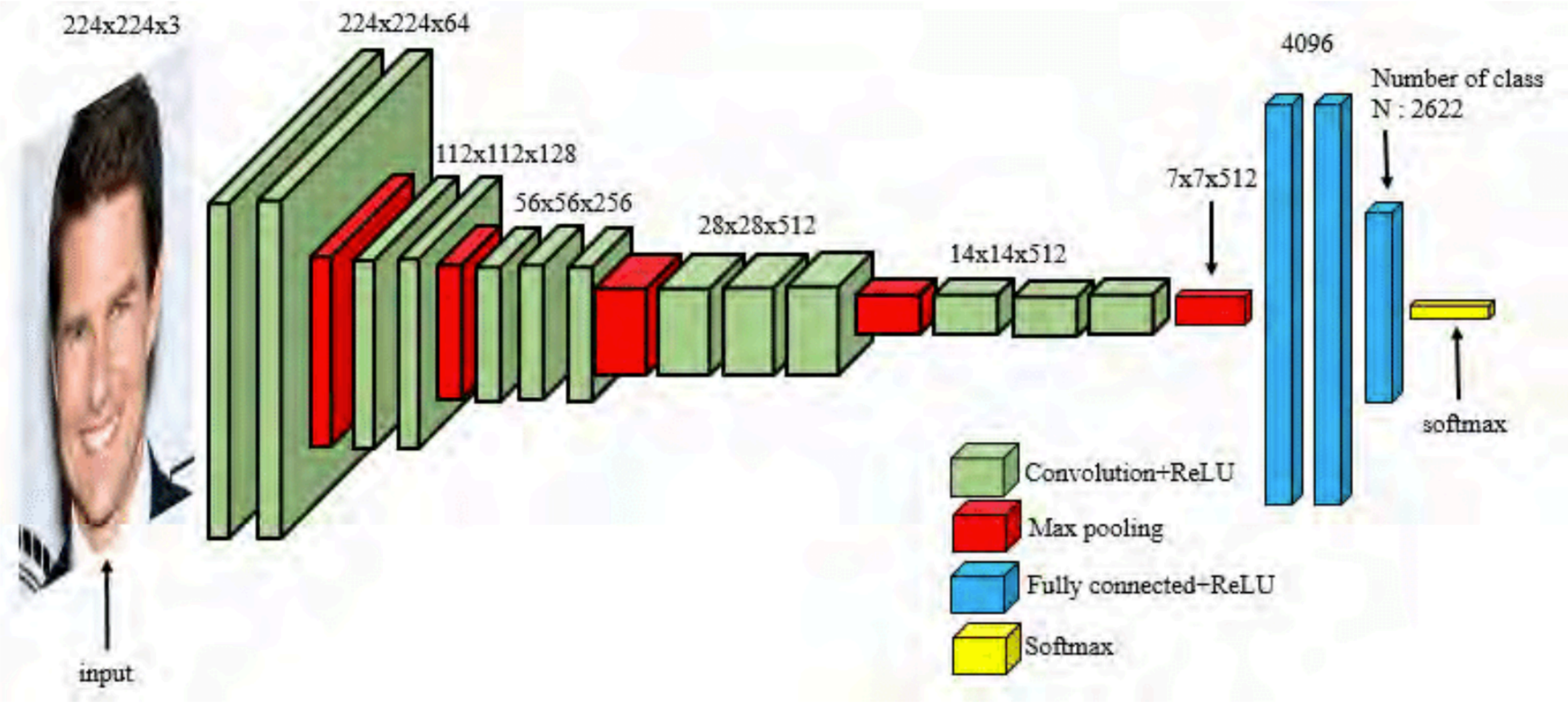
AlexNet

- 8 layers in total, about 60 million parameters and 650,000 neurons.
- Trained on ImageNet dataset
- 18.2% top-5 error
- ``ImageNet Classification with Deep Convolutional Neural Networks'', by Krizhevsky, Sustskever and Hinton, NIPS 2012.



Convolutional Neural Network

VGG Network



Convolutional Neural Network

VGG Network

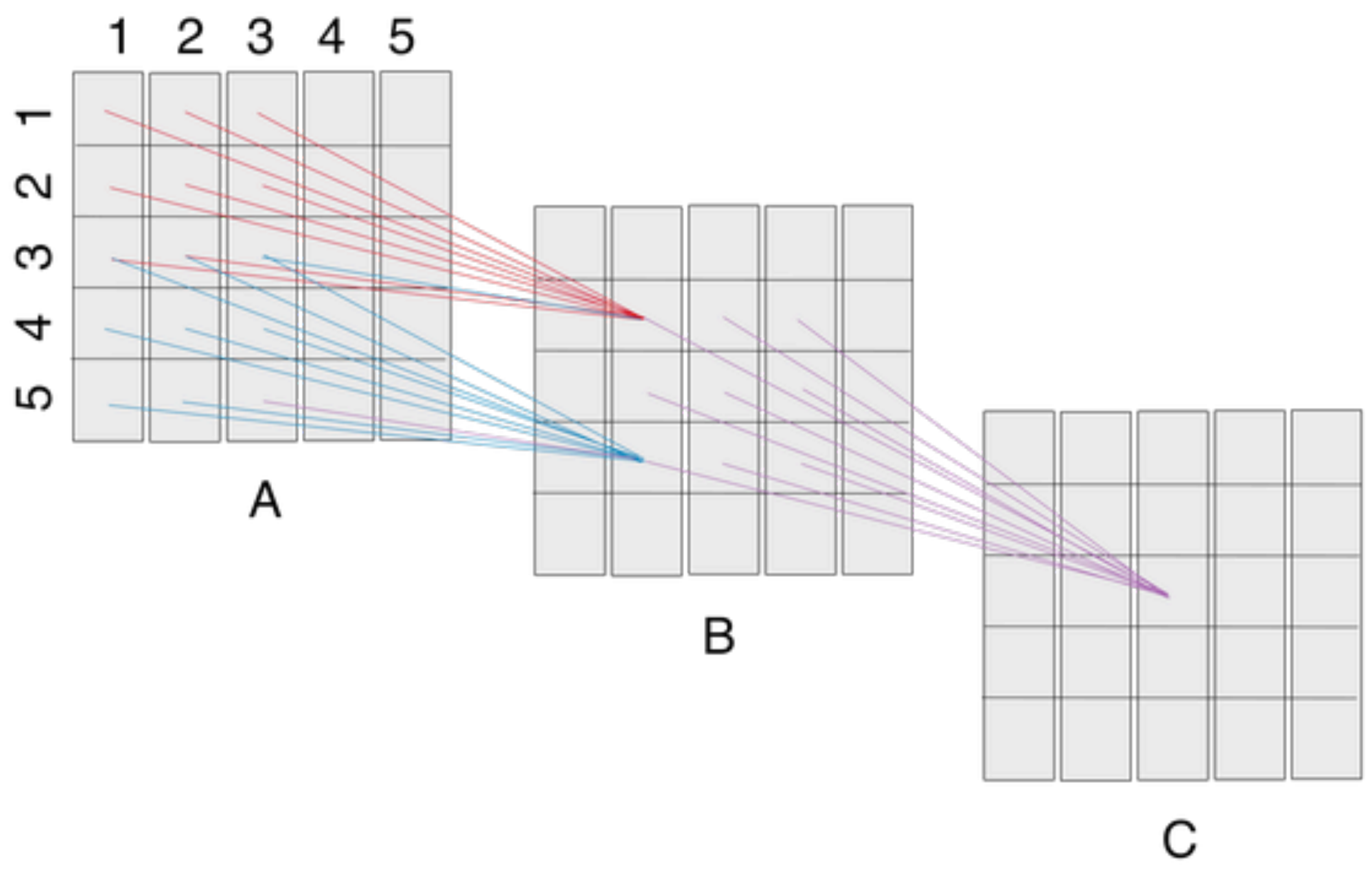
- Output provides an estimate of the conditional probability of each class

```
INPUT: [224x224x3]        memory:  224*224*3=150K   weights: 0
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*64)*64 = 36,864
POOL2: [112x112x64]  memory:  112*112*64=800K   weights: 0
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*128)*128 = 147,456
POOL2: [56x56x128]  memory:  56*56*128=400K   weights: 0
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
POOL2: [28x28x256]  memory:  28*28*256=200K   weights: 0
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512]  memory:  14*14*512=100K   weights: 0
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512]  memory:  7*7*512=25K  weights: 0
FC: [1x1x4096]  memory:  4096  weights: 7*7*512*4096 = 102,760,448
FC: [1x1x4096]  memory:  4096  weights: 4096*4096 = 16,777,216
FC: [1x1x1000]  memory:  1000 weights: 4096*1000 = 4,096,000
```

Convolutional Neural Network

What do the filters learn?

- The receptive field of a neuron is the input region that can affect the neuron's output
- The receptive field for a first layer neuron is its neighbors (depending on kernel size) ⇒ capturing very local patterns
- For higher layer neurons, the receptive field can be much larger ⇒ capturing global patterns



Convolutional Neural Network

Training

- Training:
  - Apply SGD to minimize in-sample training error
  - Backpropagation can be extended to convolutional layer and pooling layer to compute gradient!
  - Millions of parameters $\Rightarrow$ easy to overfit

Convolutional Neural Network

Revisit Alexnet

- Dropout: 0.5 (in FC layers)
- A lot of data augmentation
- Momentum SGD with batch size 128, momentum factor 0.9
- L2 weight decay (L2 regularization)
- Learning rate: 0.01, decreased by 10 every time when reaching a stable validation accuracy

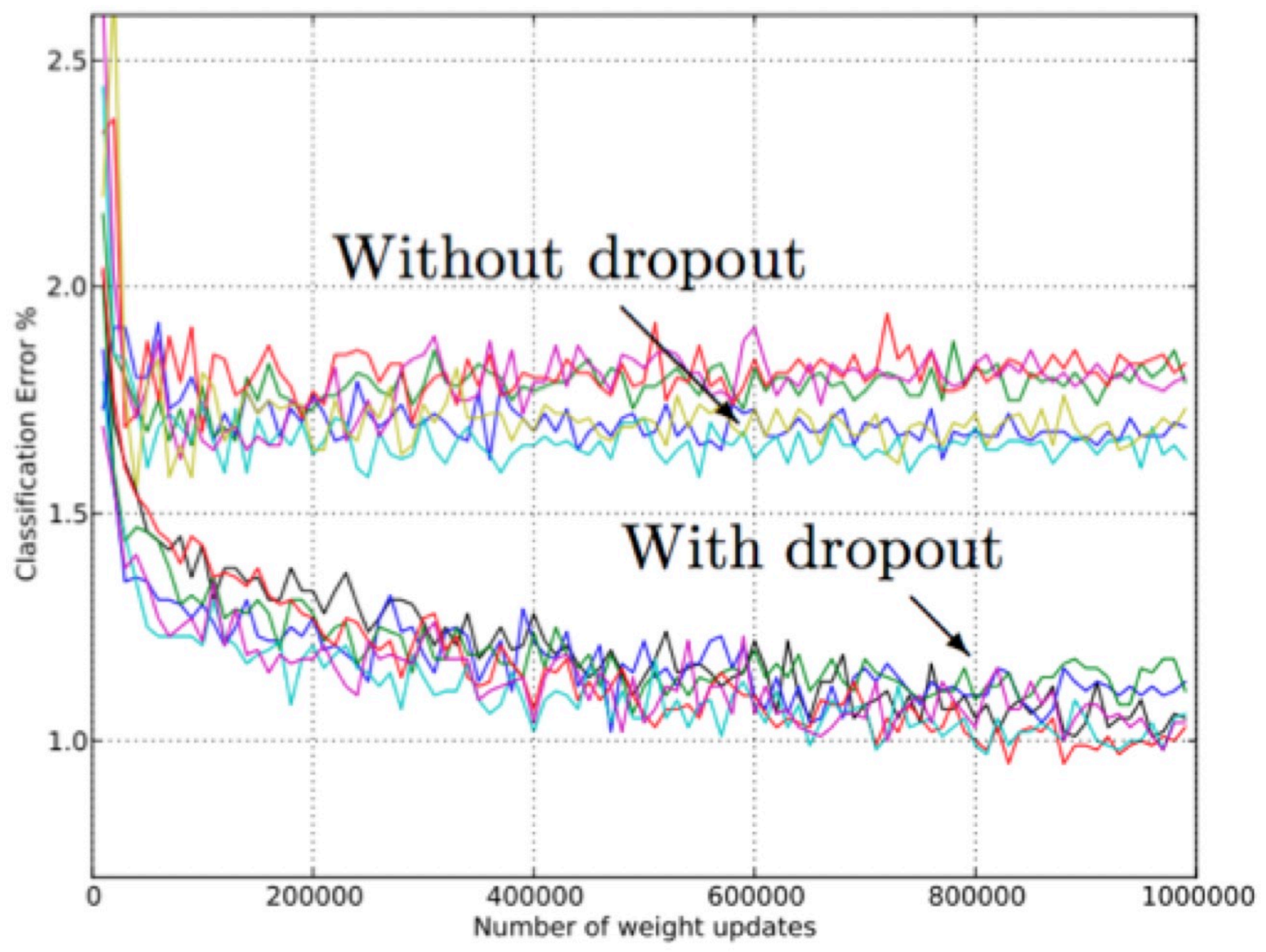
Convolutional Neural Network

Dropout

- One of the most effective regularization for deep neural networks

Method	CIFAR-10	CIFAR-100
Conv Net + max pooling (hand tuned)	15.60	43.48
Conv Net + stochastic pooling (Zeiler and Fergus, 2013)	15.13	42.51
Conv Net + max pooling (Snoek et al., 2012)	14.98	-
Conv Net + max pooling + dropout fully connected layers	14.32	41.26
Conv Net + max pooling + dropout in all layers	12.61	**37.20**
Conv Net + maxout (Goodfellow et al., 2013)	**11.68**	38.57

Table 4: Error rates on CIFAR-10 and CIFAR-100.

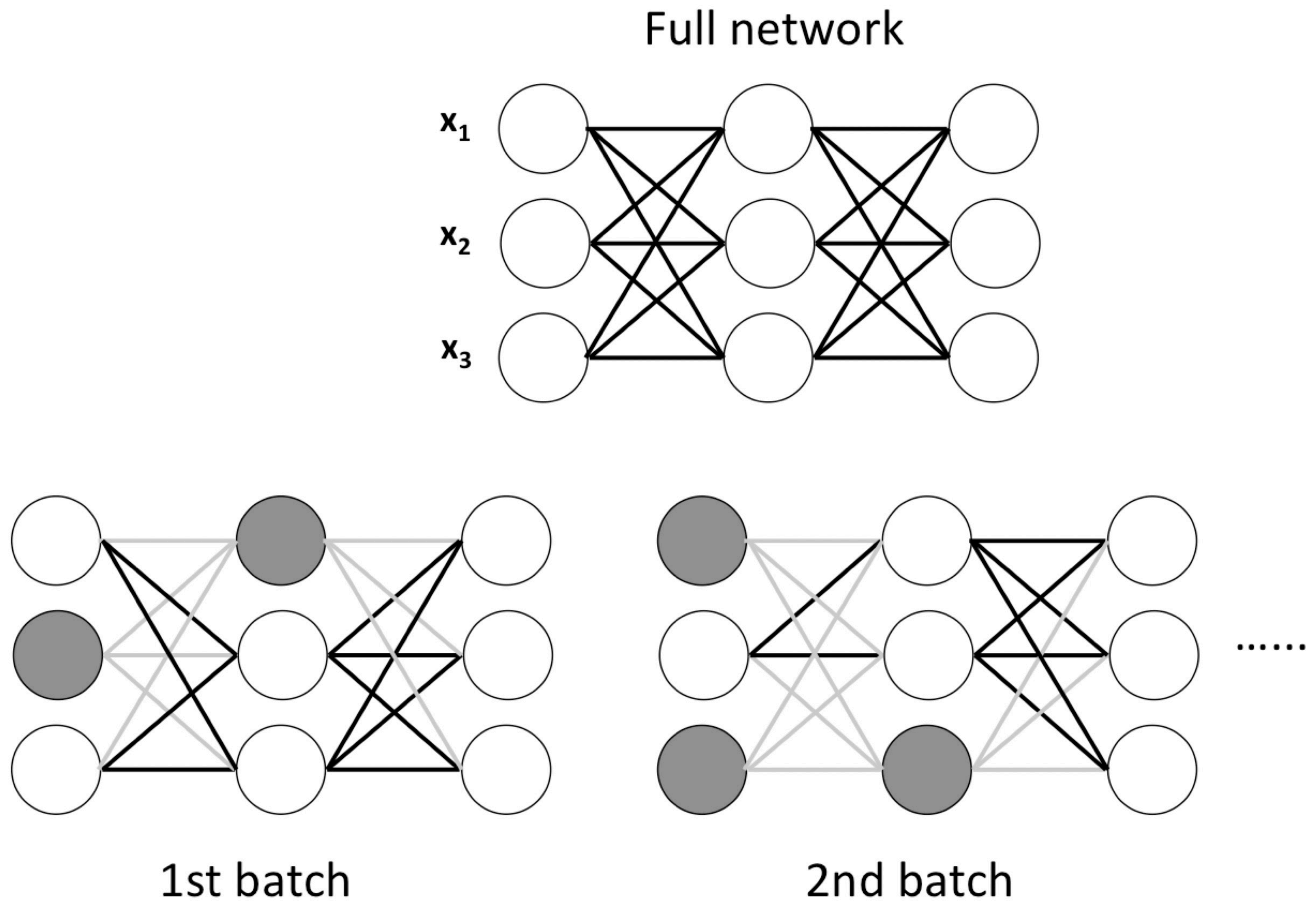


Srivastava et al, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”, 2014.

Convolutional Neural Network

Dropout(training)

- Dropout in the **training** phase:
  - For each batch, turn off each neuron (including inputs) with a probability $1 - \alpha$
  - Zero out the removed nodes/edges and do backpropogation



Convolutional Neural Network

Dropout(test)

- The model is different from the full model:
- Each neuron computes
  - $x_i^{(l)} = B\sigma(\sum_j W_{ij}^{(l)} x_j^{(l-1)} + b_i^{(l)})$
  - Where B is Bernoulli variable that takes 1 with probability α
- The expected output of the neuron:
  - $E[x_i^{(l)}] = \alpha\sigma(\sum_j W_{ij}^{(l)} x_j^{(l-1)} + b_i^{(l)})$
- Use the expected output at test time $\Rightarrow$ multiply all the weights by α

Convolutional Neural Network

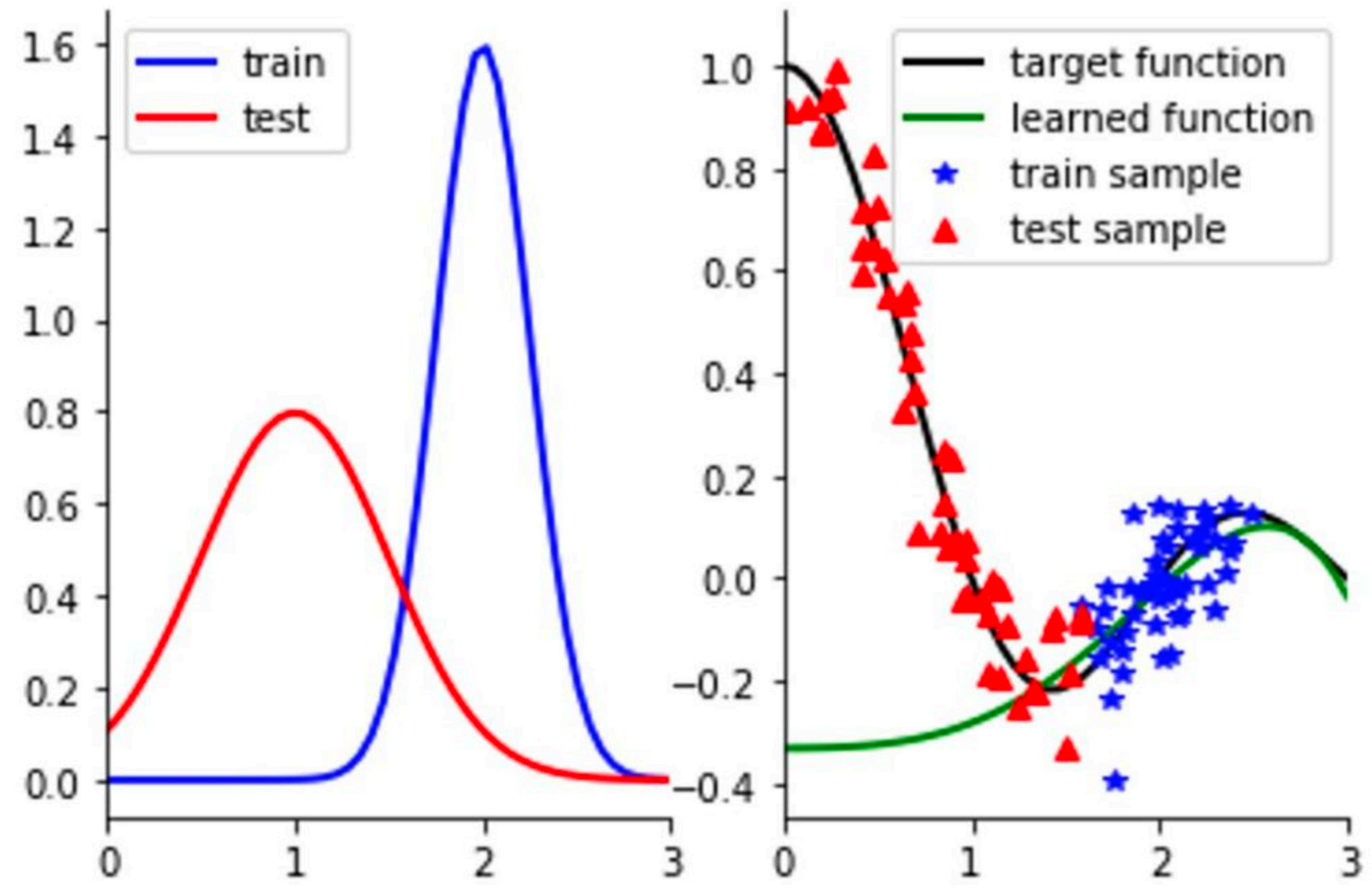
Explanations of dropout

- For a network with n neurons, there are 2^n possible sub-networks
- Dropout: randomly sample over all 2^n possibilities
- Can be viewed as a way to learn Ensemble of 2^n models

Convolutional Neural Network

Batch Normalization

- Initially proposed to reduce co-variate shift
- $$O_{b,c,x,y} \leftarrow \gamma \frac{I_{b,c,x,y} - \mu_c}{\sqrt{\sigma_c^2 + \epsilon}} + \beta \quad \forall b, c, x, y,$$
- $\mu_c = \frac{1}{|B|} \sum_{b,x,y} I_{b,c,x,y}$: the mean for channel c, and σ_c standard deviation.
- γ and β: two learnable parameters

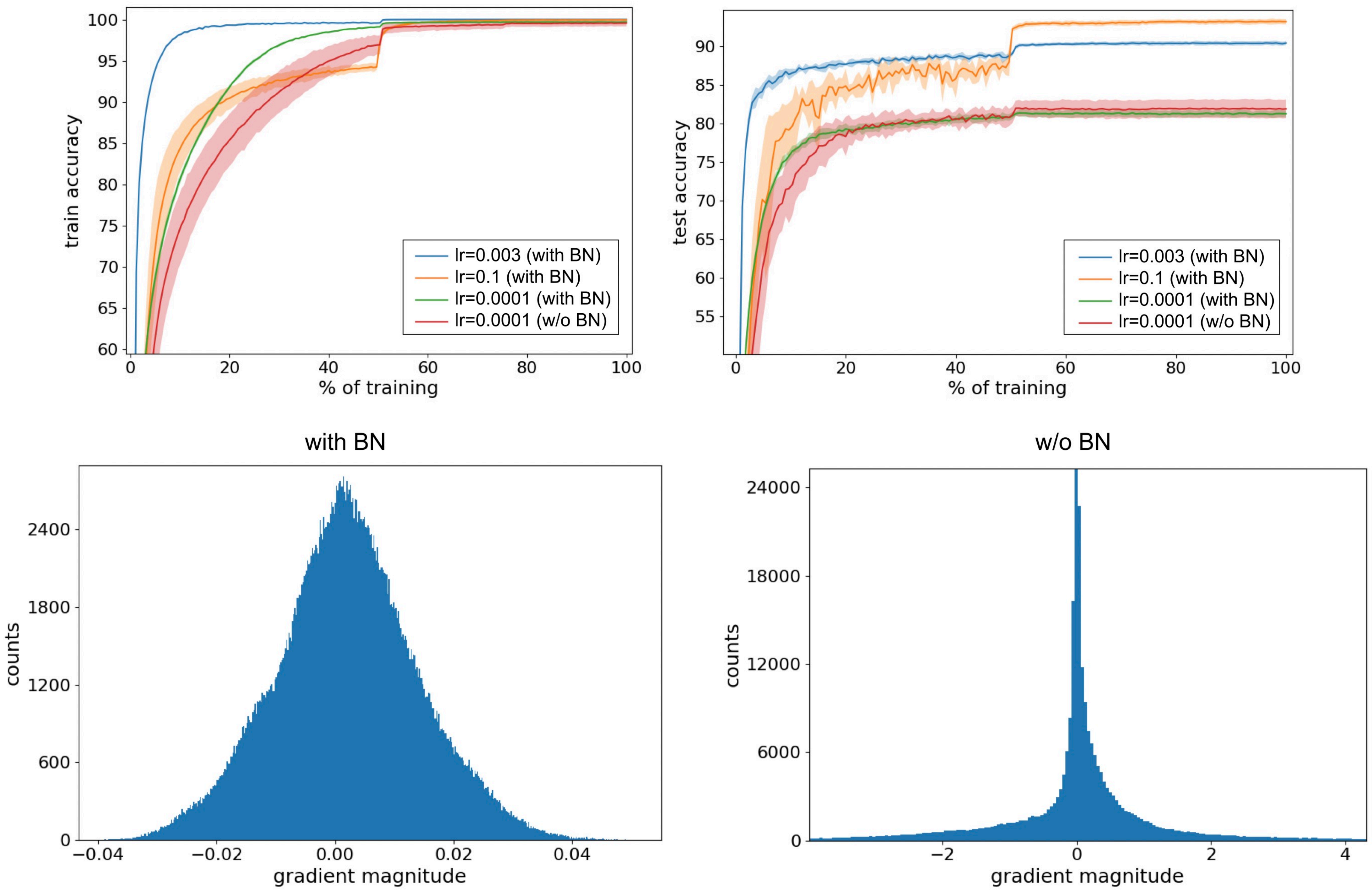


Covariate shift

Convolutional Neural Network

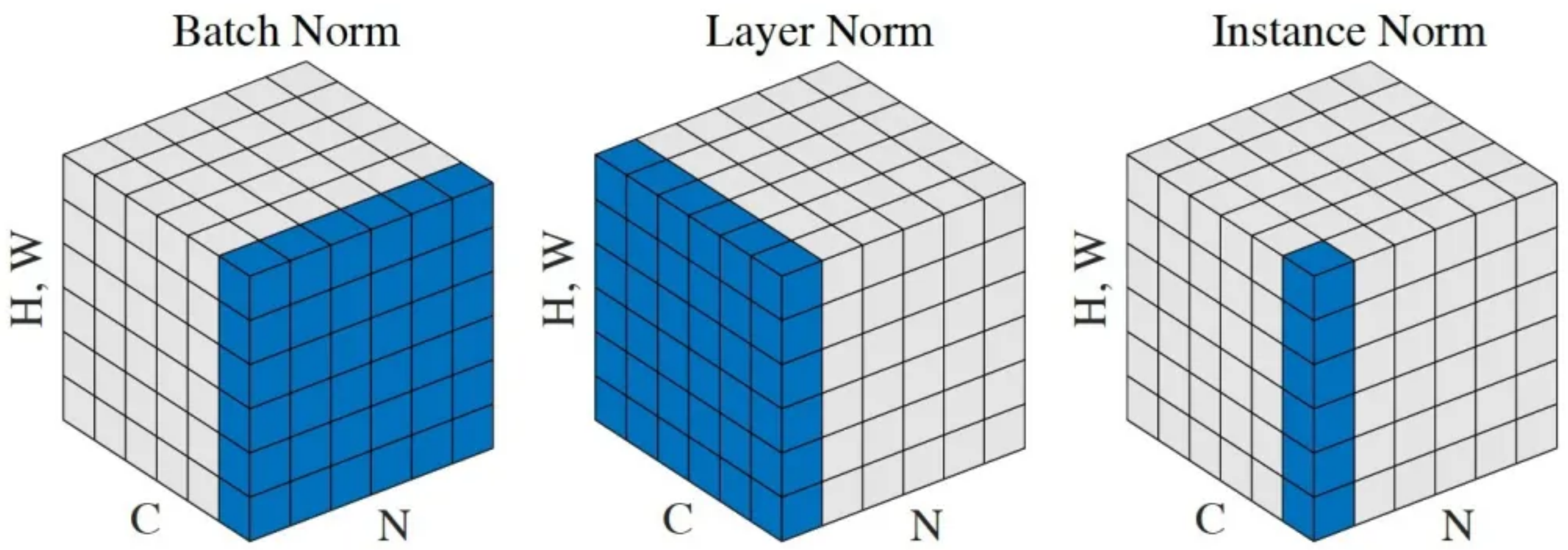
Batch Normalization

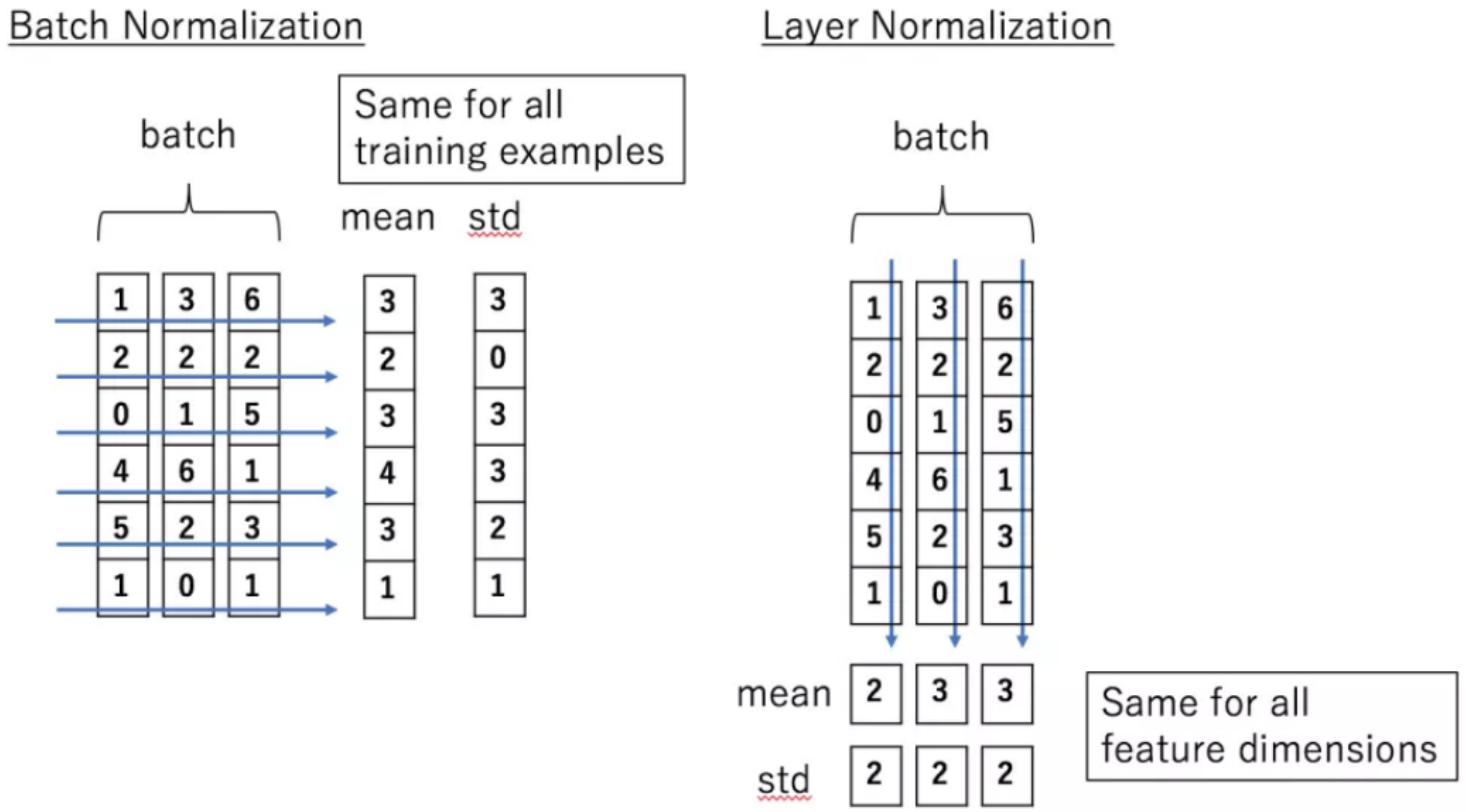
- Couldn't reduce covariate shift (Ilyas et al 2018)
- Allow larger learning rate
    - Constraint the gradient norm



Convolutional Neural Network

Other normalization

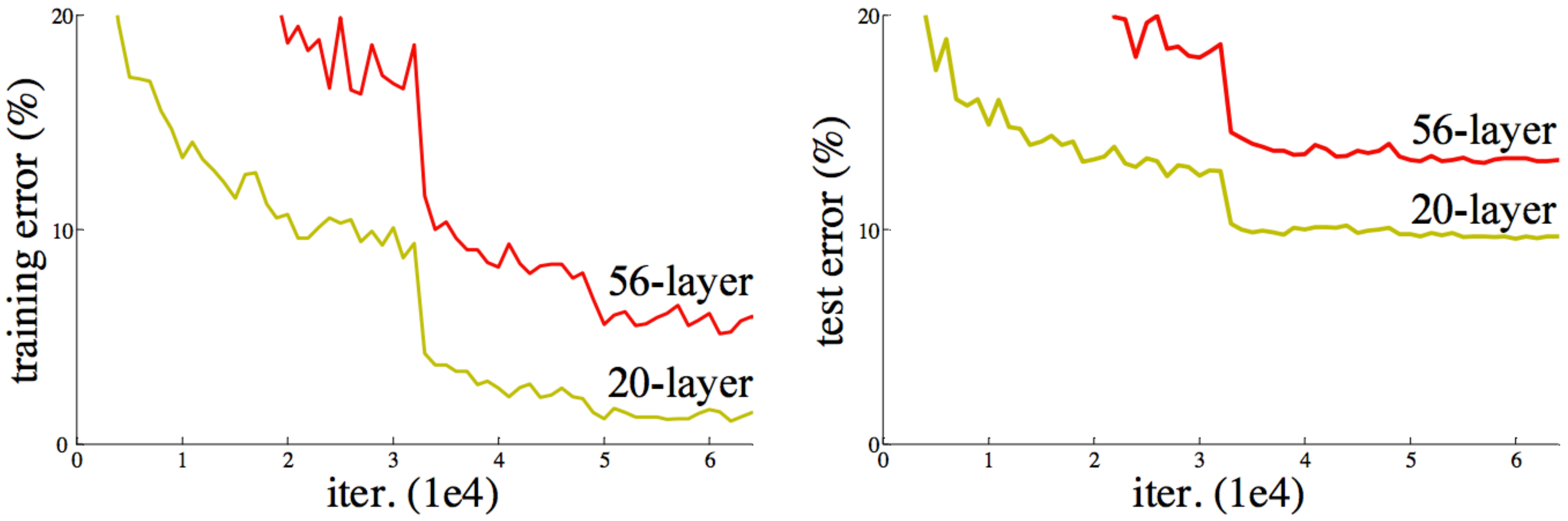




Convolutional Neural Network

Residual Networks

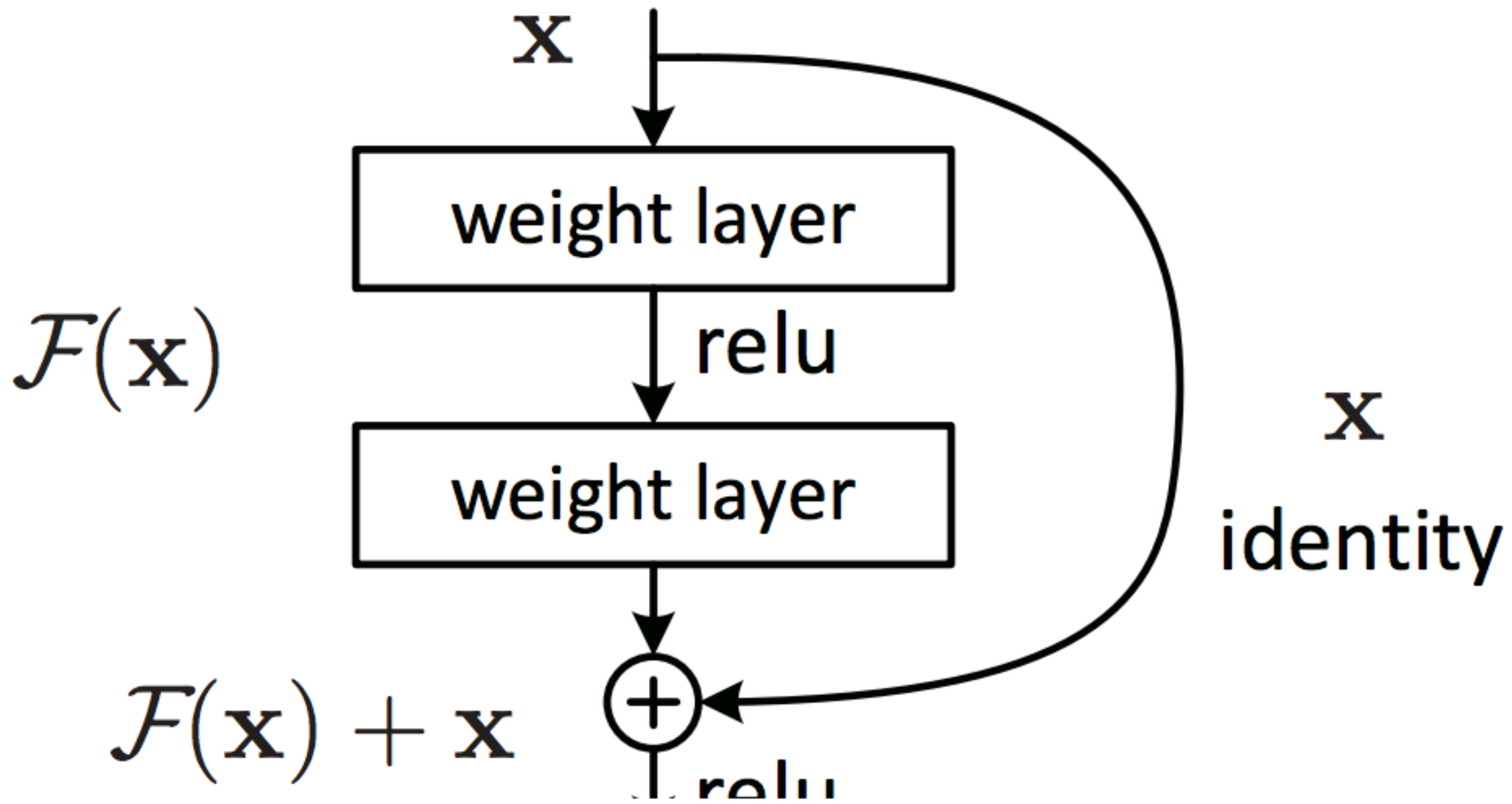
- Very deep convnets do not train well — vanishing gradient problem



Convolutional Neural Network

Residual Networks

- Key idea: introduce ``pass through'' into each layer



- Thus, only residual needs to be learned

Convolutional Neural Network

Residual Networks

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).