ECE 20875

Python for Data Science

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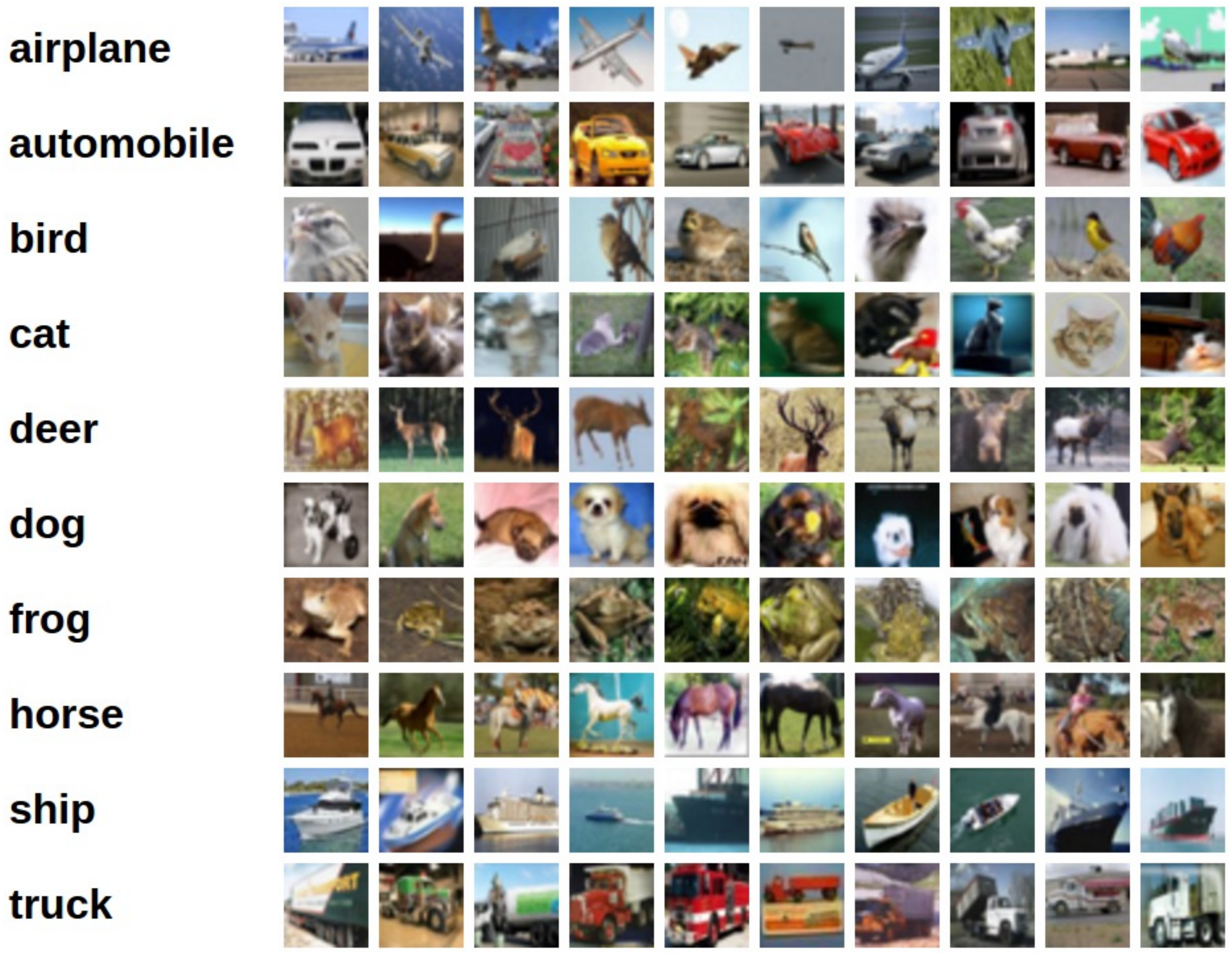
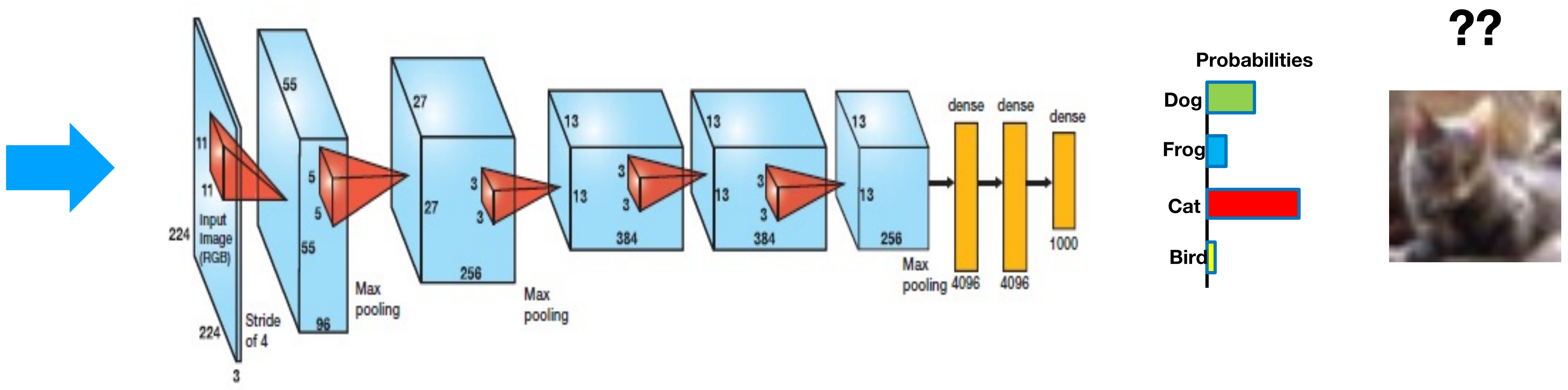
(Adapted from material developed by Profs. Milind Kulkarni, Stanley Chan, Chris Brinton, David Inouye, and Qiang Qiu)

convolutional neural network (CNN)

image classification using NN





Overall procedure:

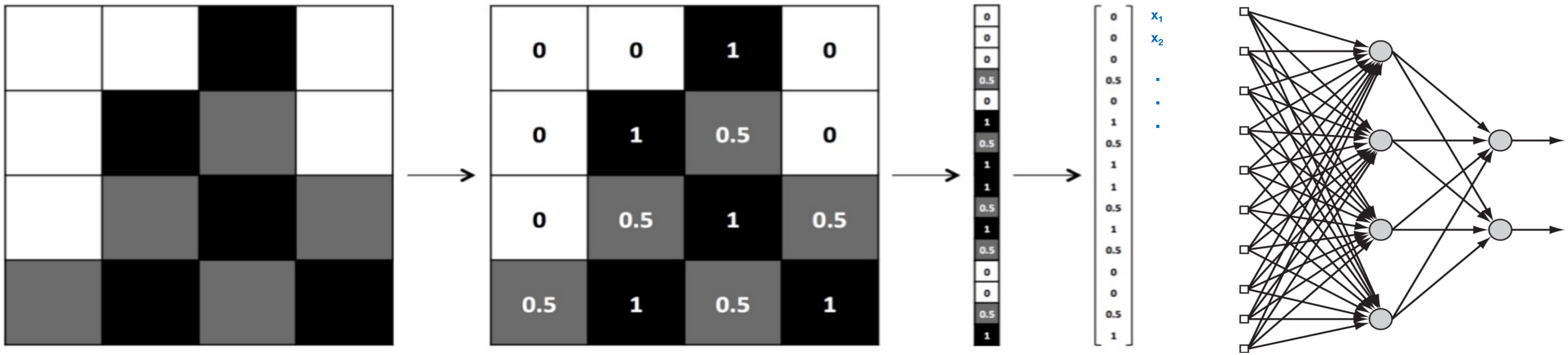
- Collect a large amount of images
- Annotate each image with a class label
- Choose a neural network structure
- Use our training samples to adjust layers and layers of parameters (backpropagation) to minimize a chosen loss

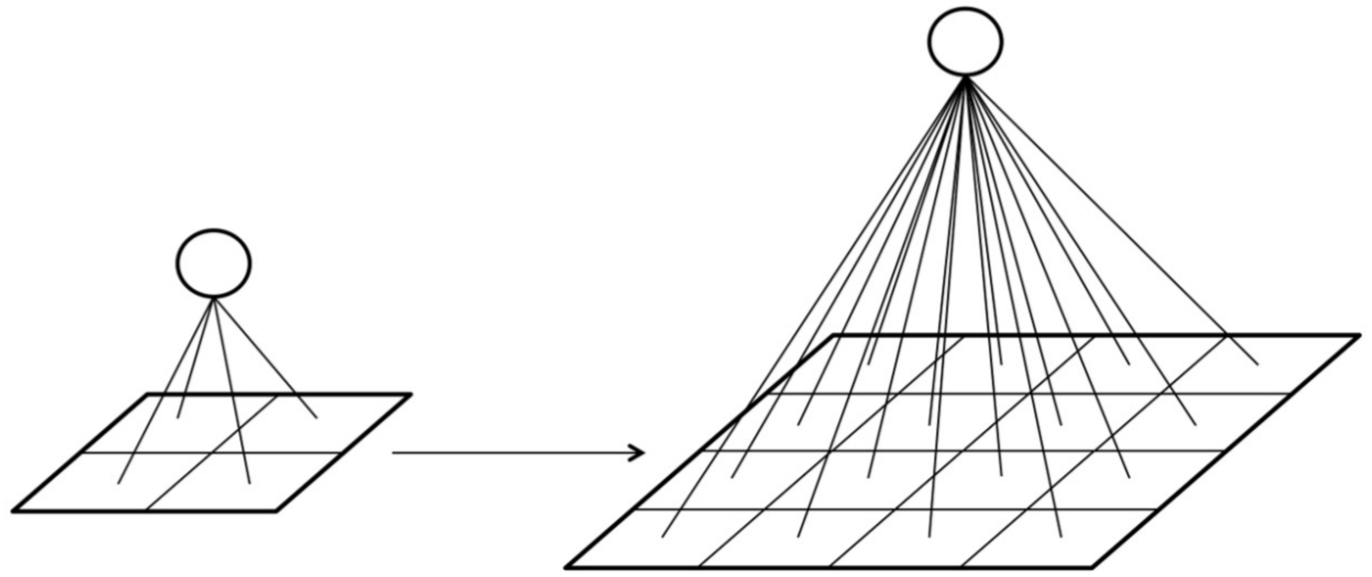
Goal: After training, when the NN sees a new image, its output should assign the highest probability to the respective class.

image vectorization

Image

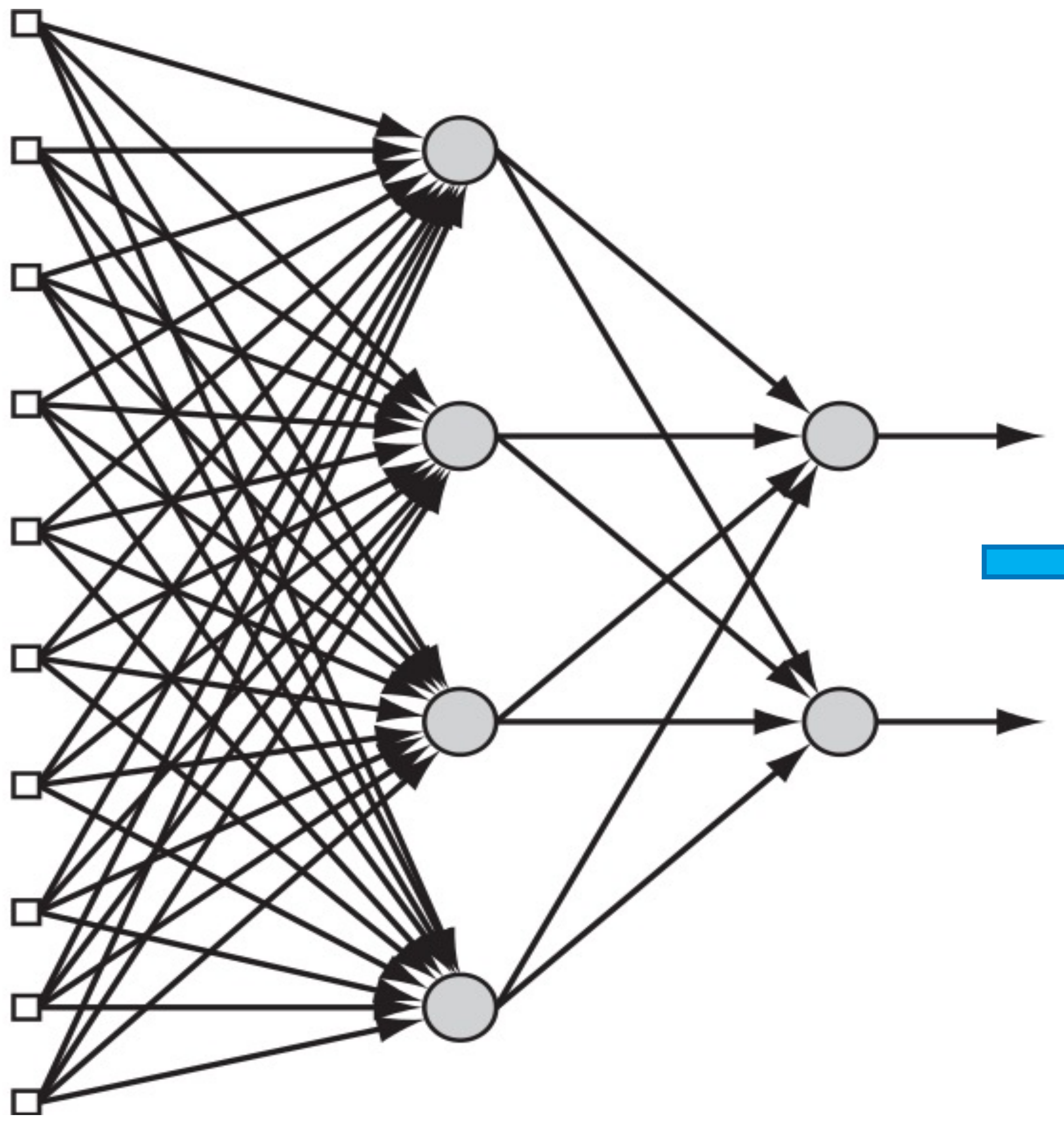
Fully-connected



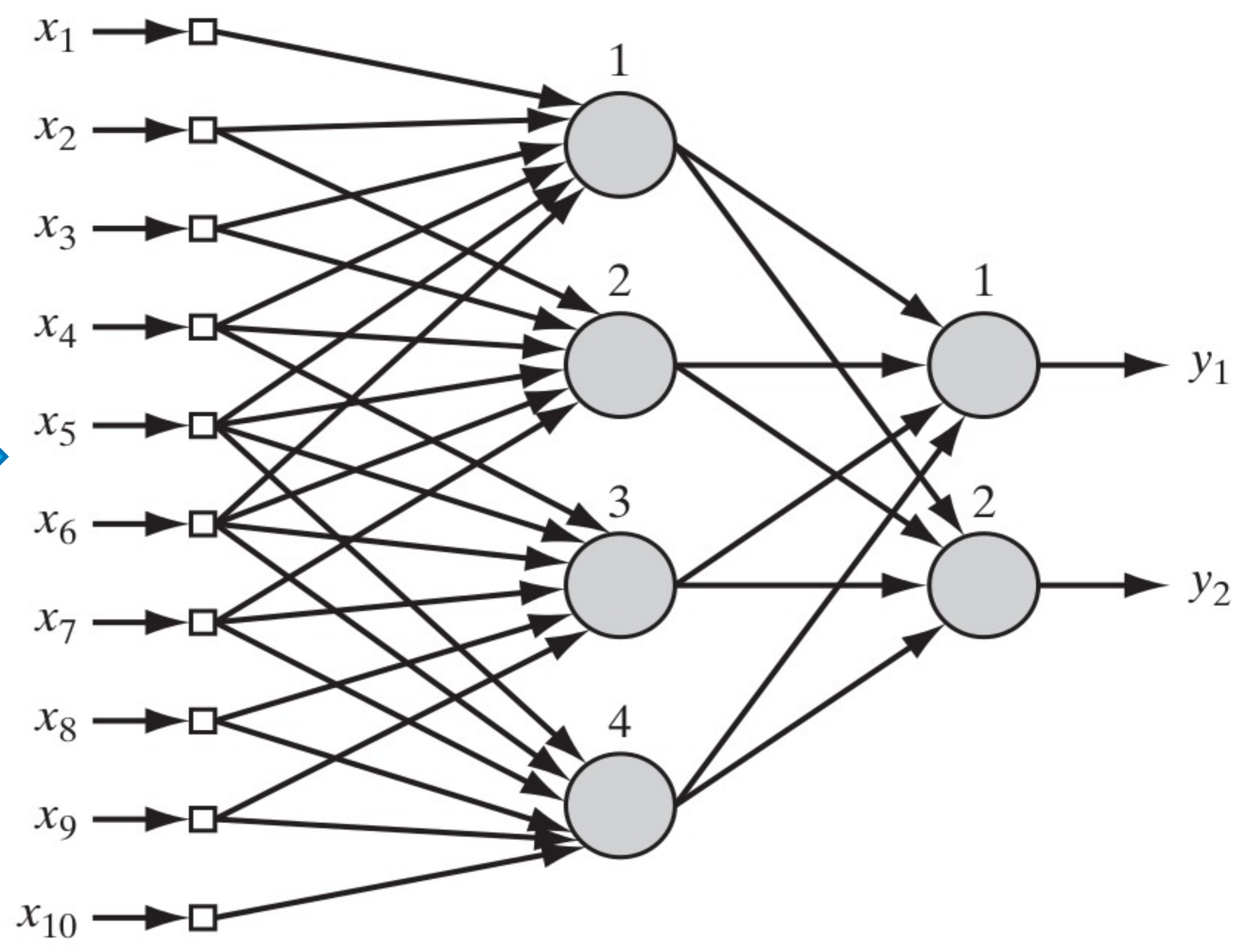


Challenge: The density of connections between layers increases intractably as the size of the image increases!!

local connections and weight sharing



Fully-connected

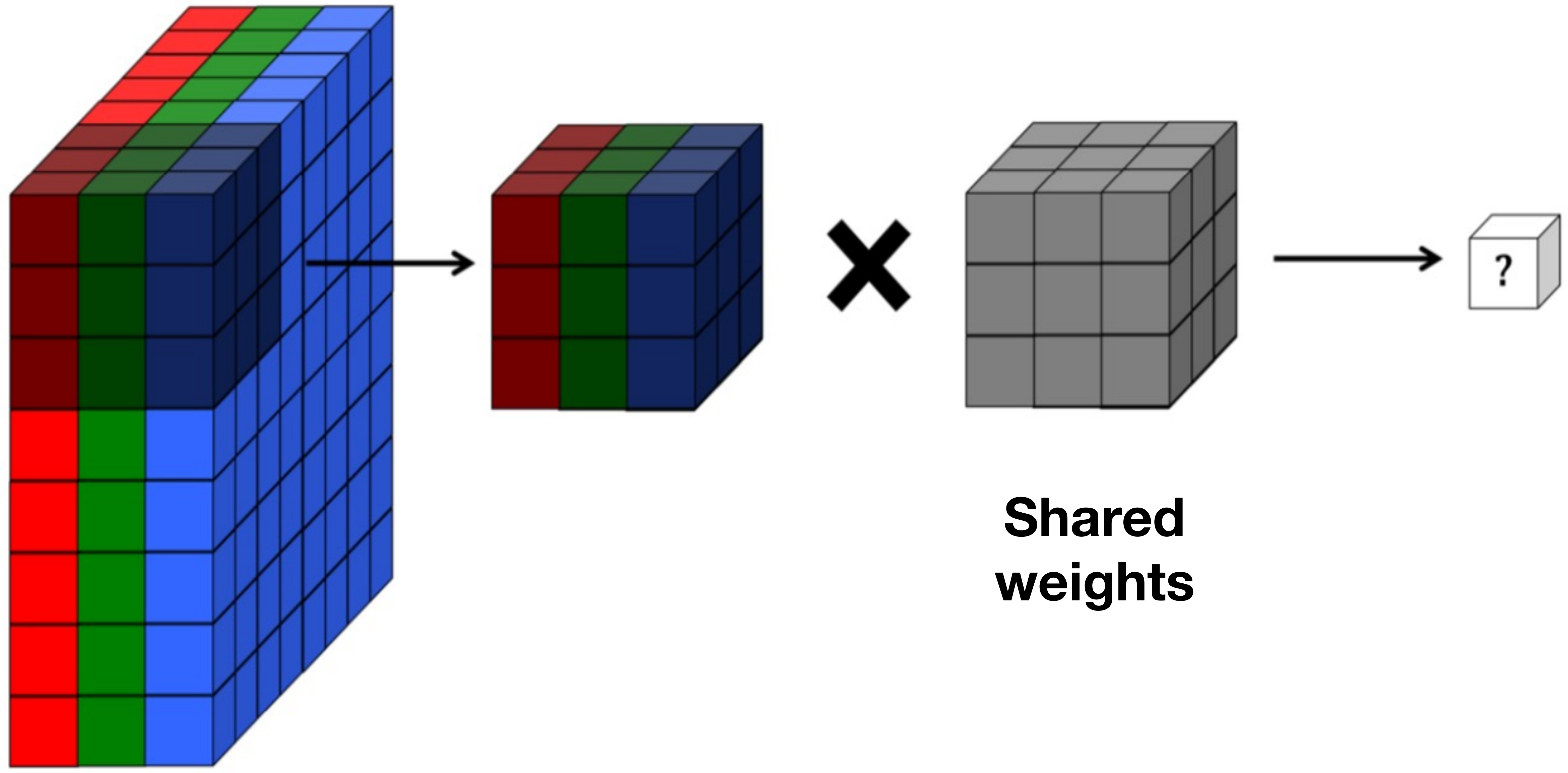


Now, all four hidden neurons
1. Share the same set of 6 weights
2. Use local connections (receptive fields)

An effective way to reduce model parameters:

- (**Local connection**) Each neuron only processes inputs from a local region
- (**Weight sharing**) Neurons within the same layer can share weights

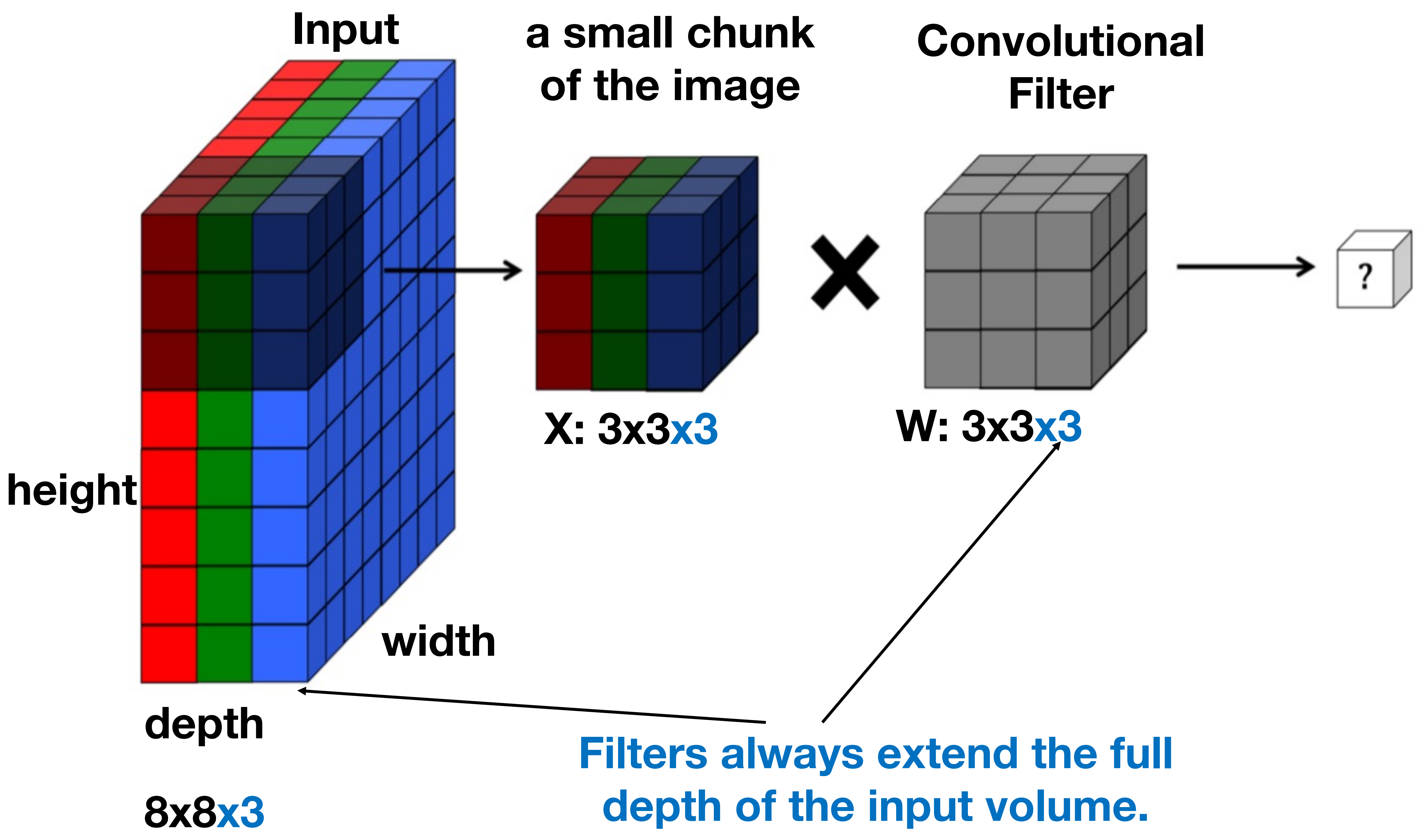
a convolution view



Another view to local connection and weight sharing:

- Convolve (slide) a block of shared weights over all spatial locations
- At each spatial location, output one value (computing dot products)

convolutional filters

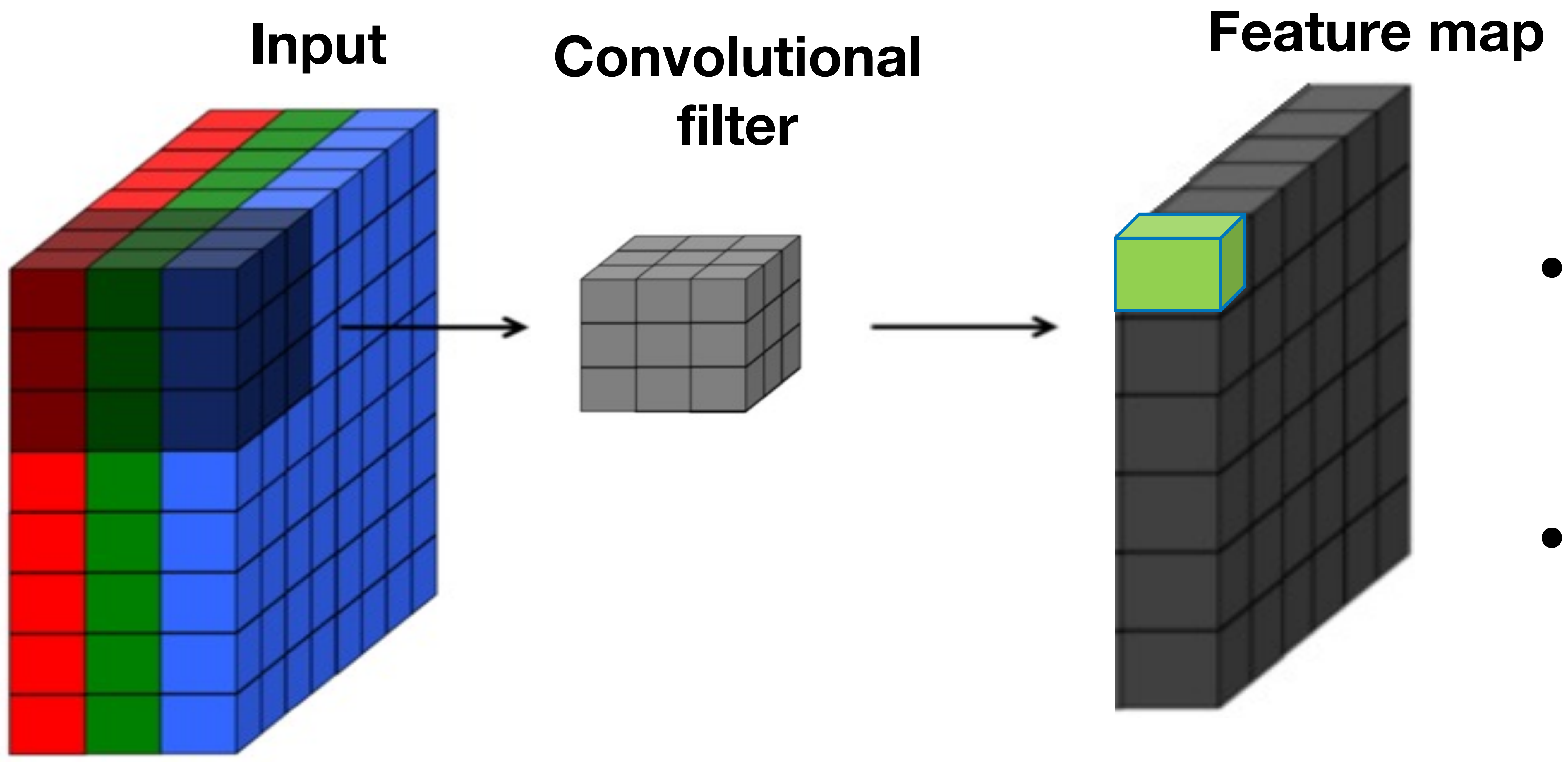


- We call this block of shared weights a **convolutional filter**

- **Convolution**: Convolve a filter with the image, i.e., slide over the image spatially, computing at each position a dot product between the filter and a small chunk of the image (plus bias), $\boldsymbol{W}^T\boldsymbol{X} + b$

- The dot product then goes through an activation function, e.g., *ReLU*, to produce the output

convolution



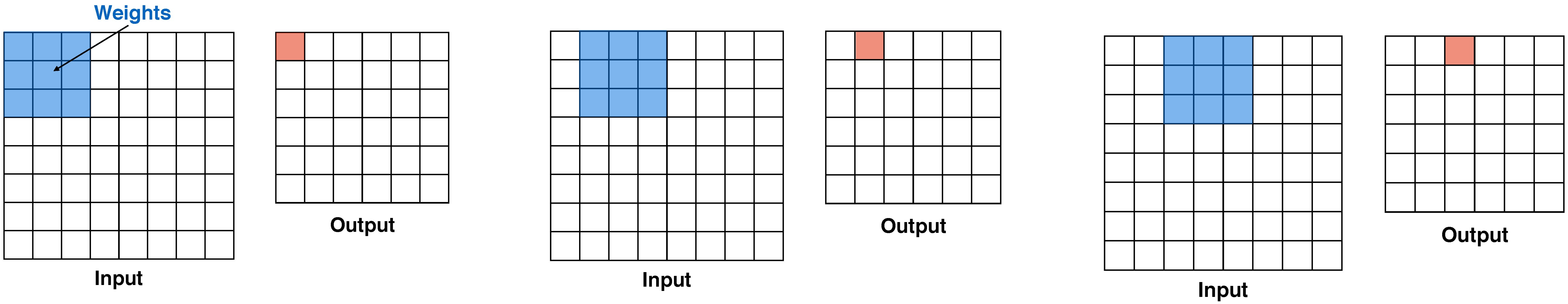
- At each spatial location, output one value

- Convolve (slide) over all spatial locations to generate an image like map, referred to as a **feature map**

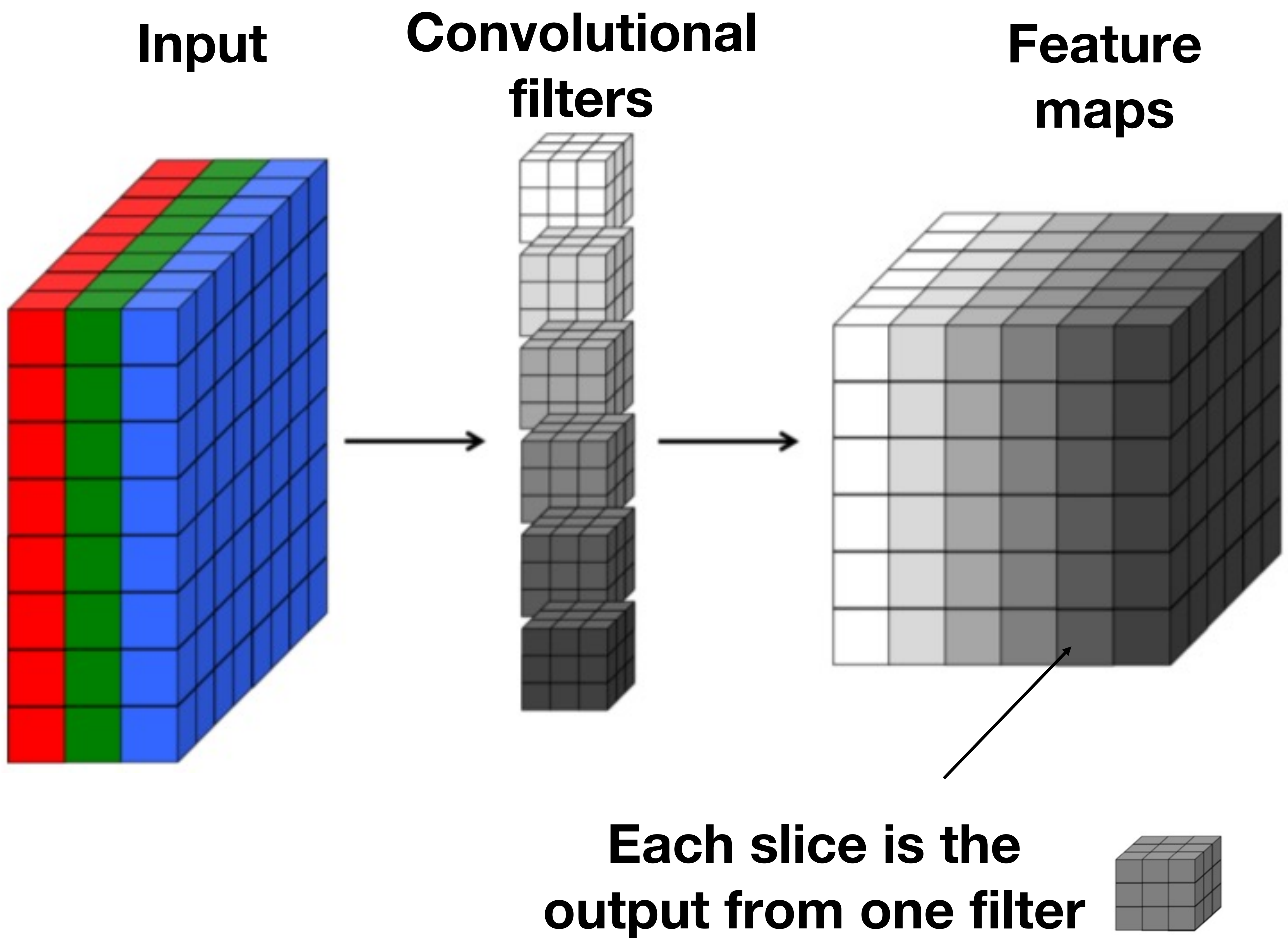
- **A convolutional layer**: Things between an input and a feature map

convolution

During convolution, the weights "slide" along the input to generate each output.



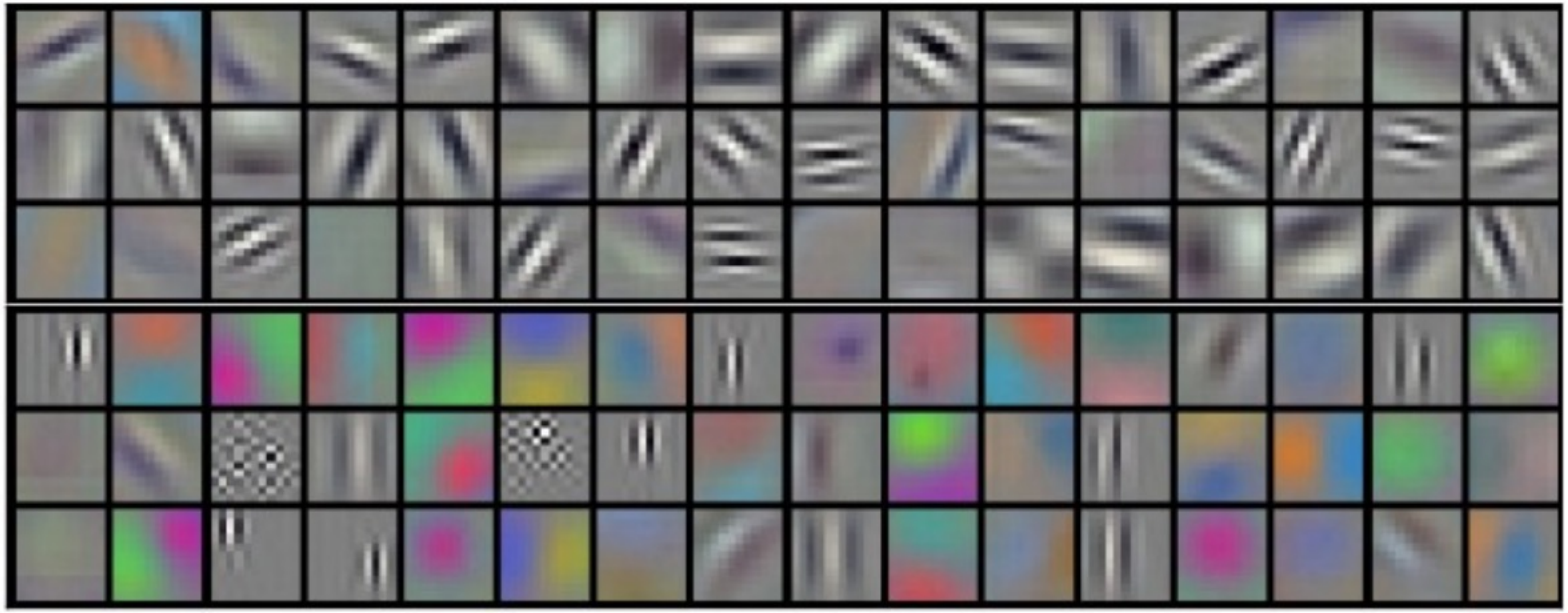
convolution



- Multiple sets of shared weights (filters) are allowed
- Each set of shared weights (filter) give one slice in the output (feature maps)
- In practice, CNN use many filters (~64 to 1024)

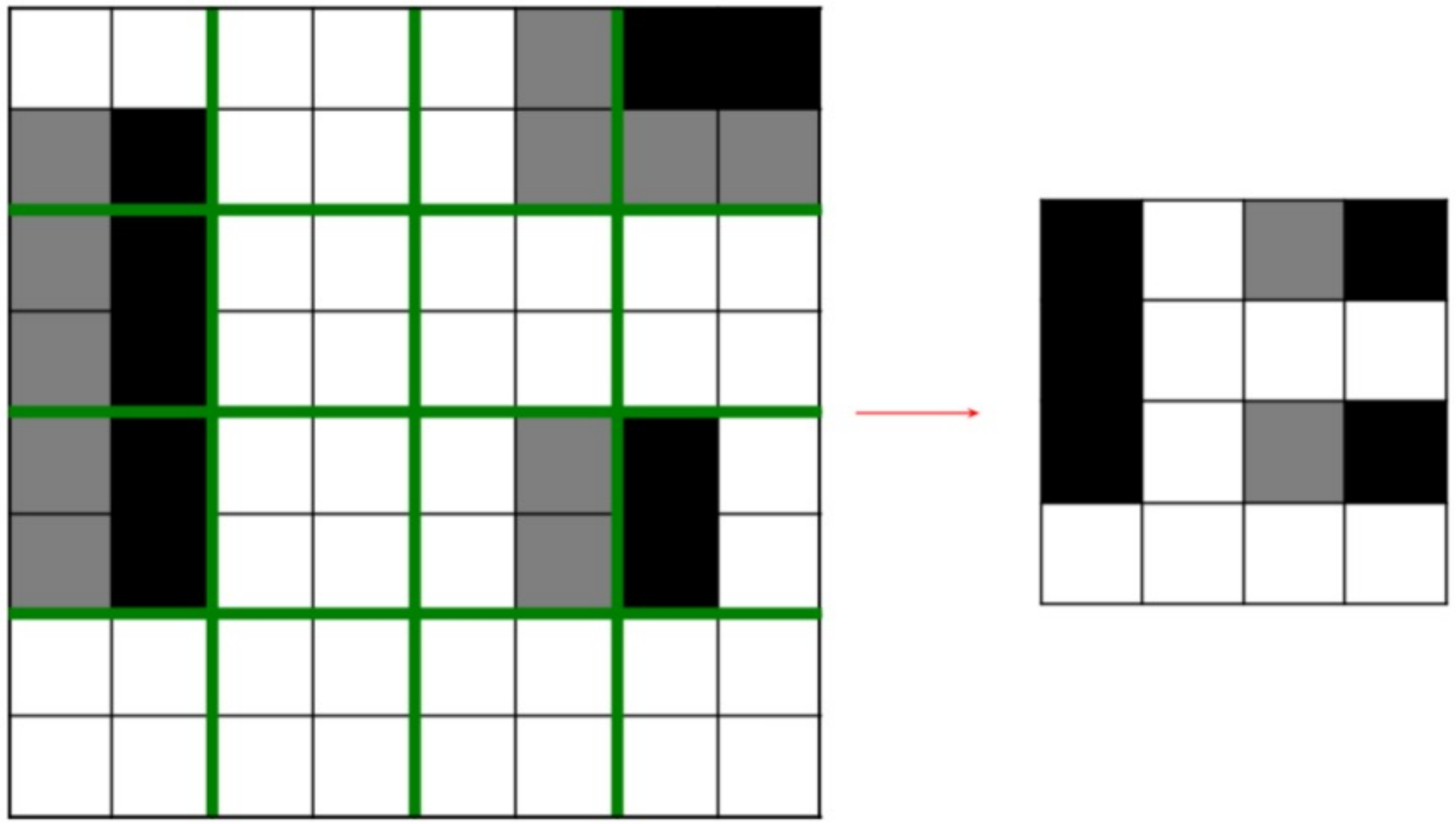
visualizing convolution

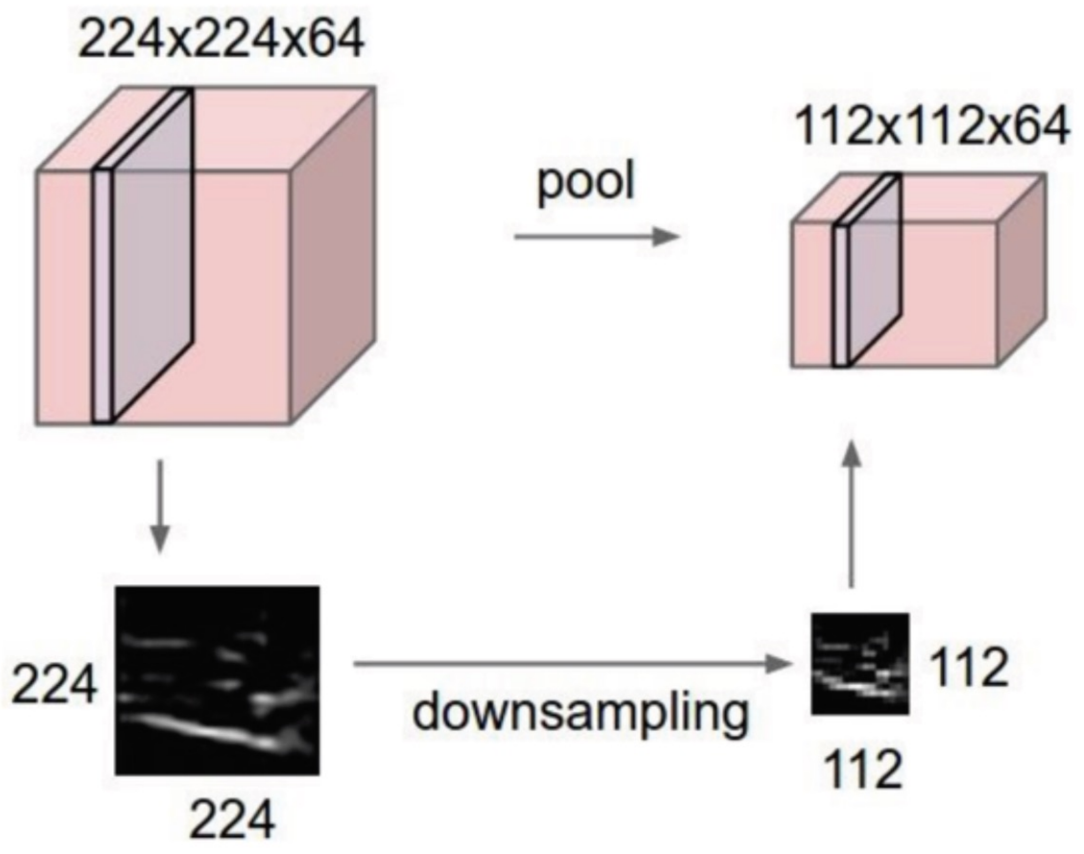
How convolutional filters may look like



pooling

Feature map

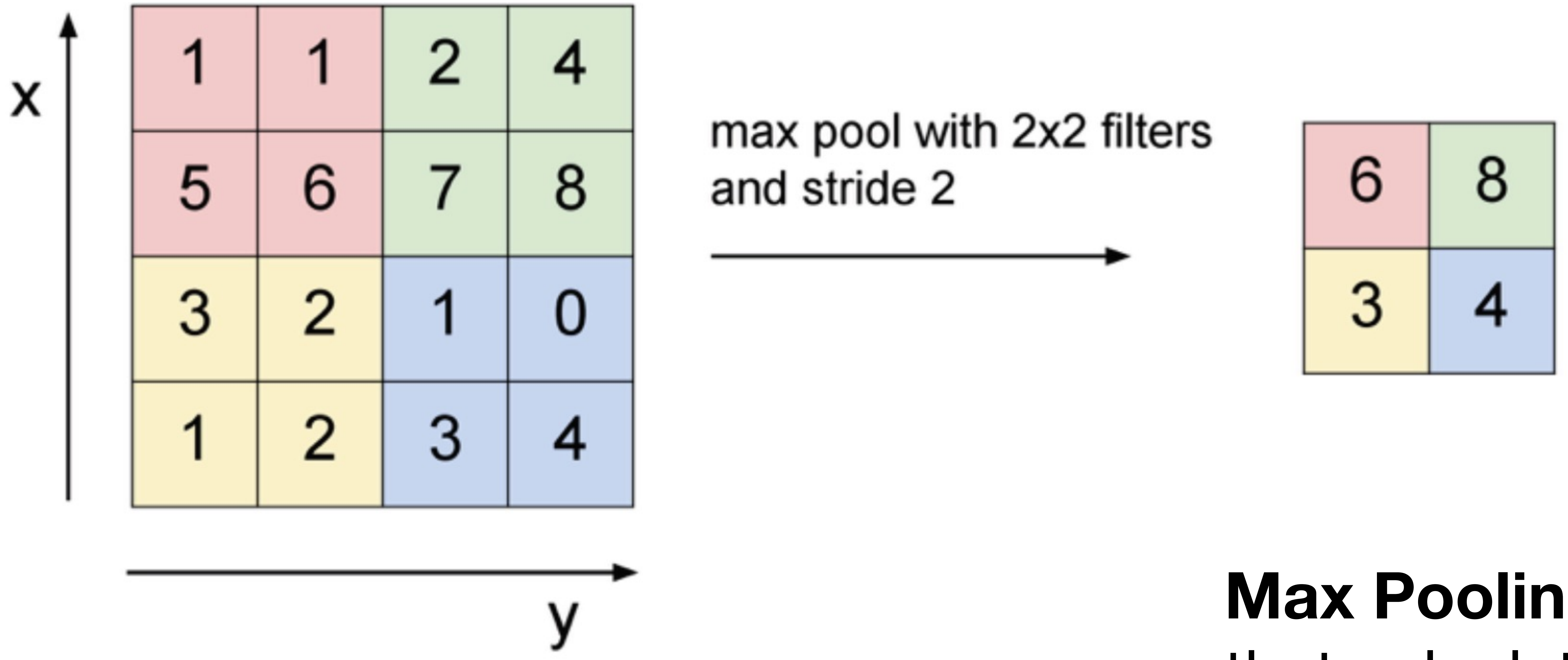




Convolution is often followed by **pooling**:

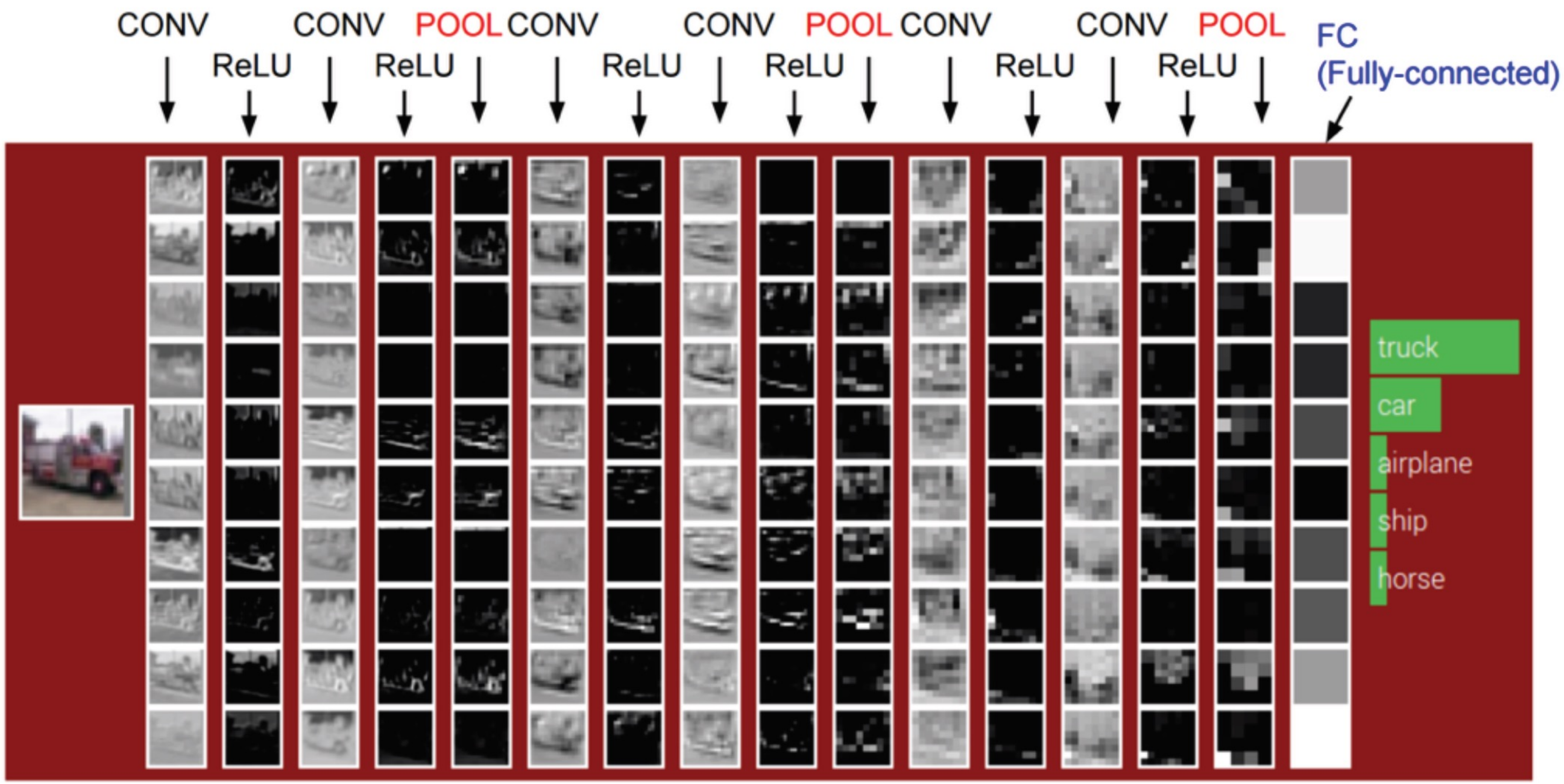
- Create a smaller and more manageable representation while retaining the most important information
- "*max*" is the most common operation
- Operate over each feature map independently

max pooling



Max Pooling is a pooling operation that calculates the maximum value for patches of a feature map.

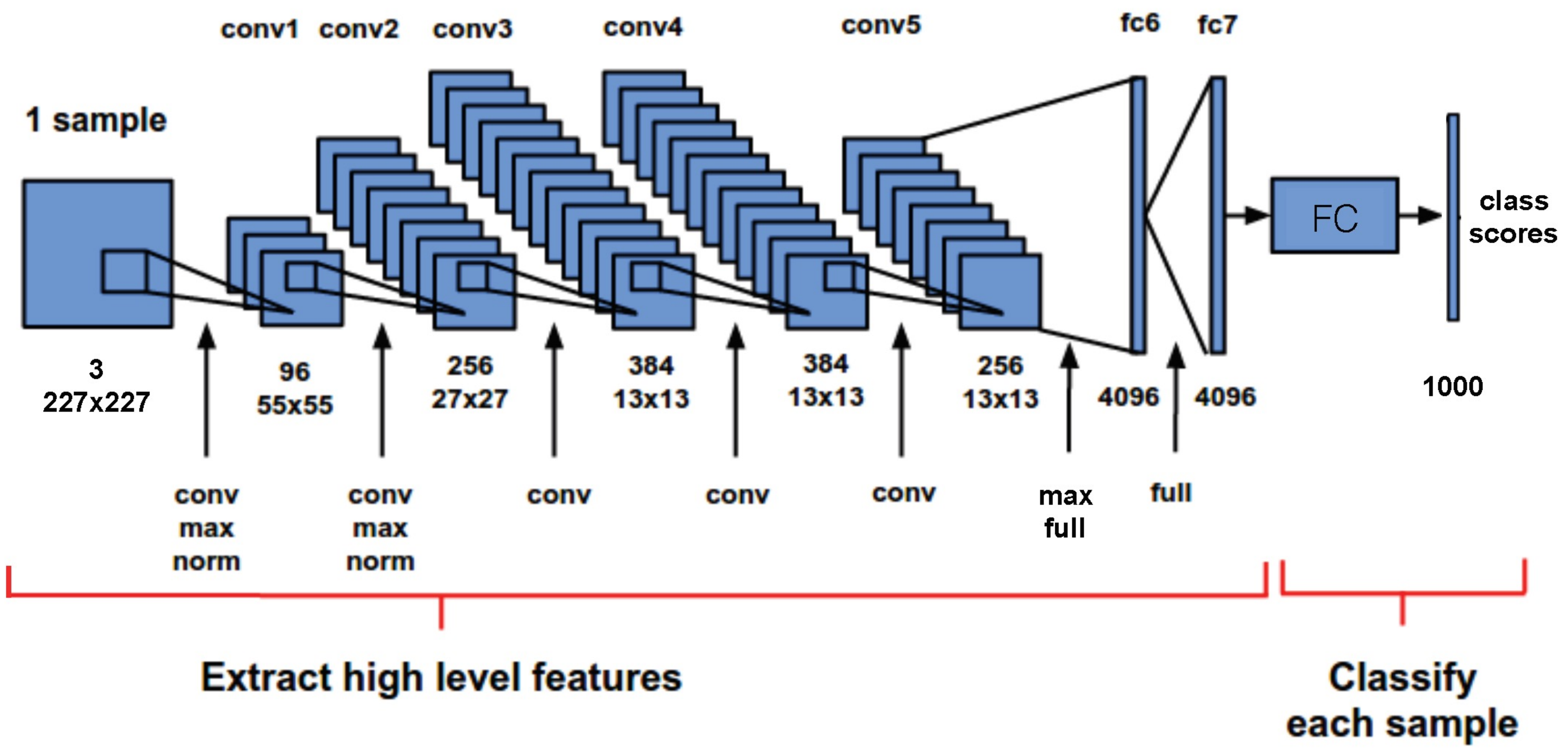
convolutional neural network (CNN)



Stack layers of convolution, activation (ReLU), pooling => CNN

how to train a CNN?

Example: AlexNet [Krizhevsky 2012]



"max": max pooling
"norm": local response normalization
"full": fully connected

Figure: [Karnowski 2015] *(with corrections)*

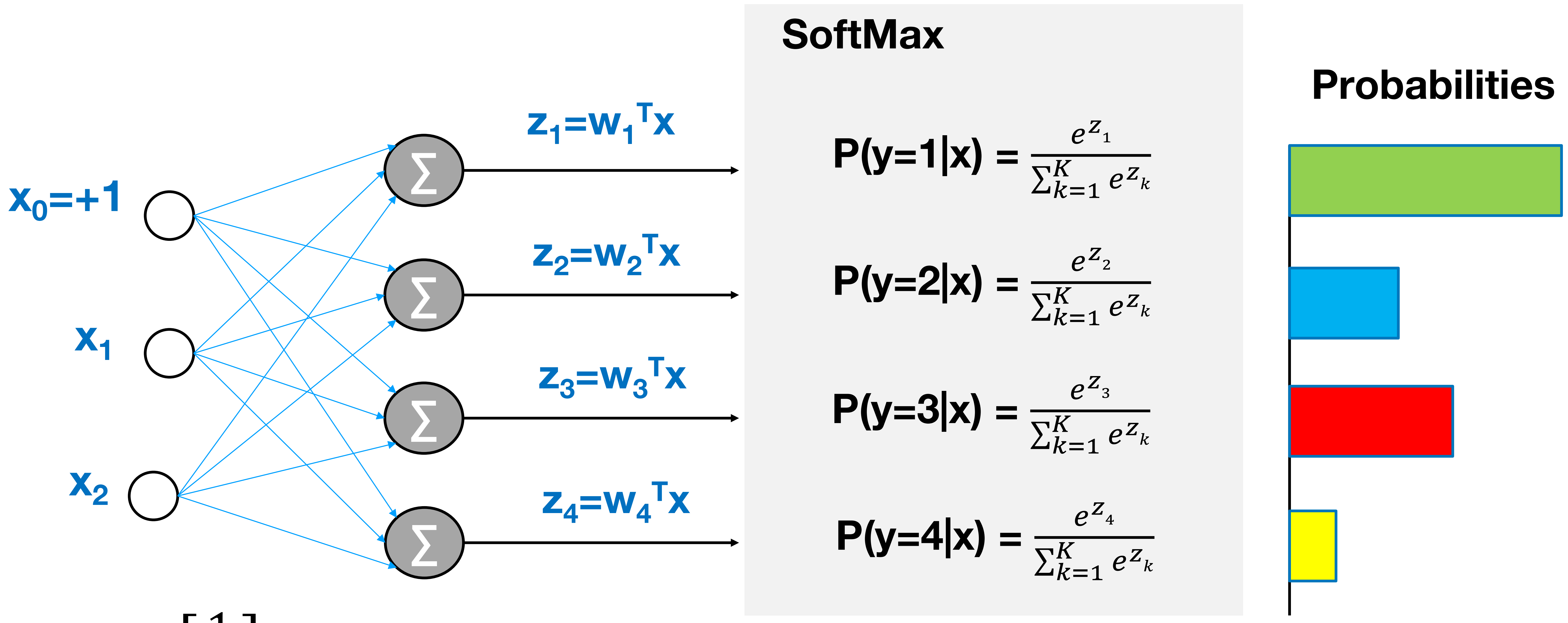
- Split the data
- Choose the network architecture
- Initialize the network weights
- Find a learning rate and regularization strength
- Minimize the loss, e.g., *softmax*

splitting the dataset

- **Train**: gradient descent and fine-tuning of parameters
- **Validation**: determining hyper-parameters (learning rate, regularization strength, etc.) and picking an architecture
- **Test**: estimate real-world performance

softmax Loss (multinomial logistic regression)

A generalization of logistic regression for multi-class classification



$$z_k=w_k^Tx = \begin{bmatrix} w_{k0} \; w_{k1} \; wk_2 \end{bmatrix} \begin{bmatrix} 1 \\ x_1 \\ x_2 \end{bmatrix}$$

training

Goal: Minimize loss ⇒ Maximize the probability of true class

- (Per-sample) Negative log-likelihood loss, e.g., for the i-th sample, $(\boldsymbol{x}^i, y^i)$

$$L(\boldsymbol{x}^i, y^i; \boldsymbol{\theta}) = -\log\big(P(y = yi|\boldsymbol{x}^i)\big) = -\log\left(\frac{e^{z_{yi}}}{\sum_{k=1}^{K} e^{z_k}}\right)$$

- **Training**: Minimizing the loss w.r.t parameters over the whole training set using backpropagation

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{N} L(\boldsymbol{x}^i, y^i; \boldsymbol{\theta})$$

regularization

Regularization reduces overfitting (as we have seen before):

$$L = L_{data} + L_{reg}$$

$\lambda = 0.001$ $\lambda = 0.01$ $\lambda = 0.1$

Higher regularization

examples of regularization terms

- **L2 regularization:** encourages small weights

$$L_{reg} = \lambda \frac{1}{2} \|W\|_2^2$$

- **L1 regularization:** encourages sparse weights

$$L_{reg} = \lambda \|W\|_1 = \lambda \sum_{i,j} |W_{ij}|$$

- **Elastic net:** combines L1 and L2 regularization terms

$$L_{reg} = \lambda_1 \|W\|_1 + \lambda_2 \|W\|_2^2$$

- **Max norm:** clamps (clips) weights to some maximum norm

$$\|W\|_2^2 \leq c$$