Today: Outline

- **Neural networks cont'd:** architectures and learning; convolutional neural networks

- Reminder: Pre-lecture Material for Tue Sept 29

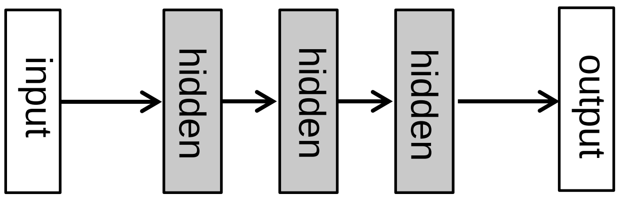
Neural Networks II

Architectures and Learning

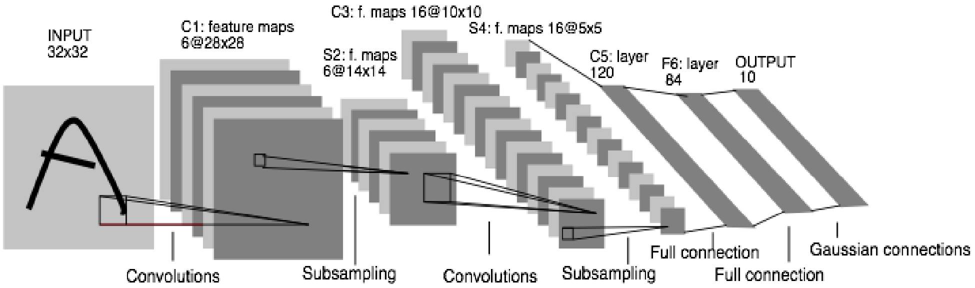
Network architectures

Feed-forward

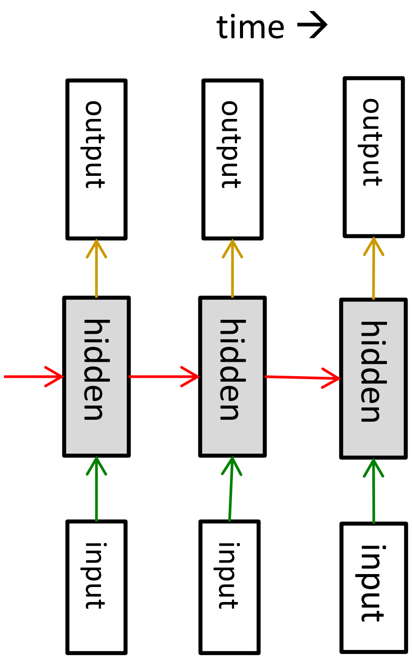
Fully connected



Convolutional



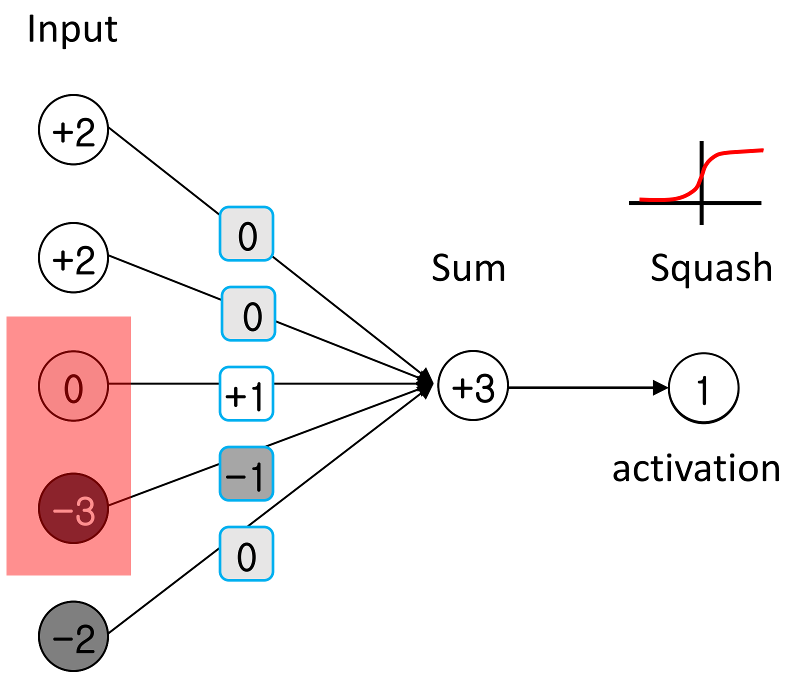
Recurrent



Neural Networks III

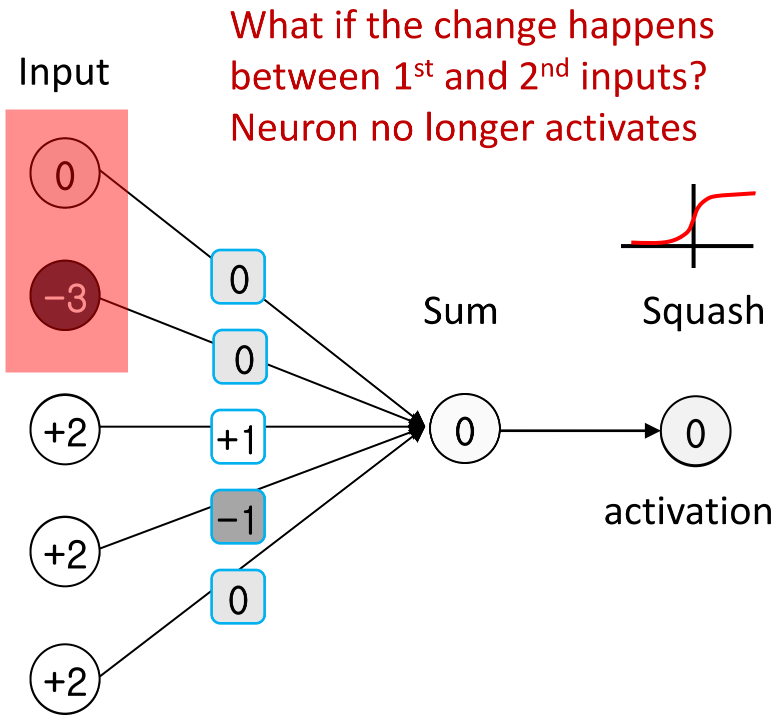
Convolutional Architectures

Multiplication vs convolution



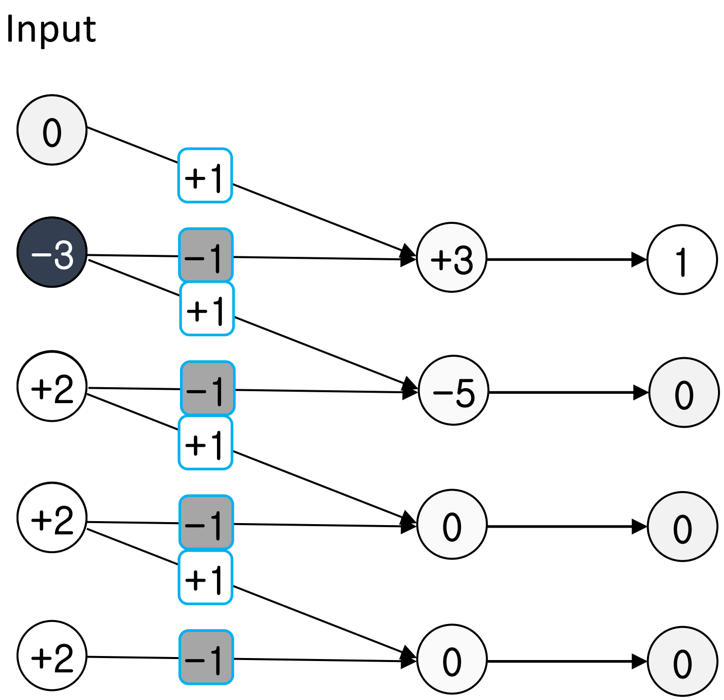
- Recall, a neuron can be thought of as learning to spot certain features in the input
- E.g., this neuron detects change from high to low (light to dark) between 3rd and 4th inputs

Multiplication vs convolution



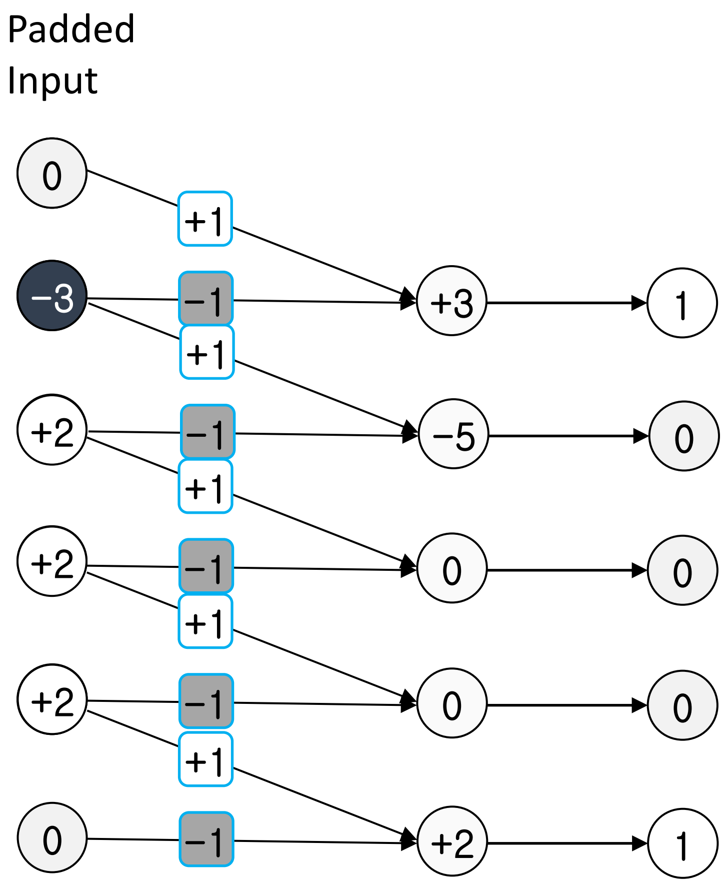
- Must have a new neuron for each new location of pattern???
- This is not efficient
- Solution: use convolution instead of multiplication

Multiplication vs convolution



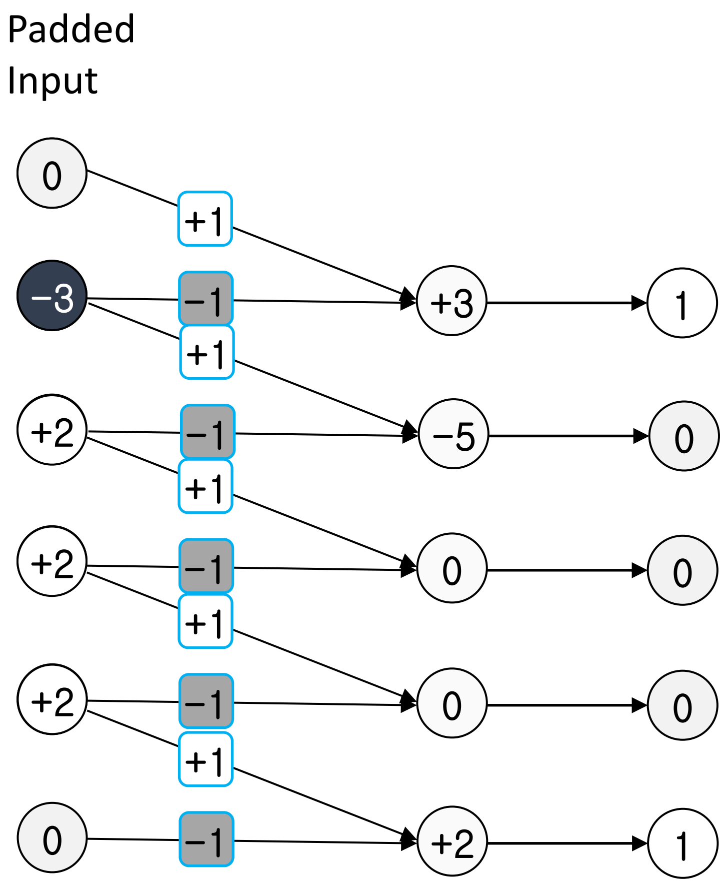
- New weights are of size 2 x 1; called filter, or kernel
- New output is the size of input minus 1 because of boundary
- New convolutional neurons all share the same weights! This is much more efficient; we learn the weights once instead of many times for each position

Multiplication vs convolution



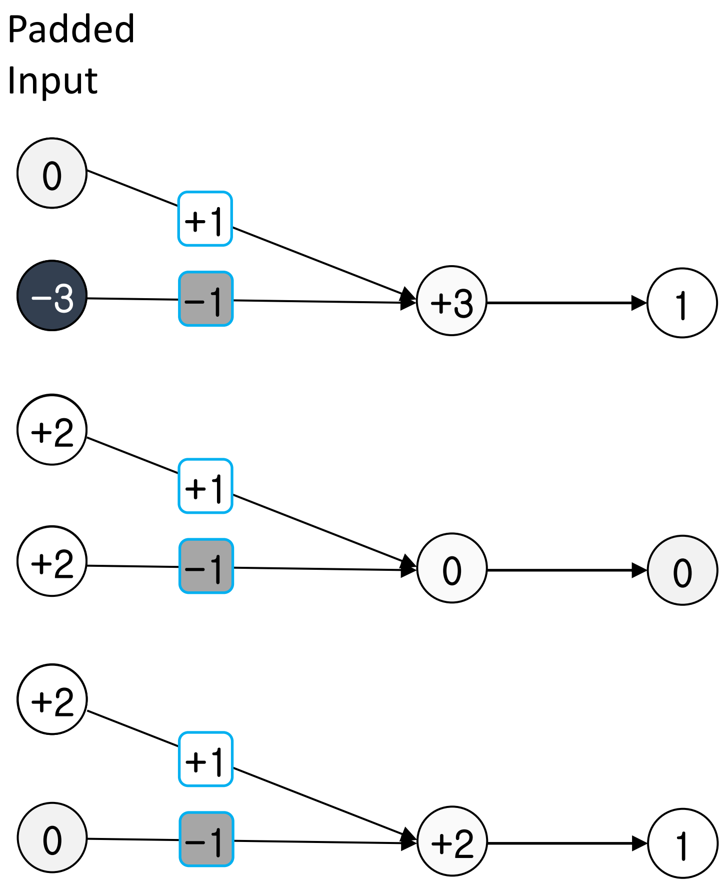
- New output is the size of input minus 1 because of boundary
- We can fix the boundary effect by padding the input with 0 and adding one more neuron

Multiplication vs convolution



- Note, we move the filter by 1 each time, this is called stride

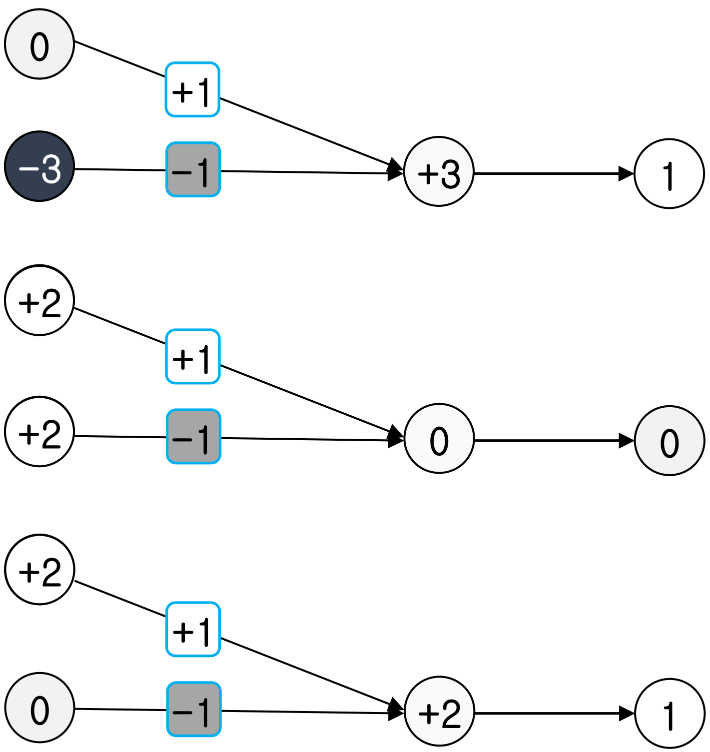
Multiplication vs convolution



- Note, we move the filter by 1 each time, this is called stride
- Stride can be larger, e.g. here is stride 2

Multiplication vs convolution

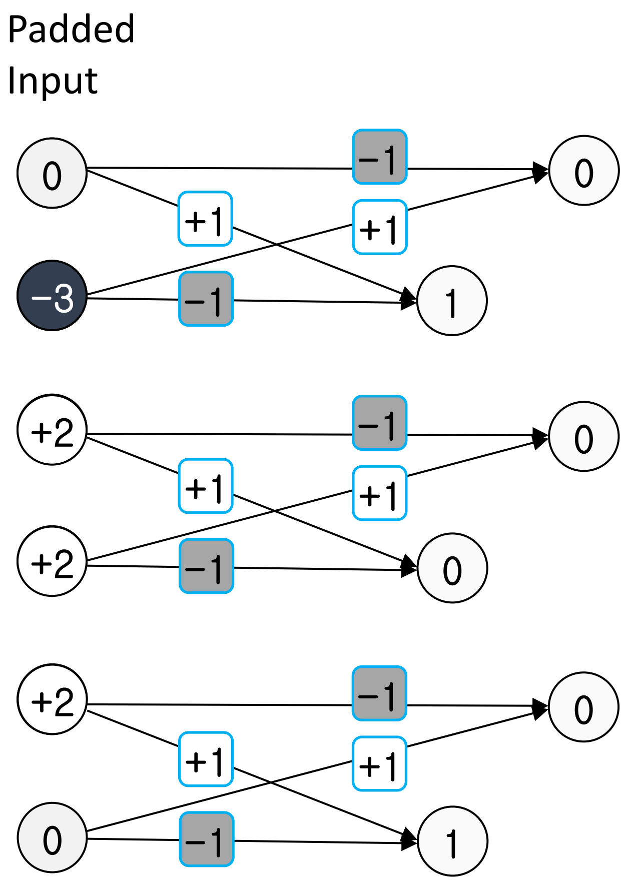
Padded
Input



To summarize, this layer has

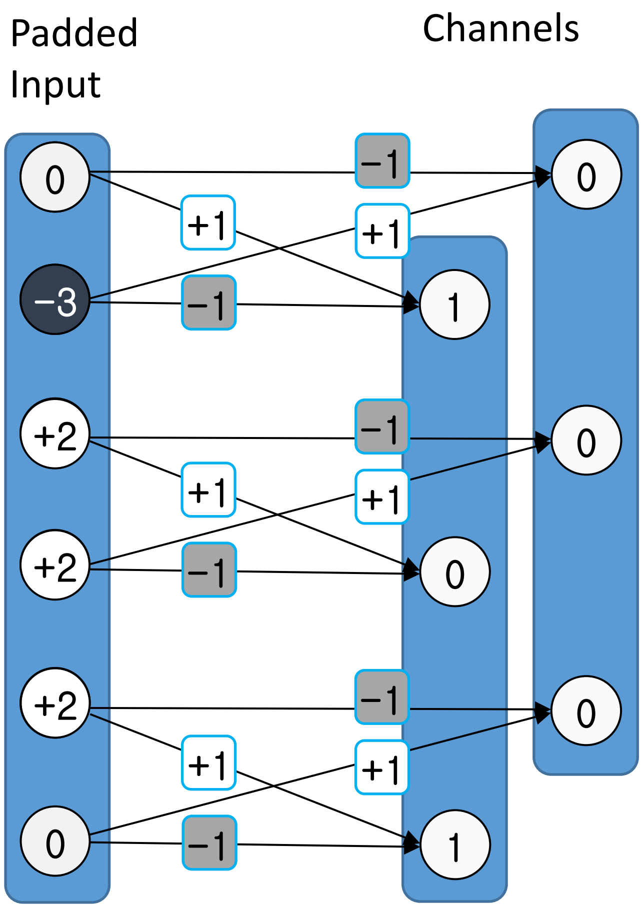
- `Input 5 x 1, padded to 6 x 1`
- `Kernel 2 x 1 with weights [+1,-1]`
- `Stride 2`
- `Output 3 x 1`

Multiplication vs convolution



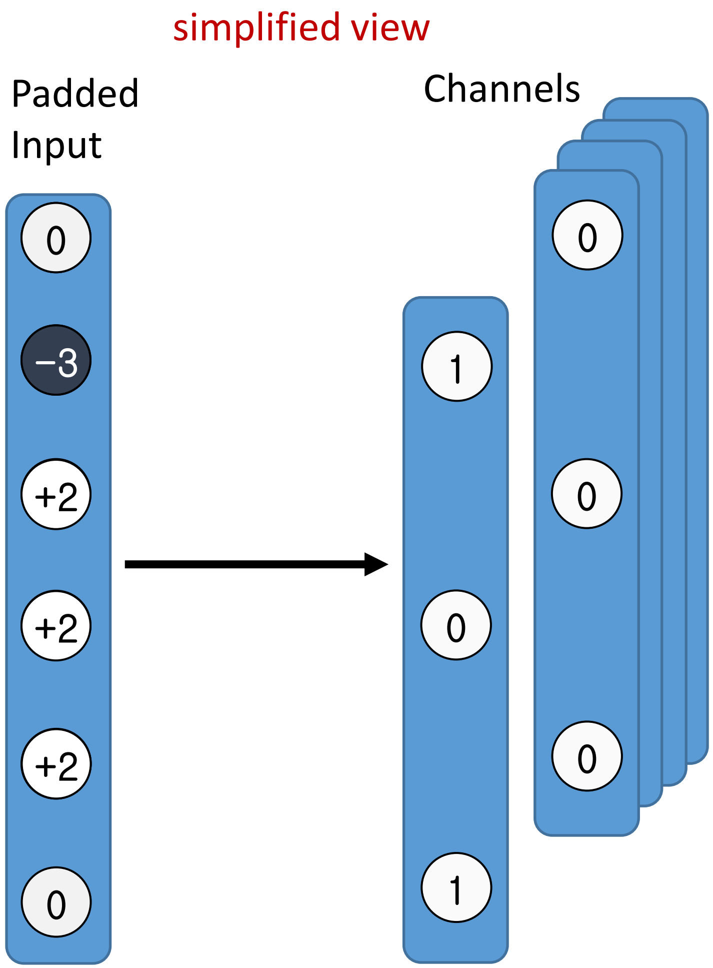
- We can add another filter, this time to detect opposite change with weights [-1 +1]
- Unique filters are called channels

Multiplication vs convolution



- We can add another filter, this time to detect opposite change with weights [-1 +1]
- Unique filters are called channels

Multiplication vs convolution



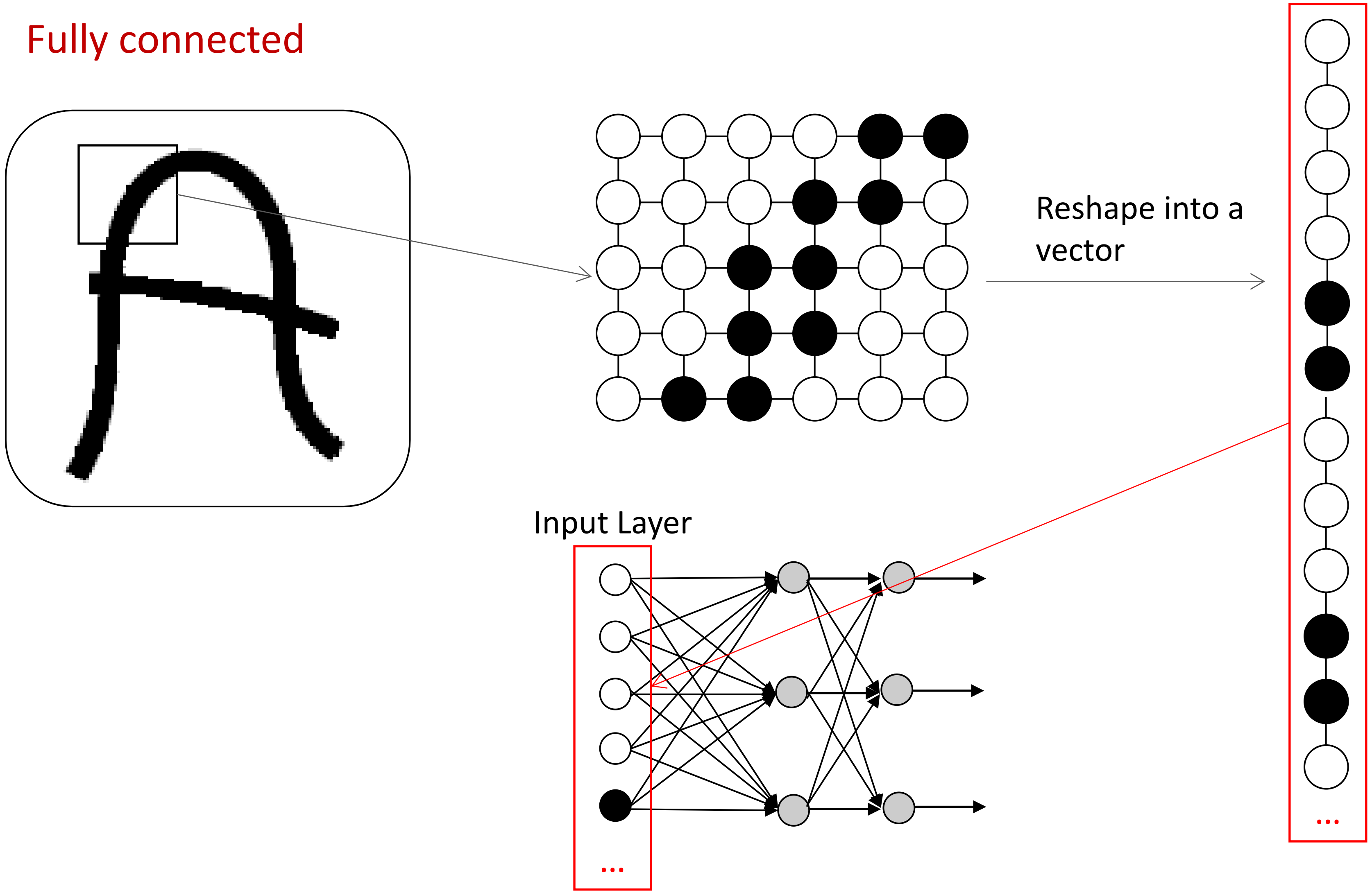
- We can add another filter, this time to detect opposite change with weights [-1 +1]
- Unique filters are called channels

Convolutional Neural Networks

For images and other 2-D signals

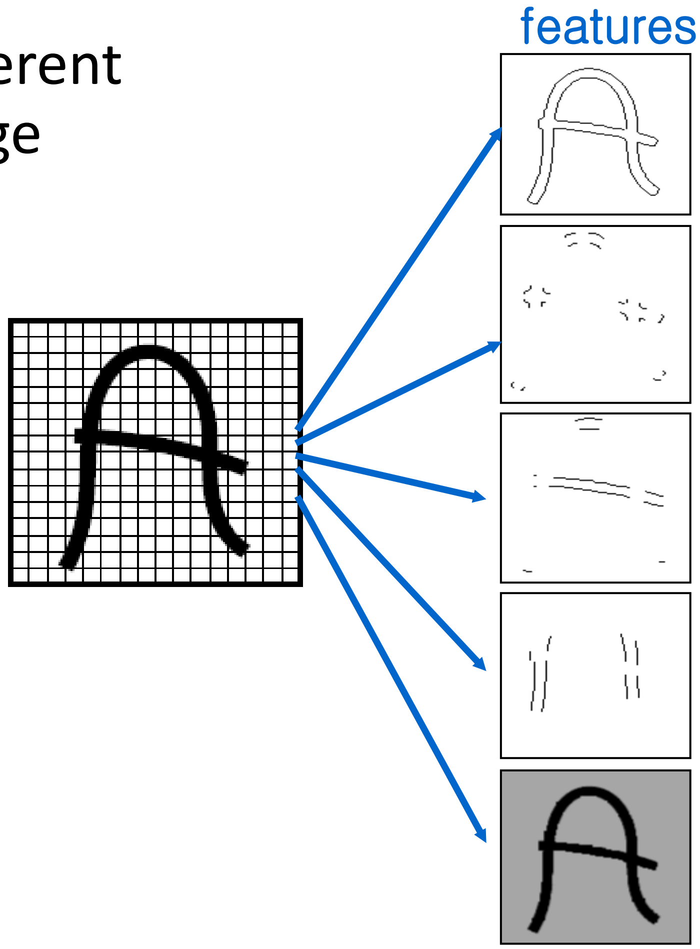
Representing images

Fully connected

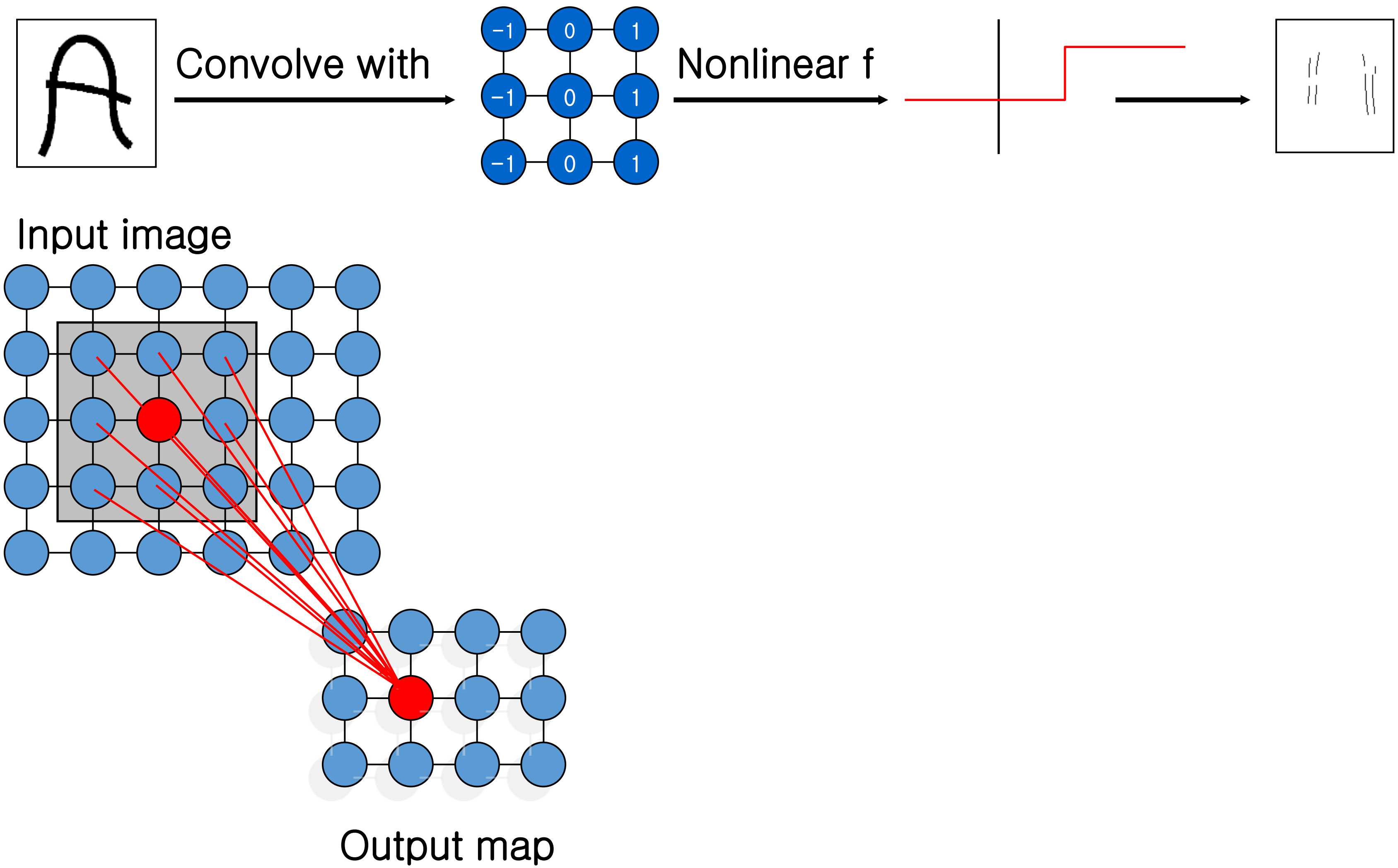


Convolution layer in 2D

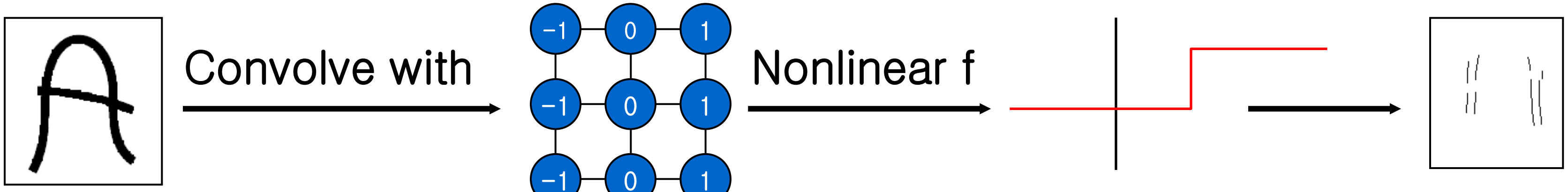
- detect the same feature at different positions in the input, e.g. image
- preserve input topology



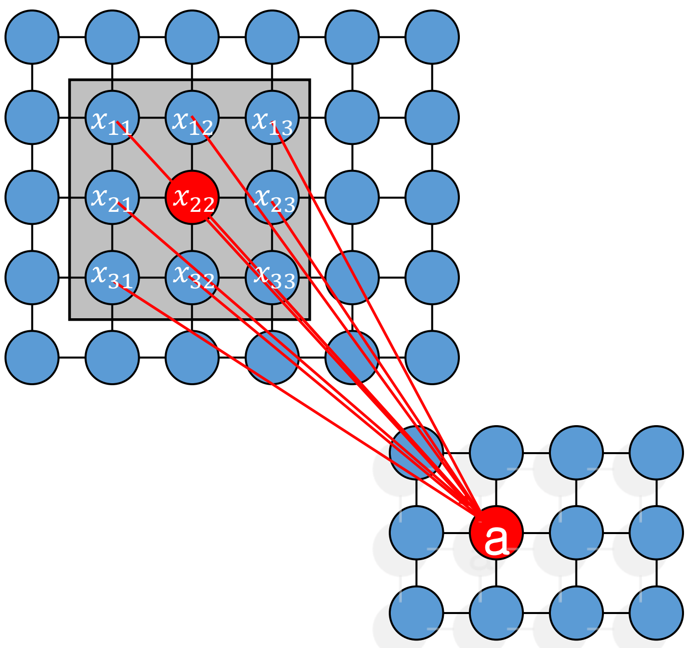
Convolution layer in 2D



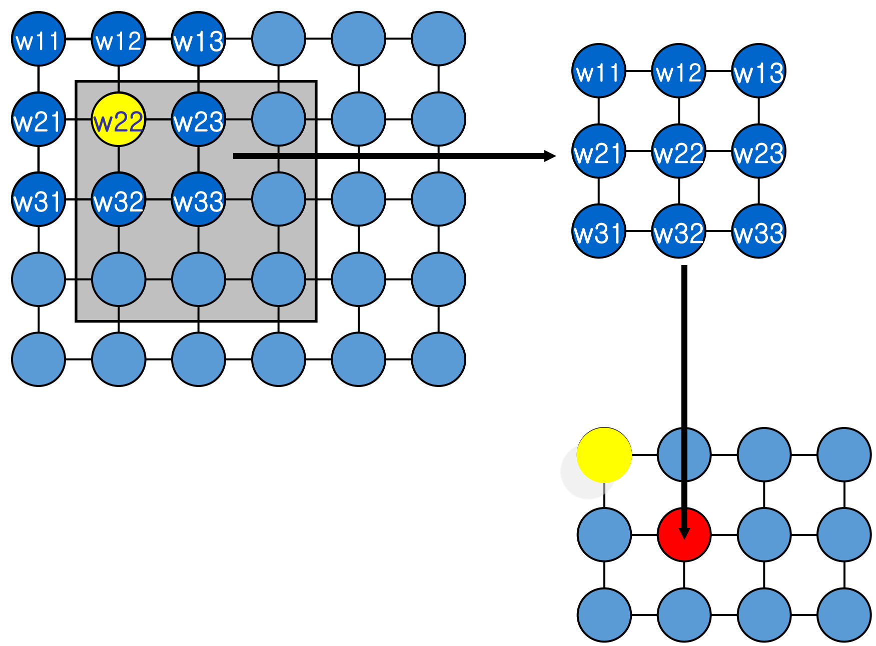
Convolution layer in 2D



Input image



Output map



Output looks like an image

$$a = f(w_{11}x_{11} + w_{12}x_{12} + w_{13}x_{13} + \cdots w_{33}x_{33})$$

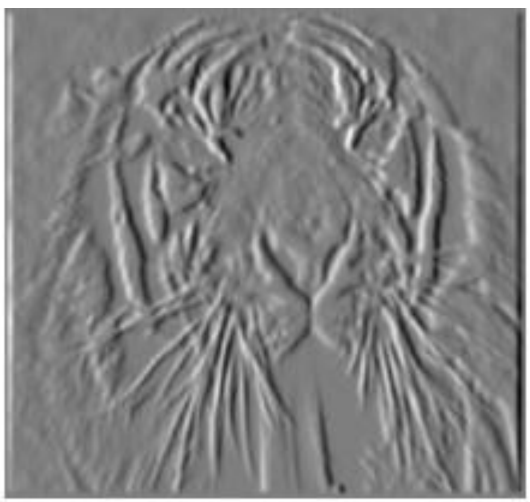
What weights correspond to these output maps?

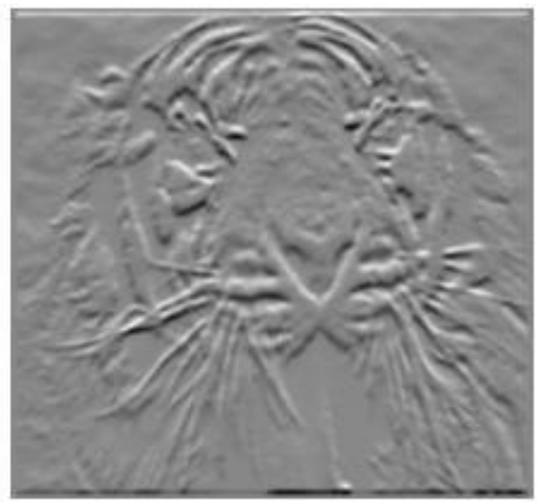
These are output maps before thresholding

Hint: filters look like the input they fire on

$$\frac{\partial f(x,y)}{\partial x}$$

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



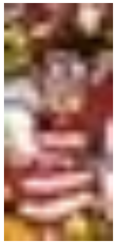


$$\frac{\partial f(x,y)}{\partial y}$$

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

Where is Waldo?

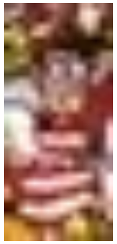
Input



filter

What will the output map look like?

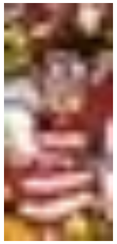
Input



filter

What will the output map look like?

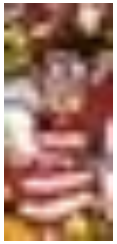
Output



filter

Here is Waldo

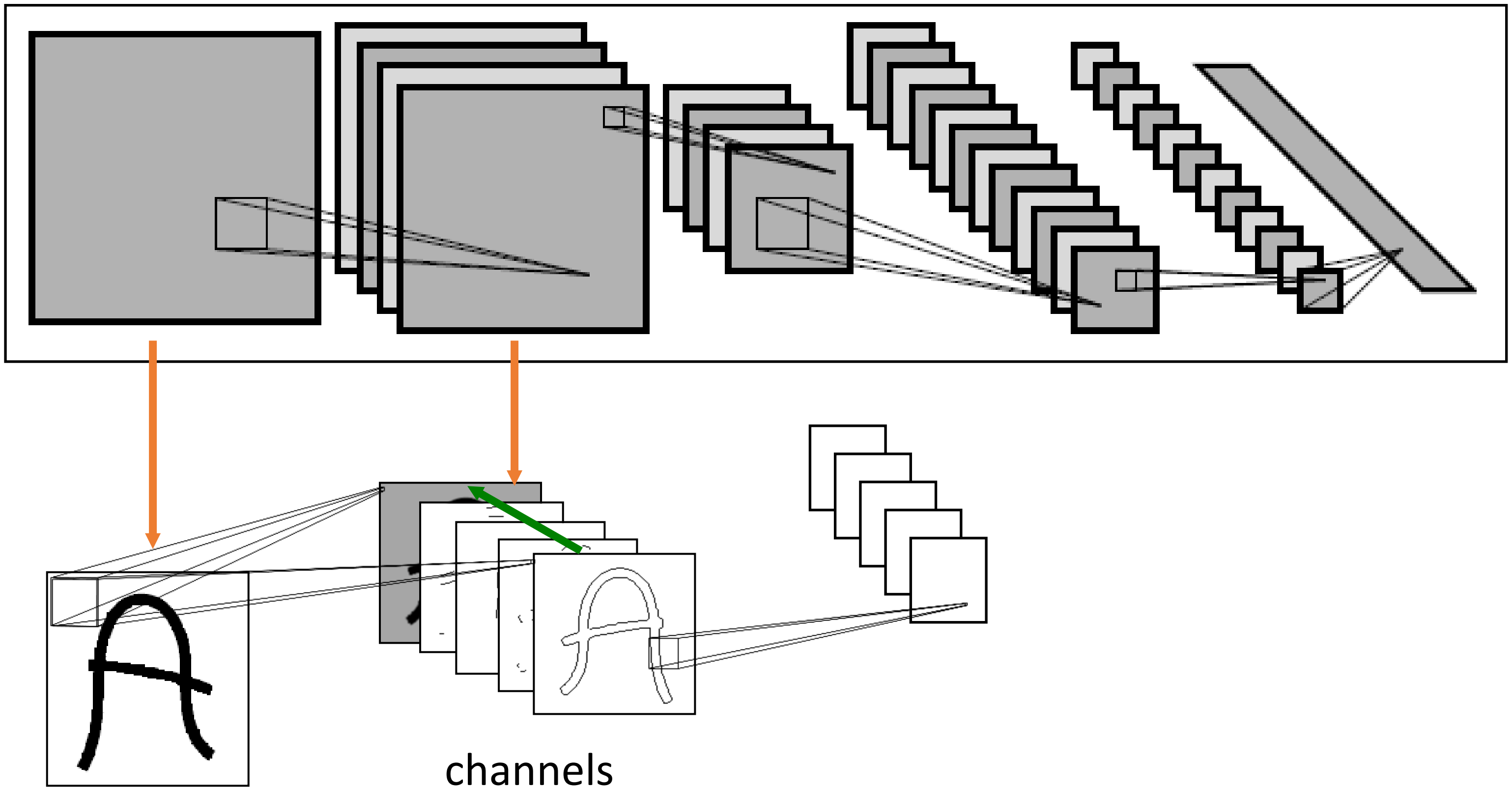
Input



filter

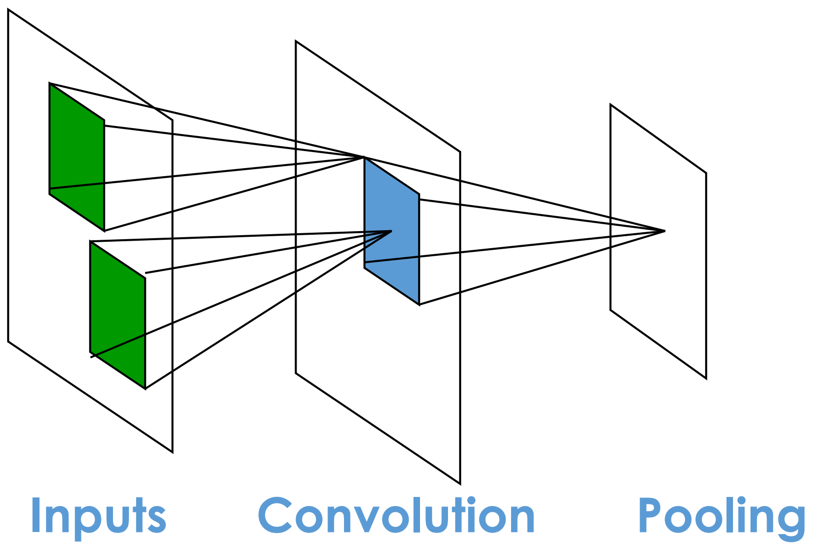
Stacking convolutional layers

- Each layer outputs multi-channel feature maps (like images)
- Next layer learns filters on previous layer's feature maps



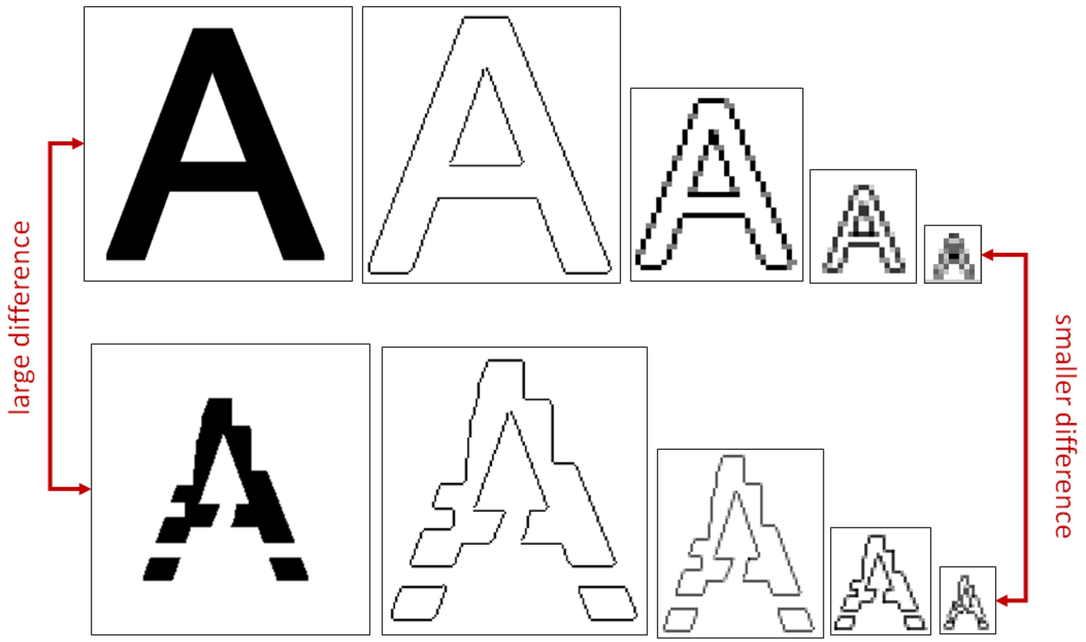
Pooling layers

- Convolution with stride > 1 reduces the size of the input
- Another way to downsize the feature map is with pooling
- A pooling layer subsamples the input in each sub-window
    - max-pooling: chose the max in a window
    - mean-pooling: take the average

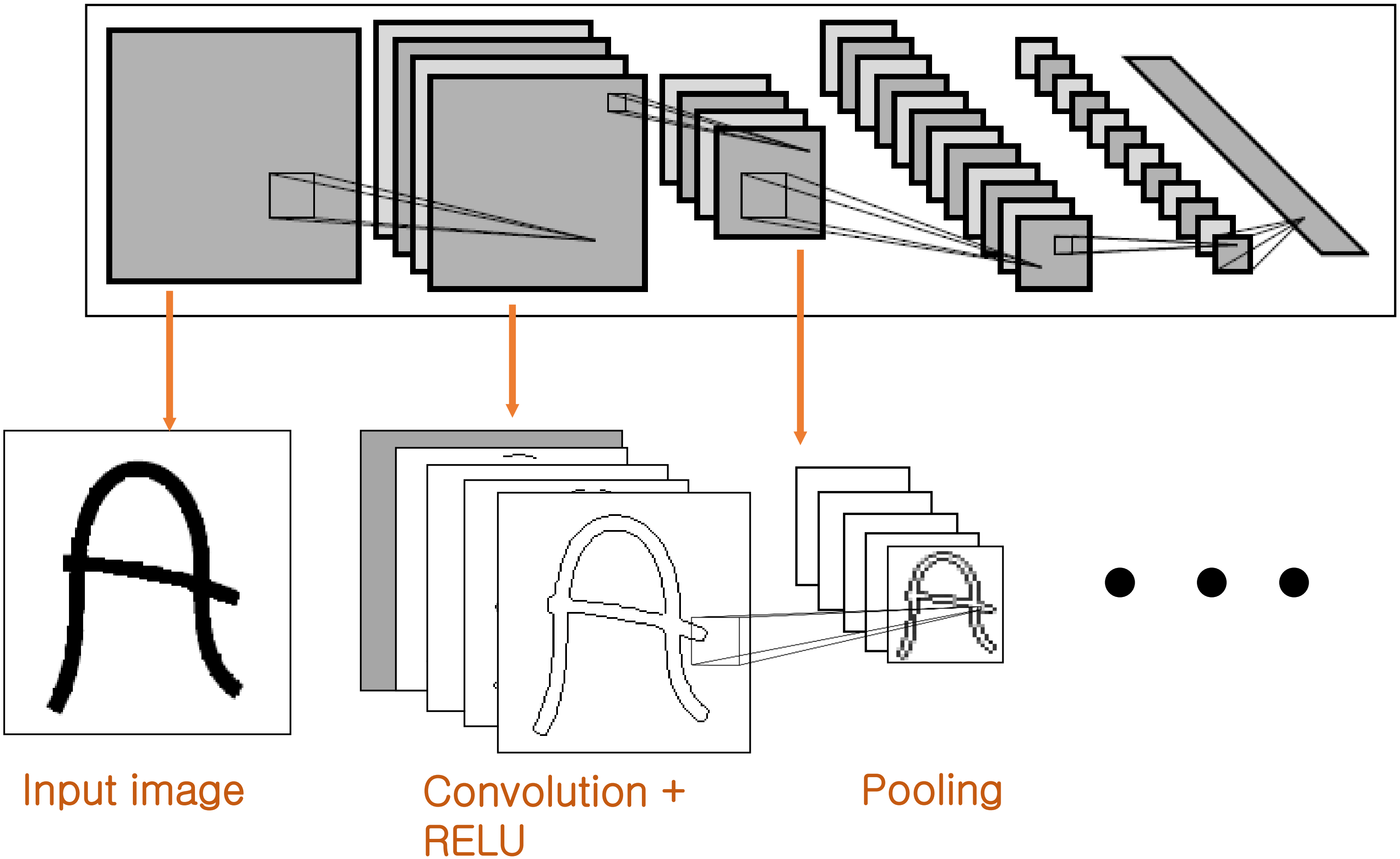


Pooling layer

- the pooling layers reduce the spatial resolution of each feature map
- Goal is to get a certain degree of shift and distortion invariance

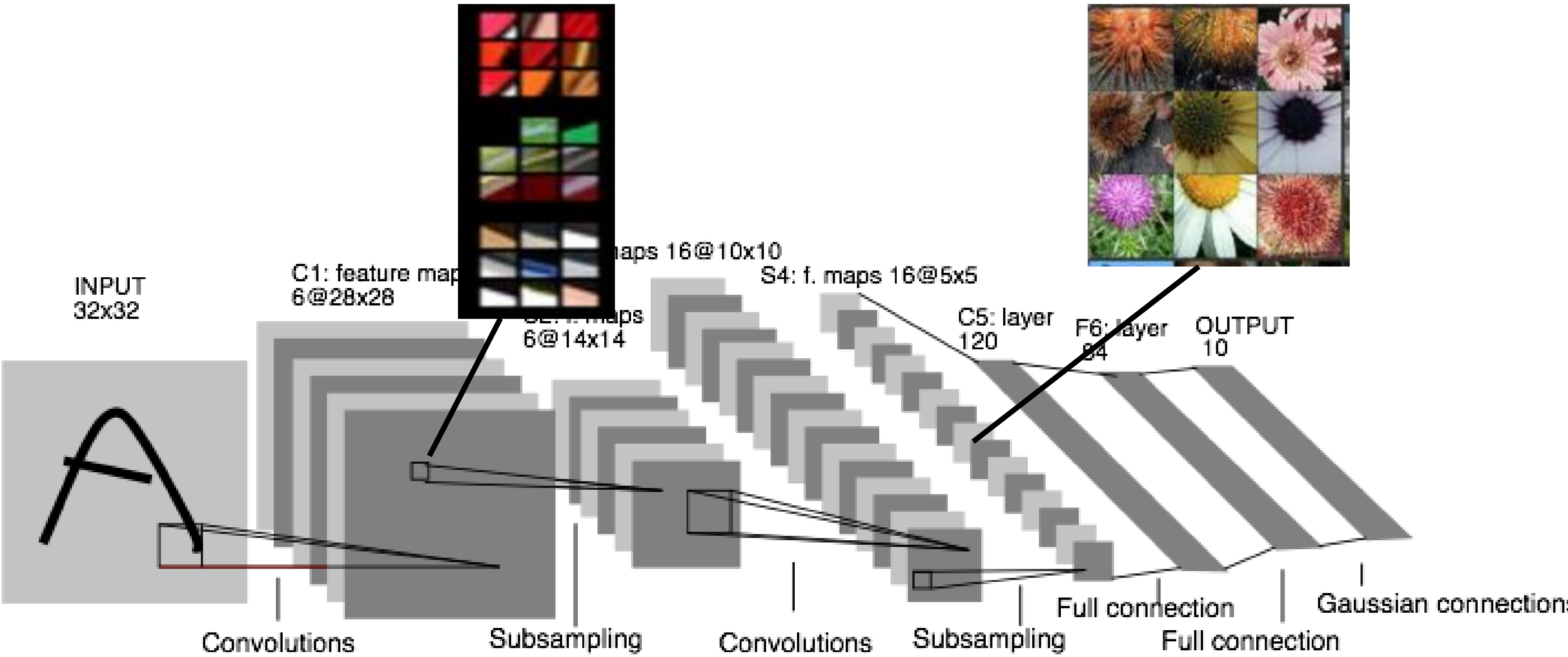


Putting it all together...



Convolutional Neural Network

A CNN is a better architecture for 2D signals



LeNet

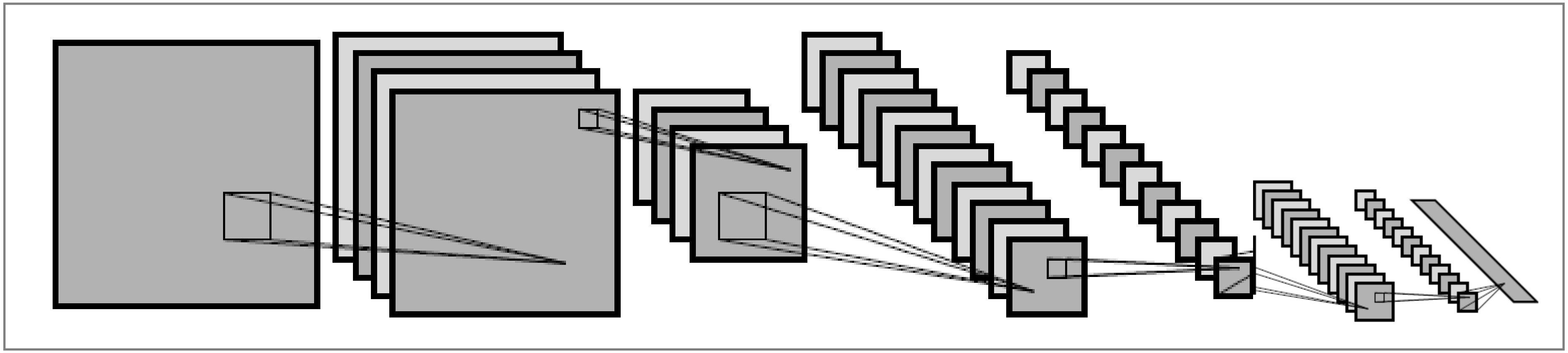
Engineering

Features -> Architectures

Convolutional Neural Nets

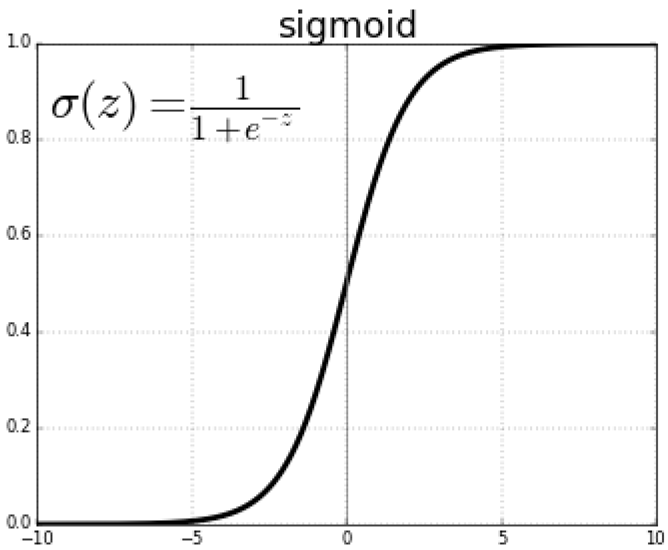
Example

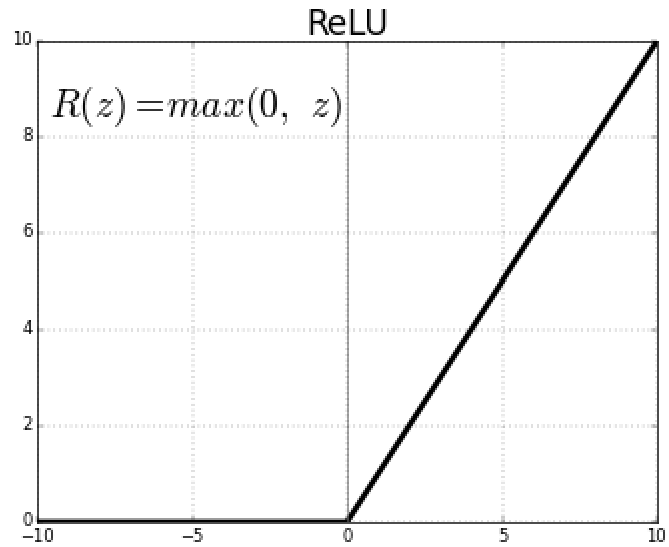
CIFAR-10 Demo ConvJS Network



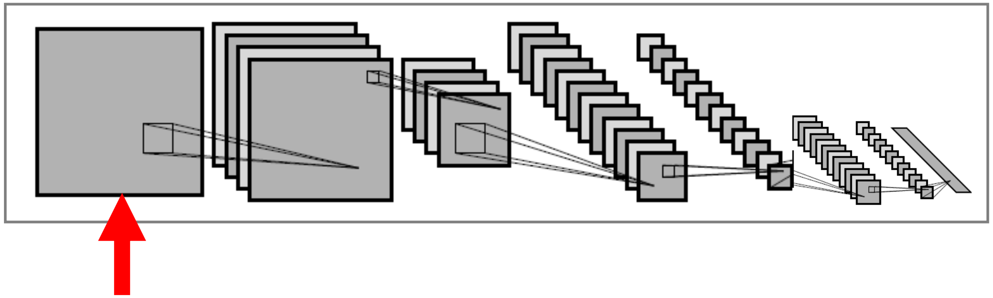
input image conv RELU pool conv RELU pool conv RELU pool fc

RELU: rectified linear unit



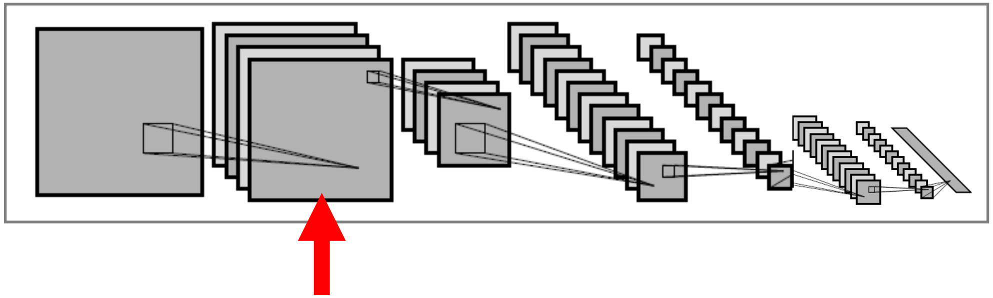


RELU function $g(x) = \max(0, x)$



input (32x32x3)

filter size 5x5x3, stride 1

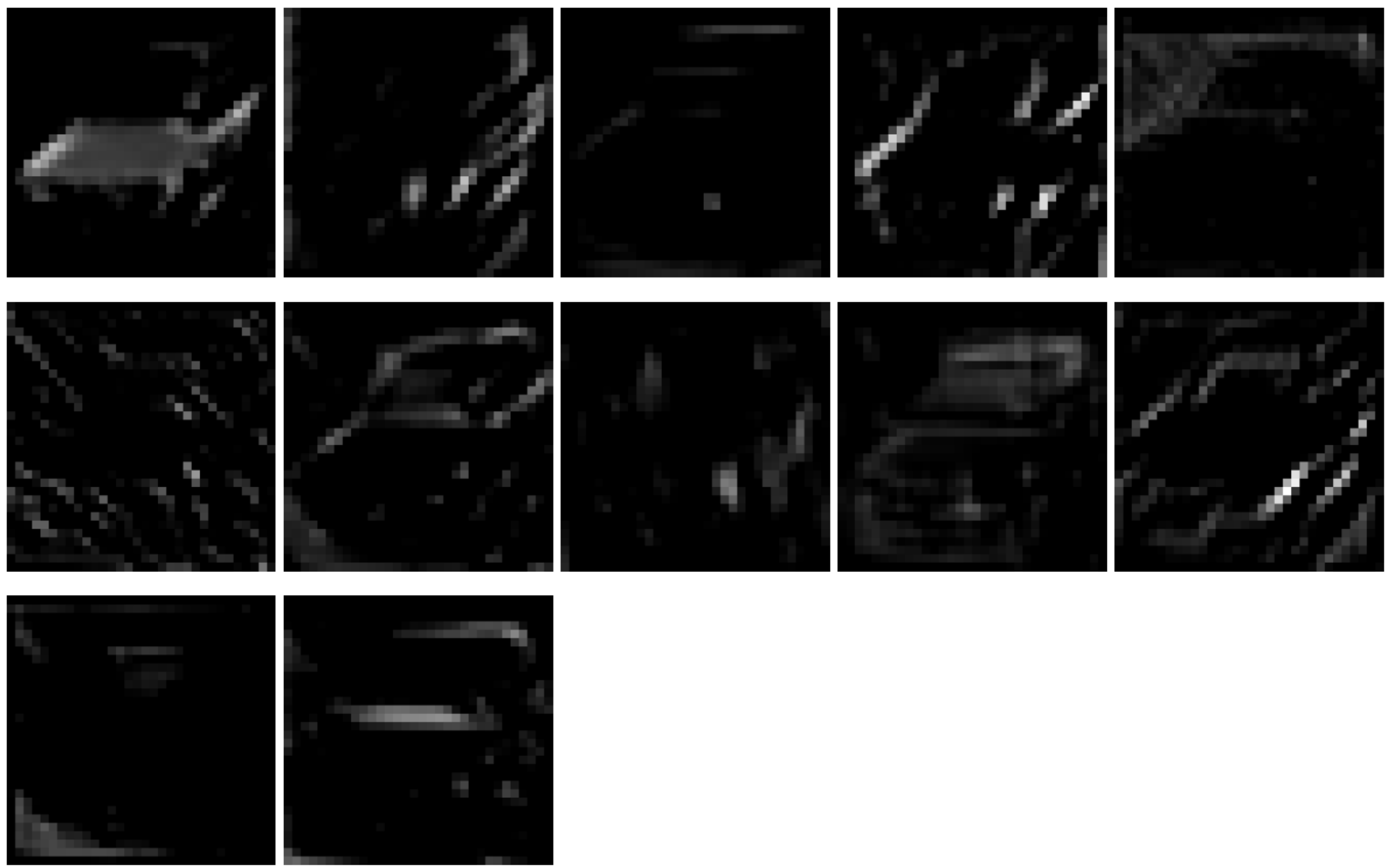


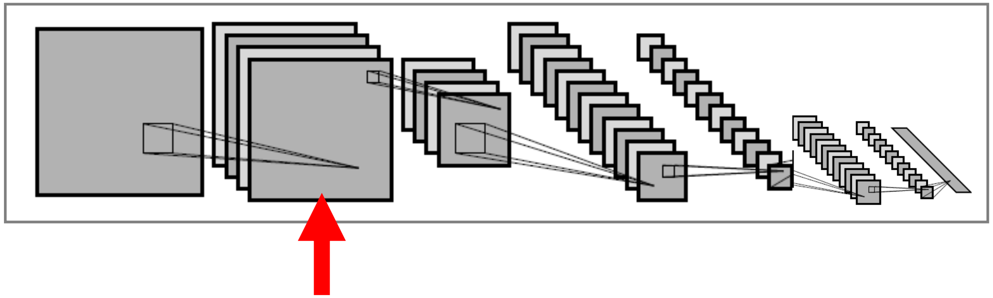
filter size 5x5x3, stride 1

input (32x32x3)

RELU

conv (32x32x16) params: 16x5x5x3+16 = 1216

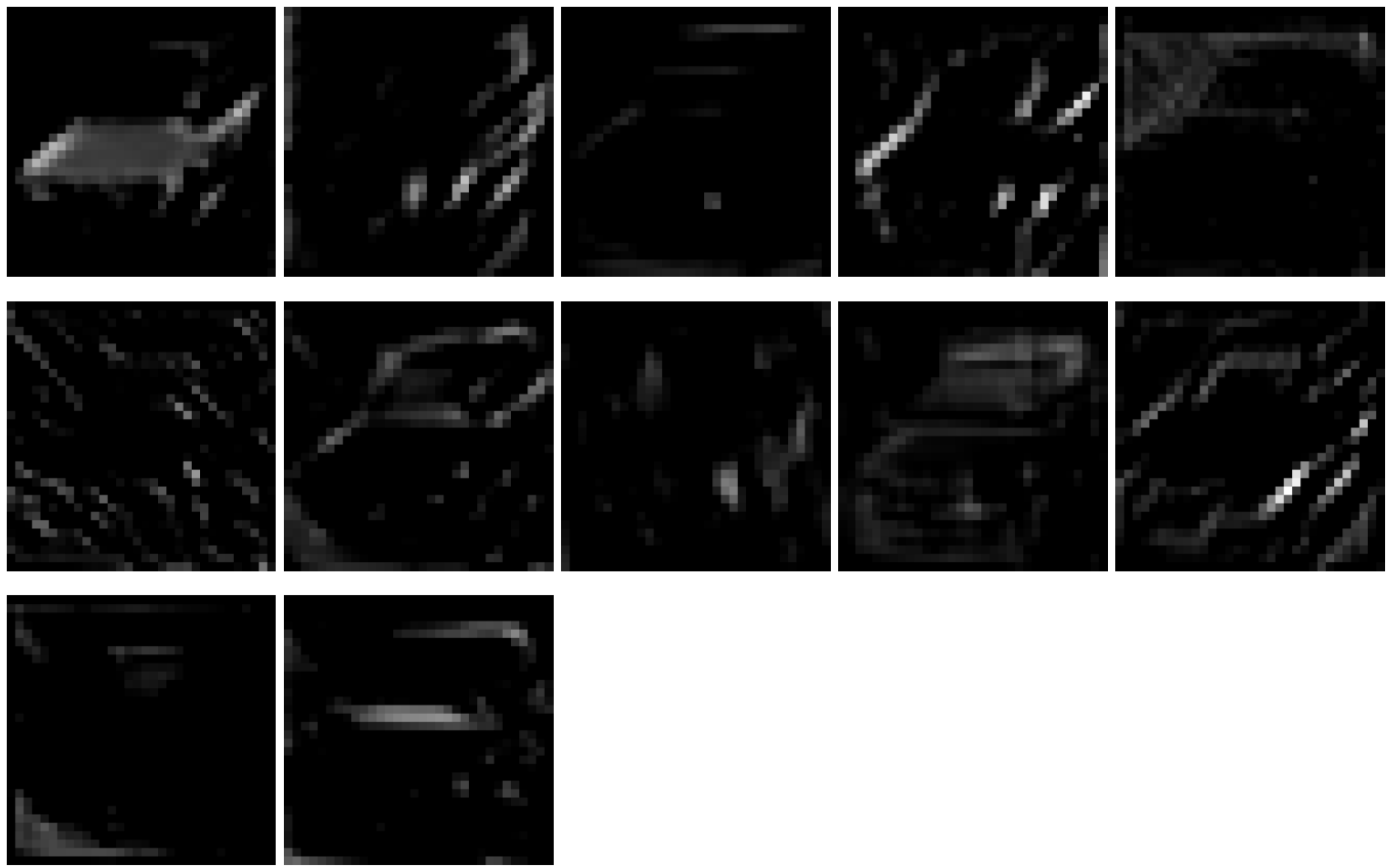


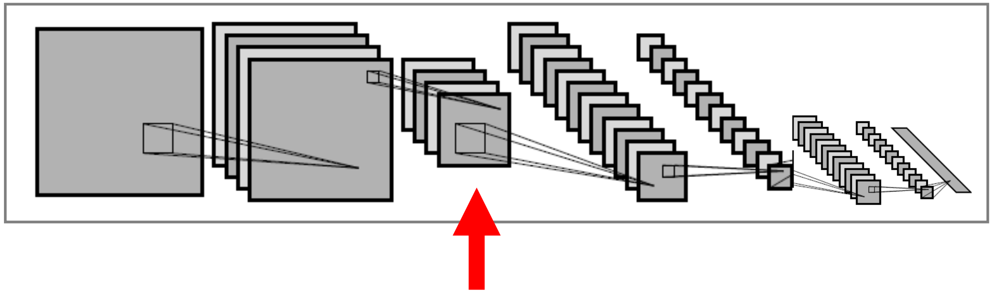


filter size 5x5x3, stride 1

input (32x32x3)

conv (32x32x16) params: 16x5x5x3+16 = 1216

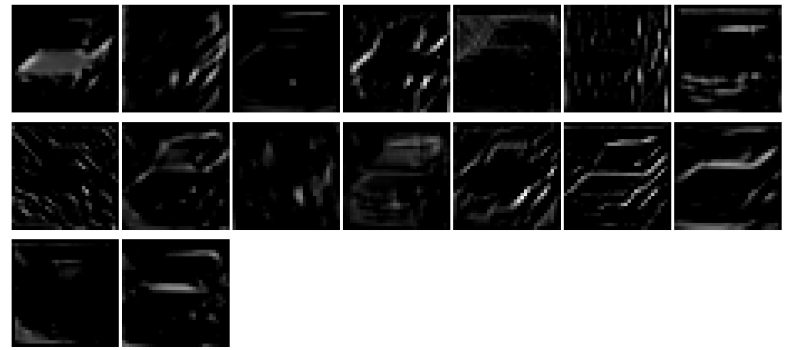




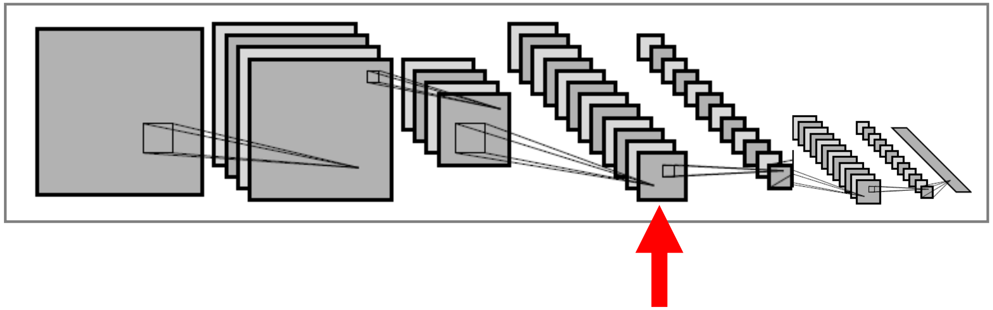
filter size 5x5x3, stride 1

input (32x32x3)

conv (32x32x16) params: 16x5x5x3+16 = 1216



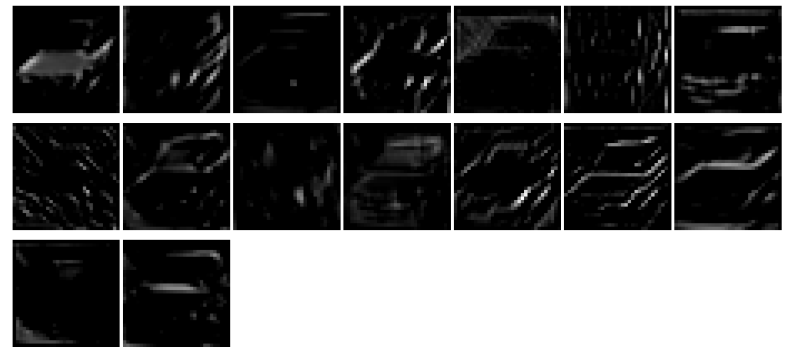
pool (16x16x16)
pooling size 2x2, stride 2



filter size 5x5x3, stride 1

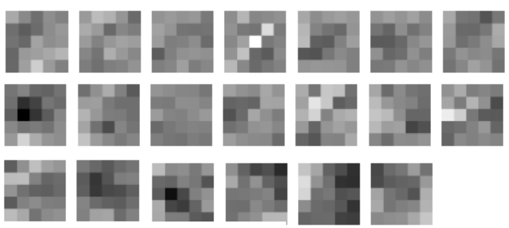
input (32x32x3)

conv (32x32x16) params: 16x5x5x3+16 = 1216



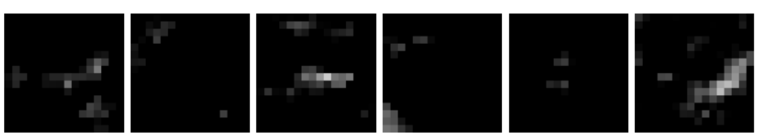
pool (16x16x16)
pooling size 2x2, stride 2

filter size 5x5x16, stride 1

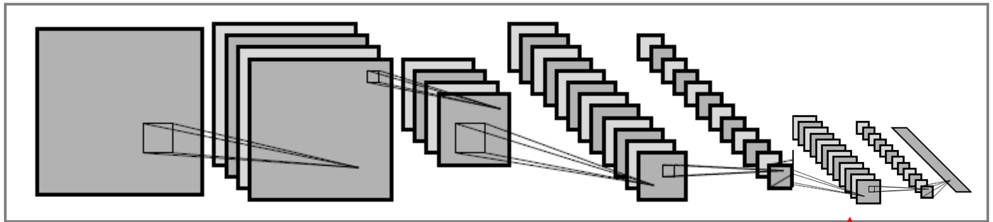


RELU

conv (16x16x20) params: 20x5x5x16+20 = 8020



pool (8x8x20)
pooling size 2x2, stride 2



One more conv+RELU+pool:

conv (8x8x20)
filter size 5x5x20, stride 1
relu (8x8x20)
pool (4x4x20)
pooling size 2x2, stride 2
parameters: 20x5x5x20+20 = 10020

input (32x32x3)

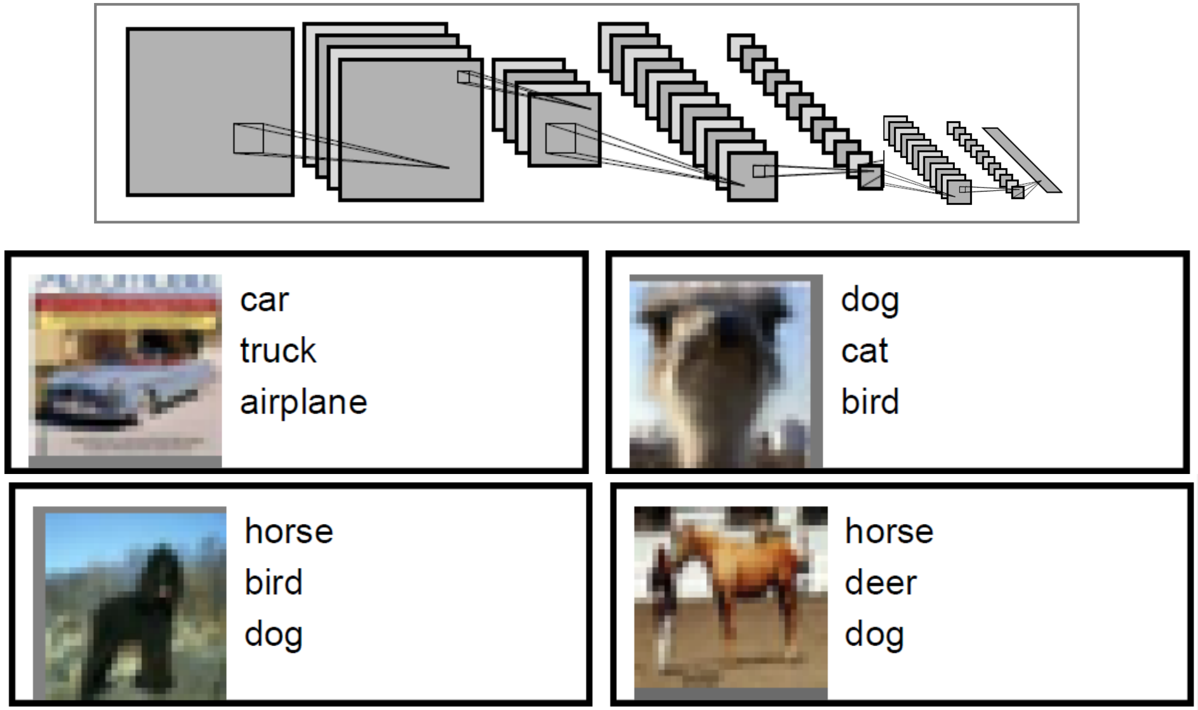
fc (1x1x10); parameters: 10x320+10 = 3210

softmax (1x1x10)

Dog cat Car ⋮

Testing the network

- Show top three most likely classes



http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html