

Image Featurization

CovNet style

Objectives

- Be able to explain what a convolution is, and how it works
- Understand the basic structure of a convolutional neural network
- Comprehend the three basic ideas behind convolutional networks :
 - (1) Local receptive field
 - (2) Shared weights
 - (3) Pooling
- Be aware of general strategies for building convolutional neural networks

Convolutions

In image processing, a kernel, convolution matrix, or mask is a small matrix useful for blurring, sharpening, embossing, edge-detection, and more. This is accomplished by means of **convolution** between a kernel and an image.

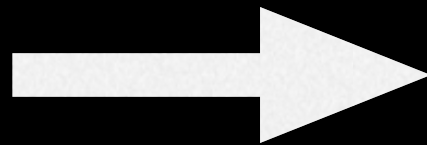
-Wikipedia

Convolutions

A Kernel

1	0	1
0	1	0
1	0	1

Applied Over



A Simple Image

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature

Example Kernels - Edge Detectors

Vertical Edge Detector

-1	0	+1
-2	0	+2
-1	0	+1

Horizontal Edge Detector

-1	-2	-1
0	0	0
+1	+2	+1

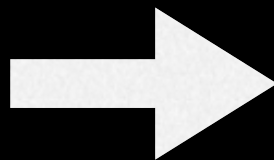
Sobel filter



How do we tell that
this is a door?



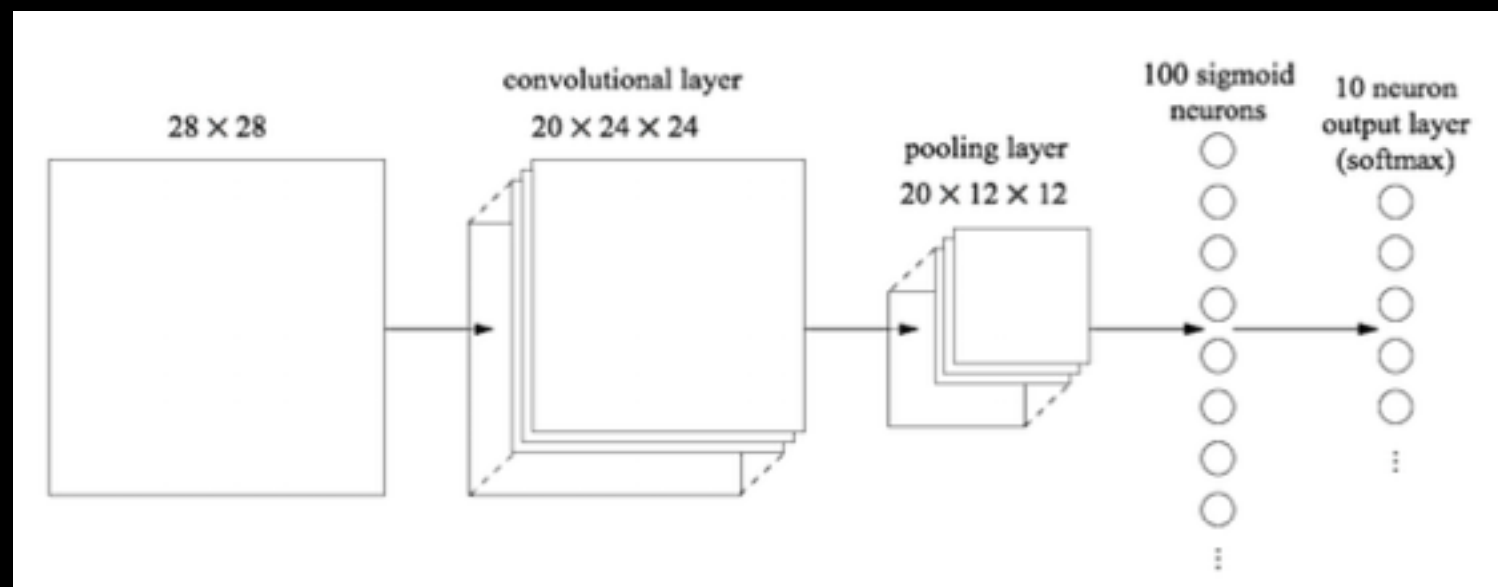
What if we applied our edge detectors to the image?



Convolutional Neural Networks (CNNs)

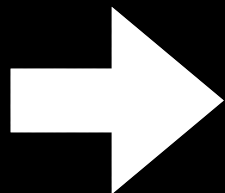
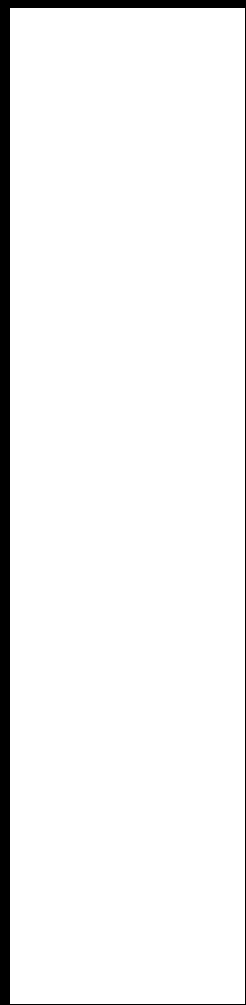
What if we could get a computer to build it's own kernels, apply those to images, and then interpret those results to perform object recognition?

Enter convolutional neural networks....

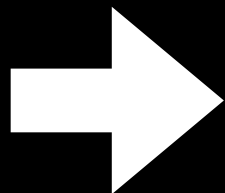


General Structure

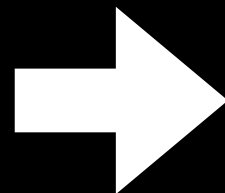
Input Layer



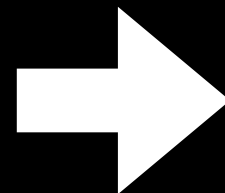
Convolutional
Layers



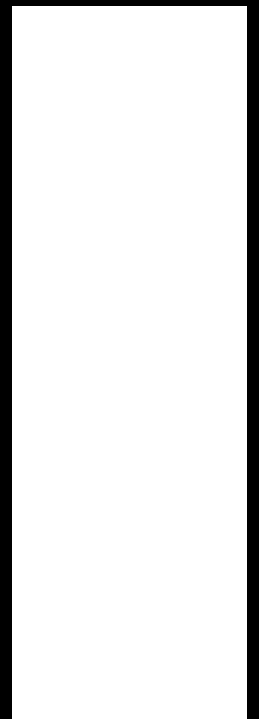
Pooling
Layers



Fully
Connected
Layers



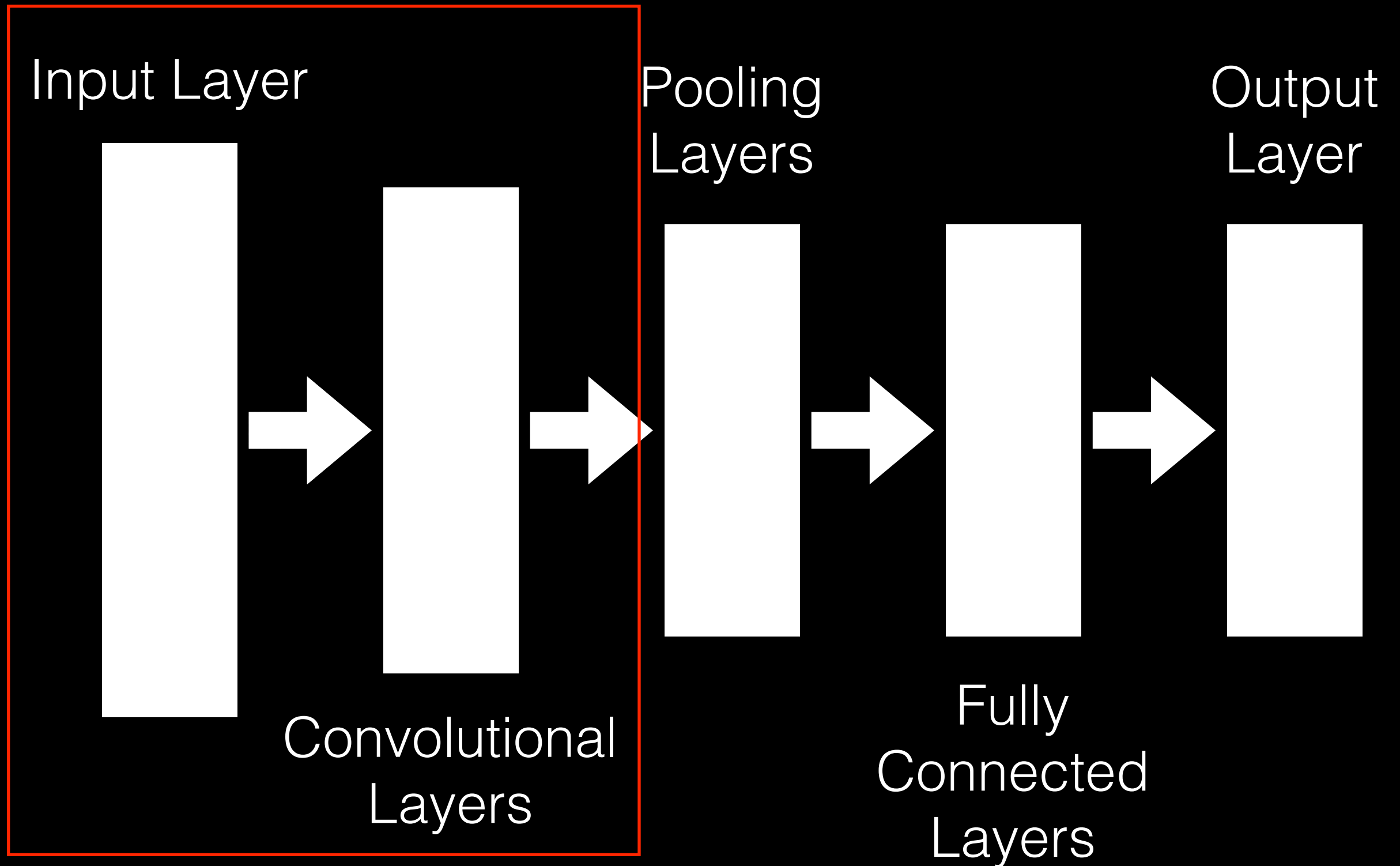
Output
Layer



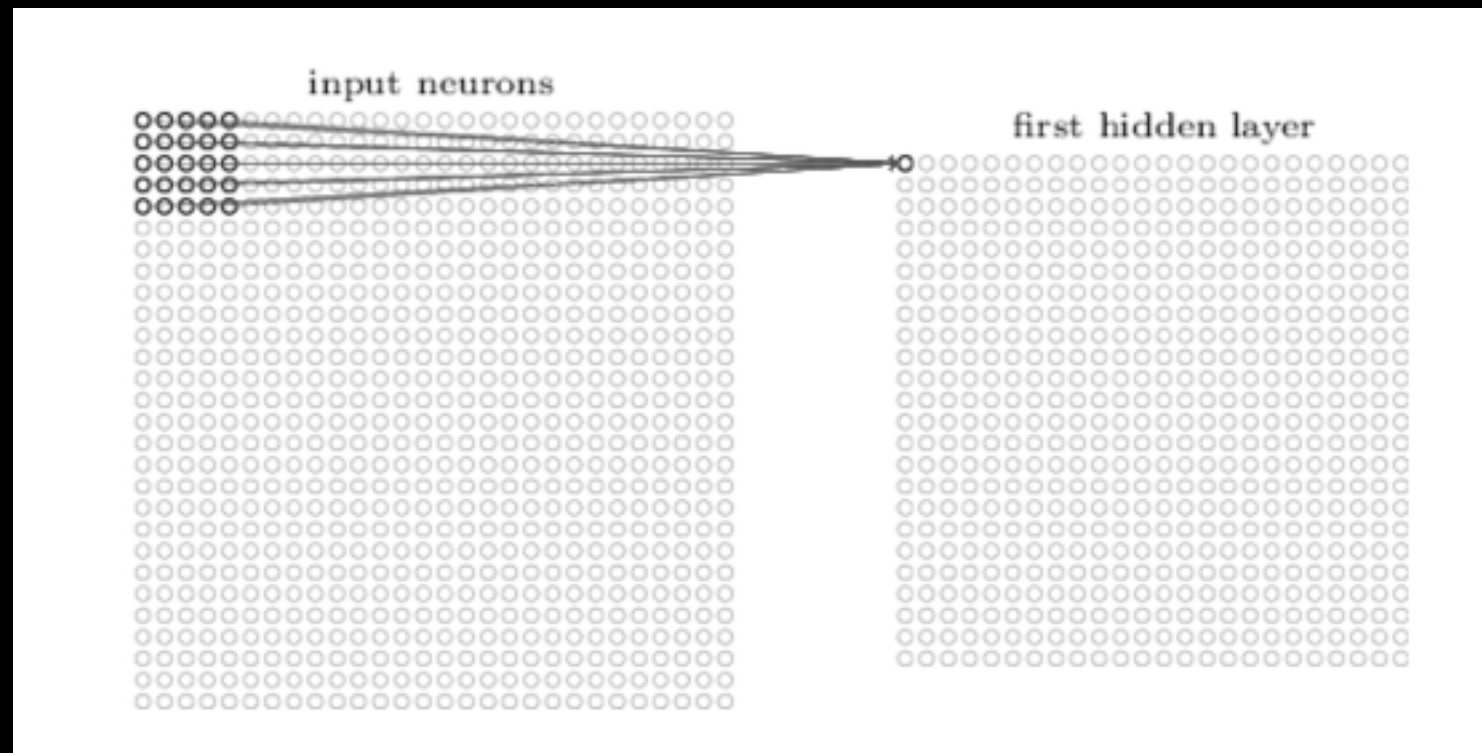
Three Main Ideas...

- Local Receptive Fields
- Shared Weights
- Pooling

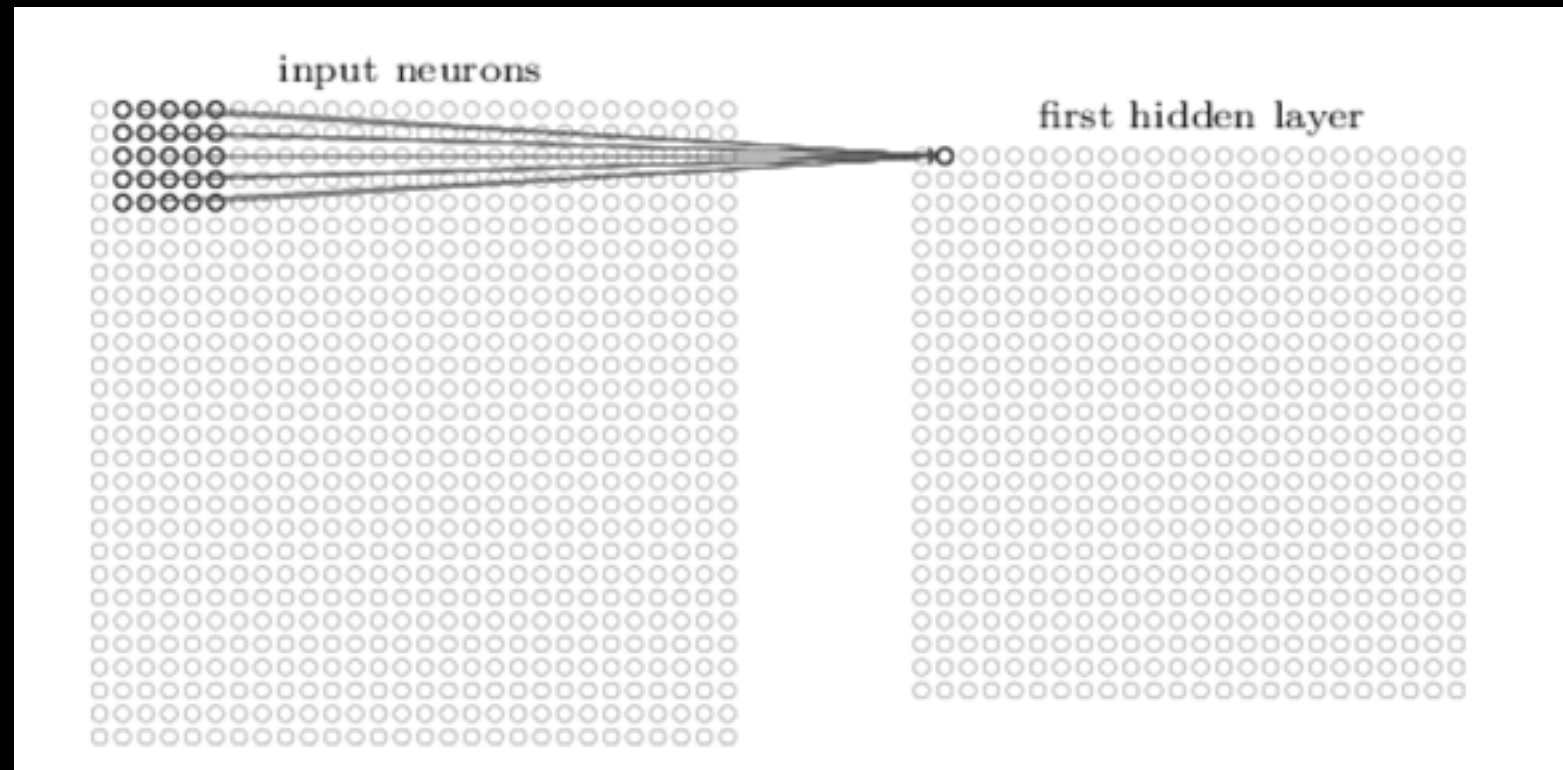
General Structure



Input Image



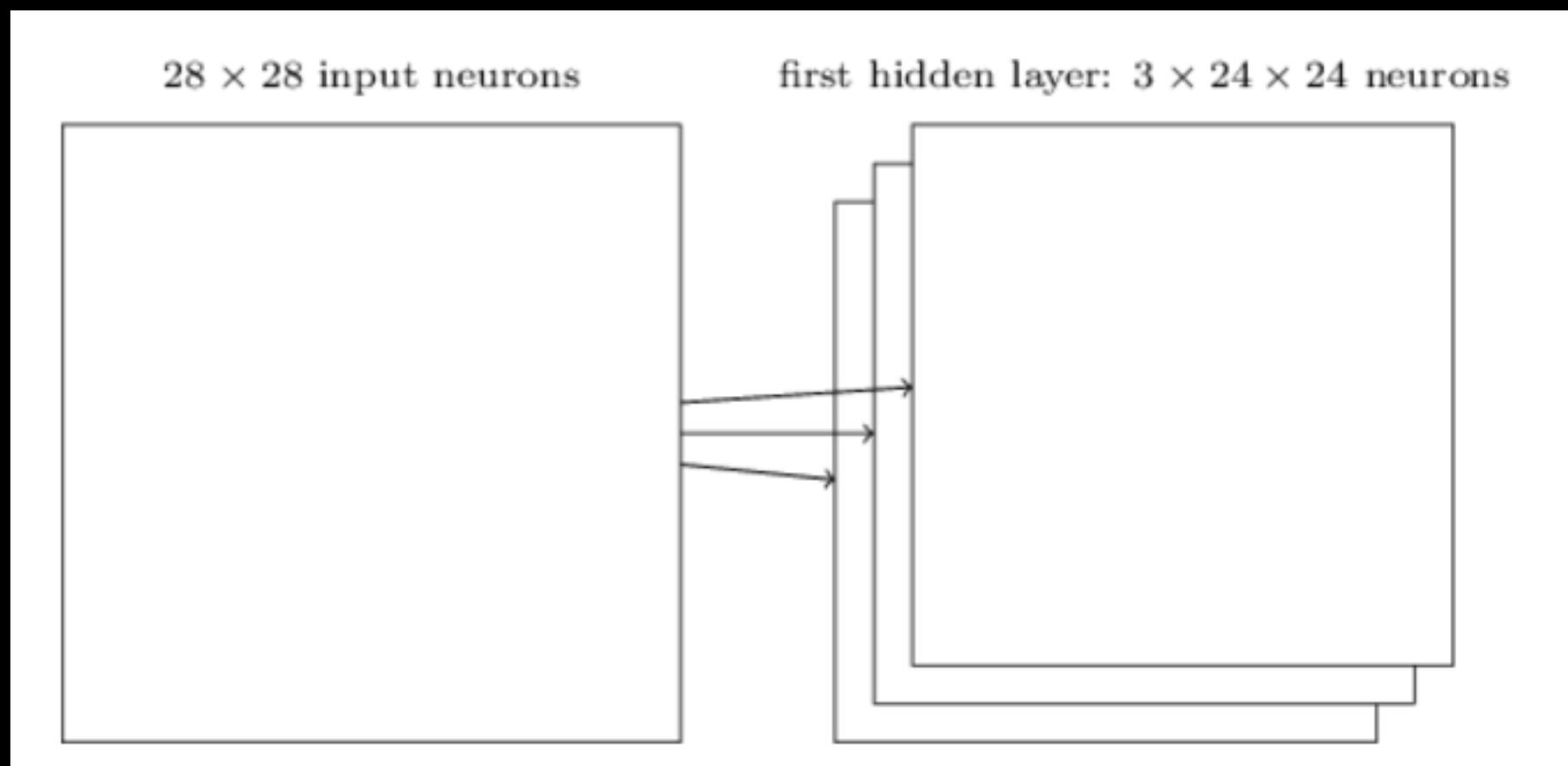
Local Receptive Fields



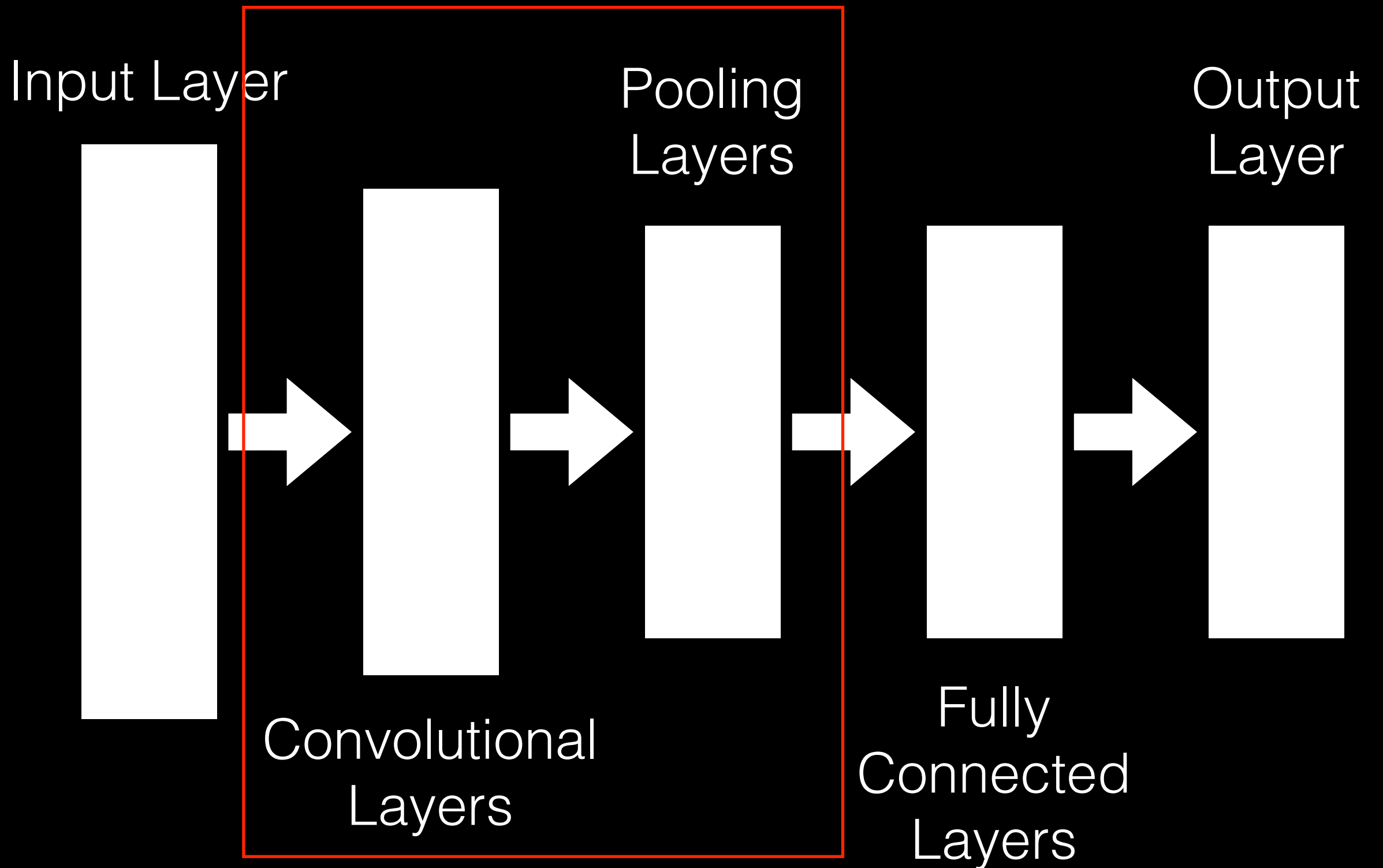
- This group of pixels is a ****local receptive field****, and its size is defined by the size of your kernel
- We then slide this kernel across the entire image

Convolutional Layers

We apply multiple kernels to the image, which results in multiple learned kernels per hidden layer



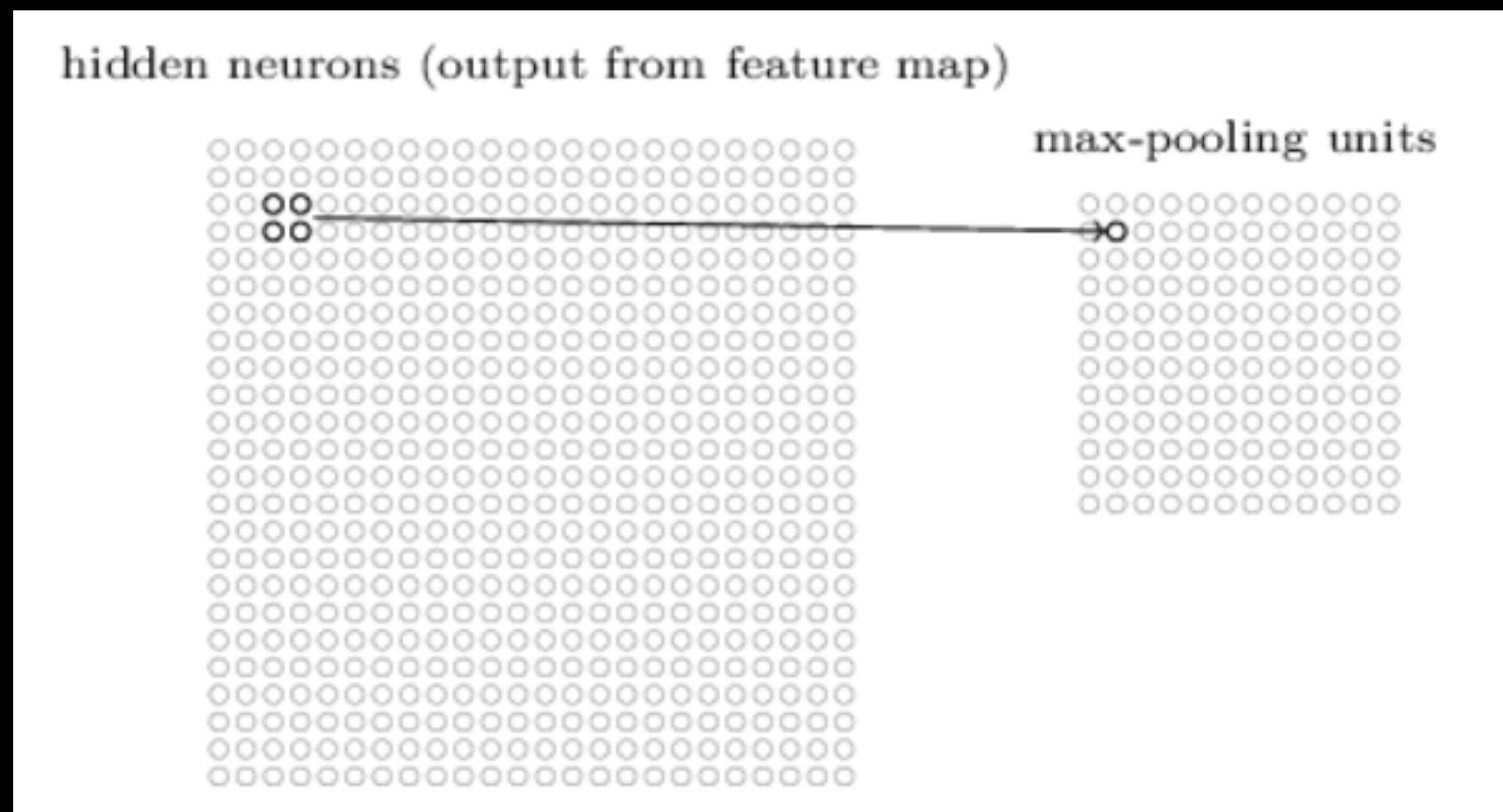
General Structure



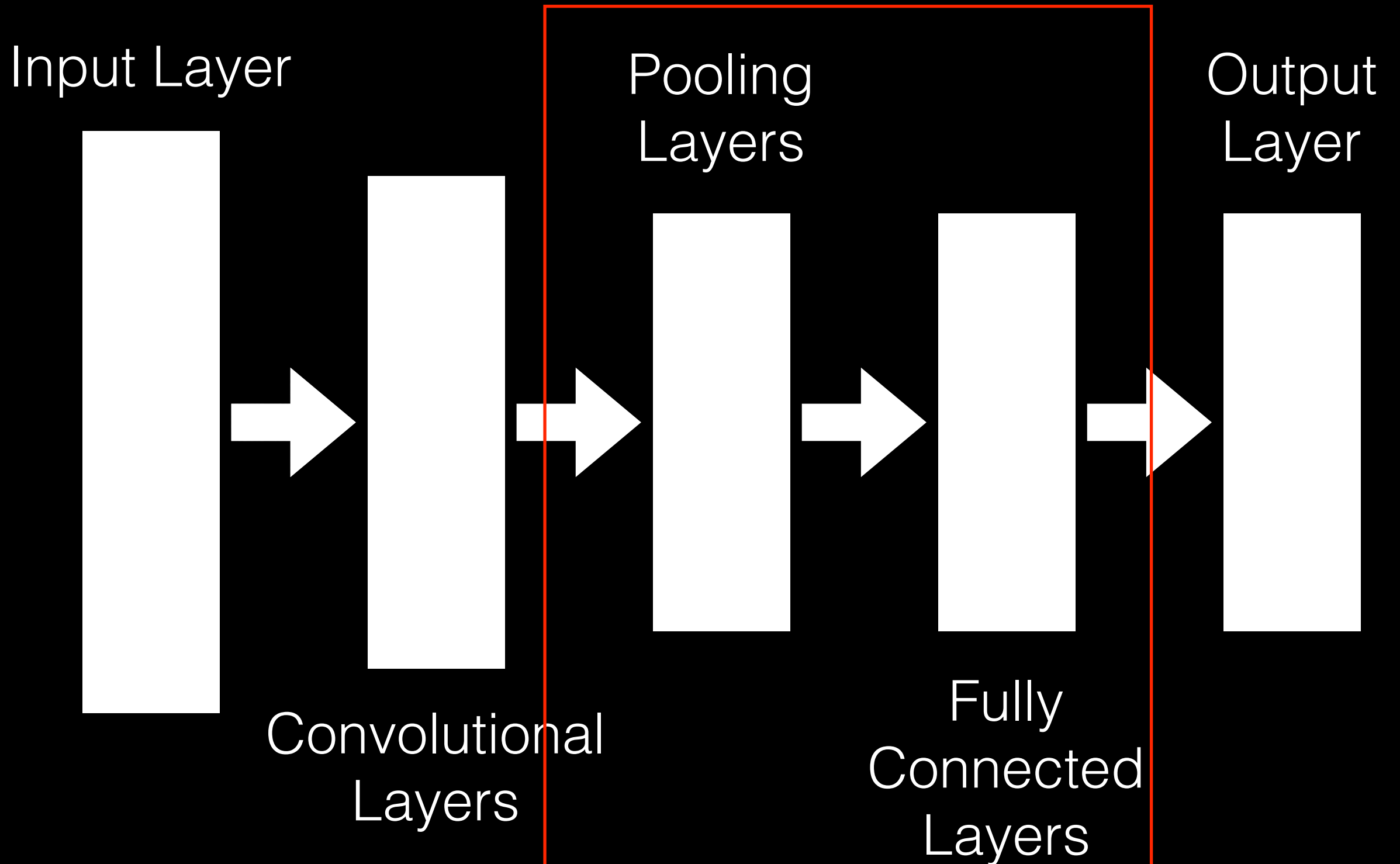
Pooling Layers

- Used immediately after convolutional layers, and simplify the information in the output from the convolutional layer.
 - Reduces the computational complexity for later layers
 - Provides a form of translational invariance

Max Pooling



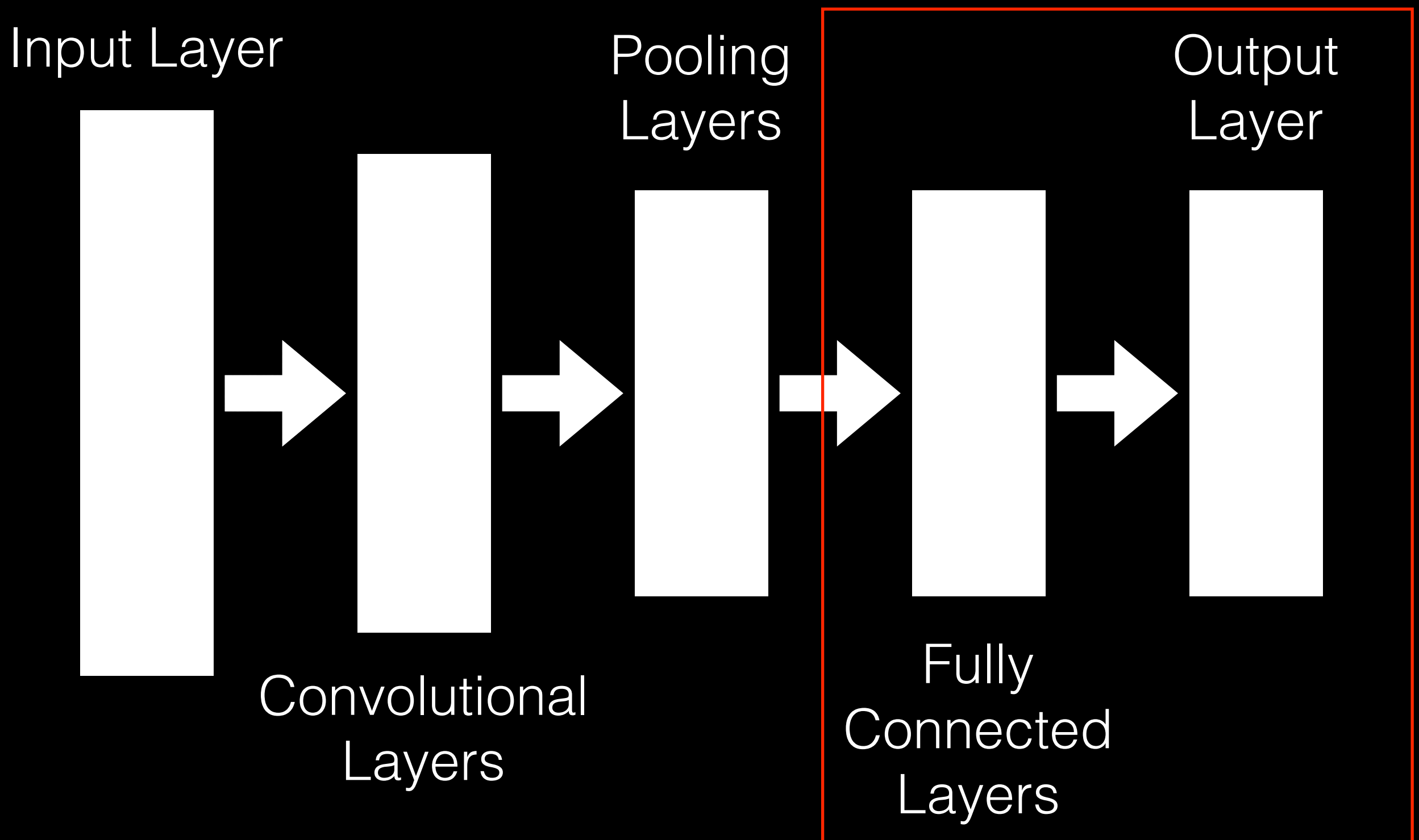
General Structure



Fully Connected Layers

Used to aggregate all of the information that has been learned in the convolutional and pooling layers.

General Structure



Output Layer

- For object recognition, always composed of softmax activation units
- Outputs the probability that your image is of a certain class

Tips and Tricks

- We of course have all the image processing techniques that we learned about - resizing, denoising, etc.
(denoising is not actually common to use with CNN's, but available)
- New set of image processing techniques for getting more images - rotate images, flip images, etc.

General Structure

Normalities

- It is not too common to use dropout after convolutional layers (but it is common to use it after you're fully connected layers)
- It's common to have multiple convolutional layers in between pooling layers
- ReLU activation units are incredibly popular with CNN's

Don't know where to start?

If you're confused about the general CNN structure that you should start off, you should find a research paper in your domain space that uses CNN's. Start off trying to get something working that uses the same structure they did, and go from there.