ADACS

ASTRONOMY DATA AND COMPUTING SERVICES

# Astroinformatics school - "Rise of the machines"

Curtin University

THE CURTIN INSTITUTE FOR COMPUTATION

4 to 6 February 2019

Presented by Rebecca Lange and Dan Marrable

# Convolutional Neural Networks

Curtin Institute for Computation

# What is a convolutional neural network (CNN)

Most commonly used for analyzing visual imagery

Image classification

Object detection

Image segmentation

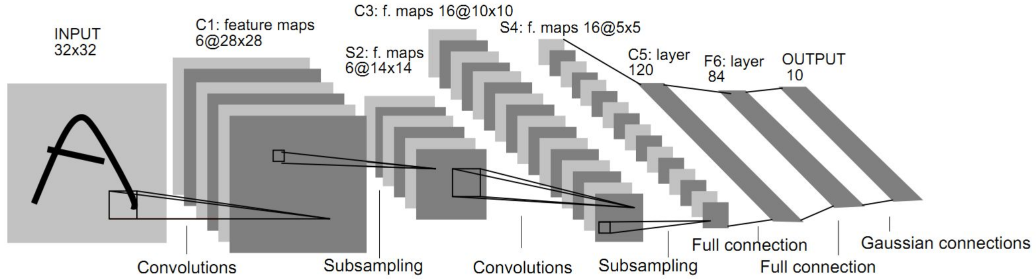
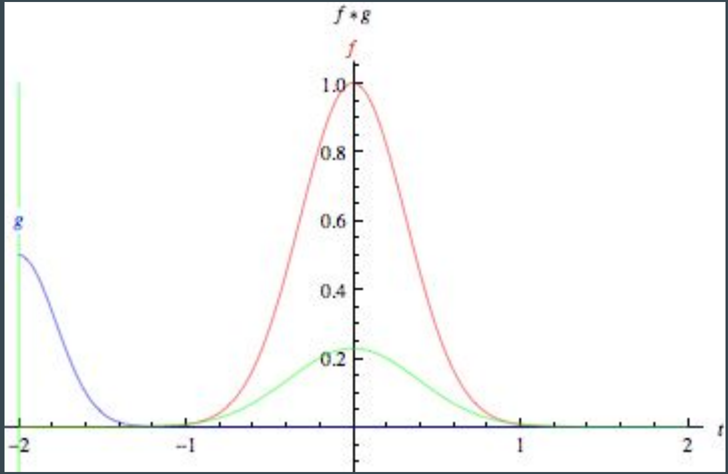



Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

LeNET-5 One of the first ever CNNs

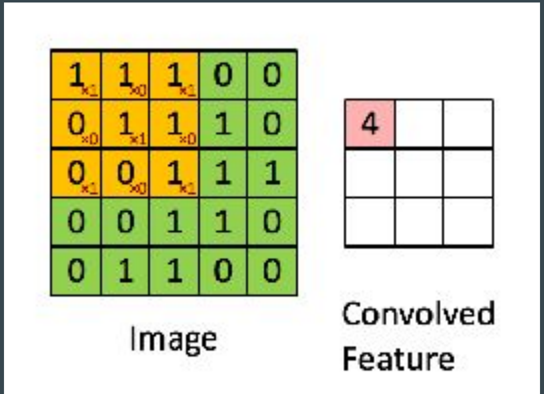
# What is a convolution?

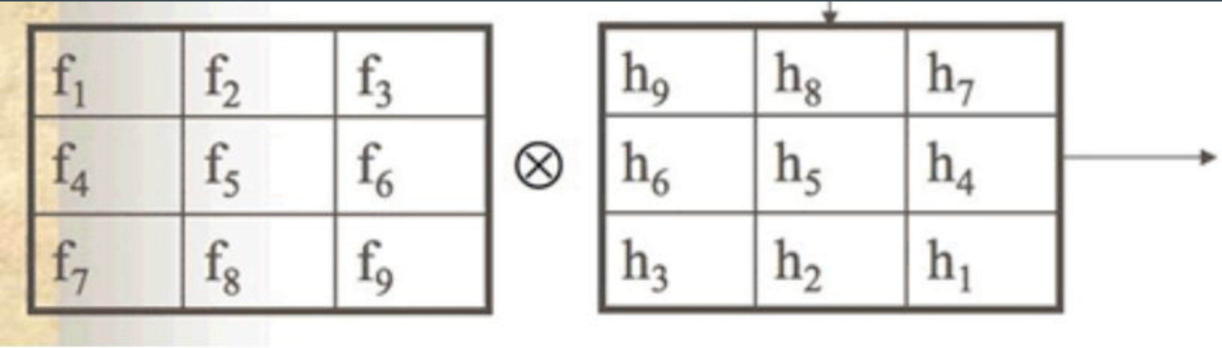
A convolution is an integral that expresses the amount of overlap of one function as it is shifted over another function . It therefore "blends" one function with another.




$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)g(t-\tau)\,d\tau$$
$$= \int_{-\infty}^{\infty} f(t-\tau)g(\tau)\,d\tau.$$

# Descretised Convolution in 2D

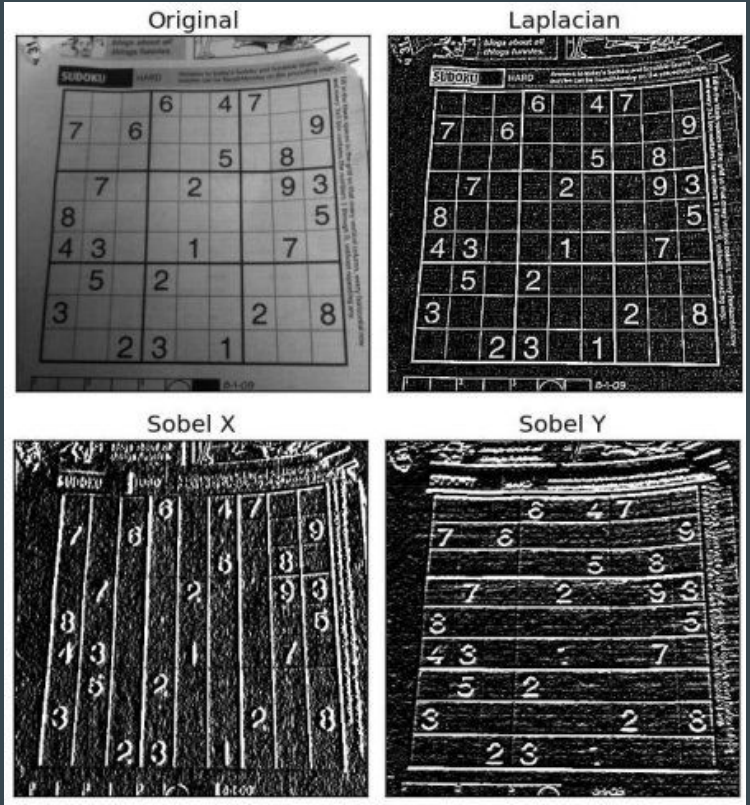



$$\begin{aligned} f * h = {} & f_1 h_9 + f_2 h_8 + f_3 h_7 \\ & + f_4 h_6 + f_5 h_5 + f_6 h_4 \\ & + f_7 h_3 + f_8 h_2 + f_9 h_1 \end{aligned}$$

# Image filters

Features




Filters

Laplacian

| | | |
|---|---|---|
| 0 | −1 | 0 |
| −1 | 4 | −1 |
| 0 | −1 | 0 |

Sobel X

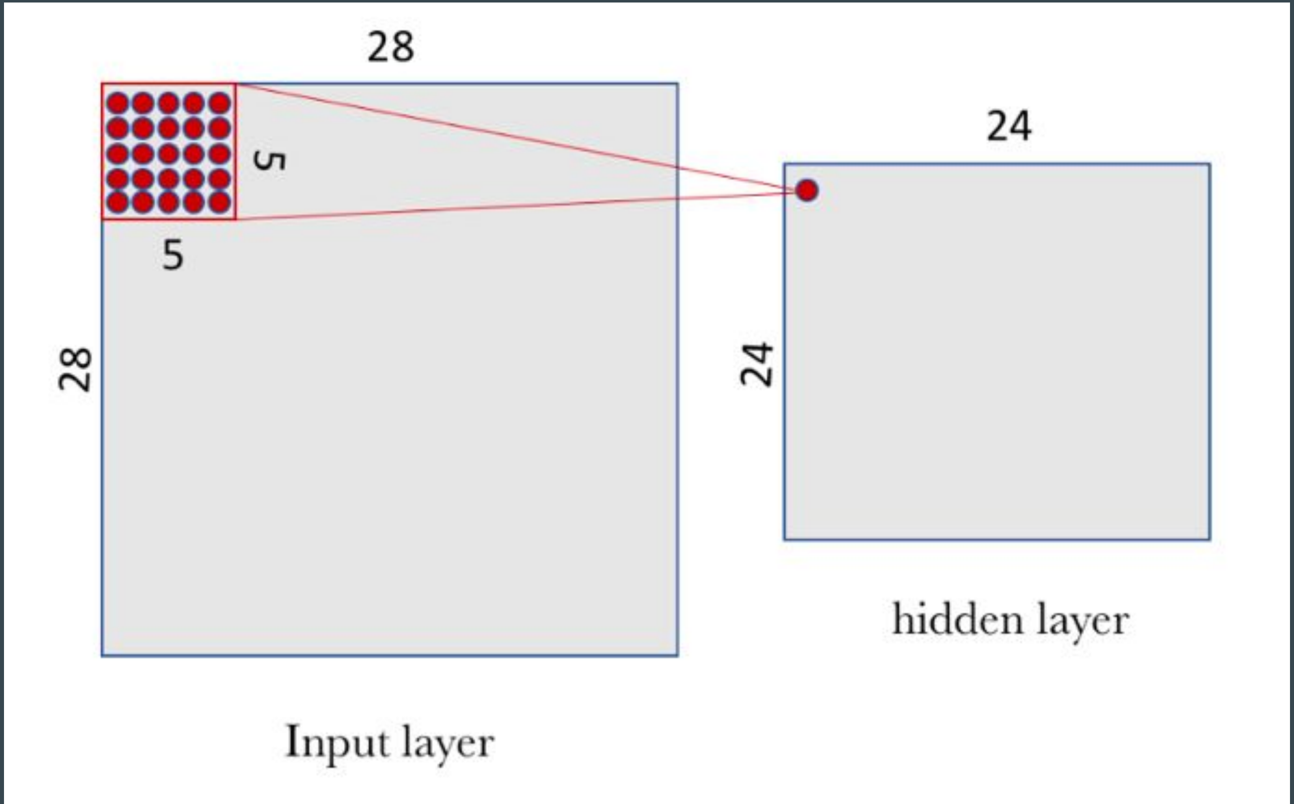
| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

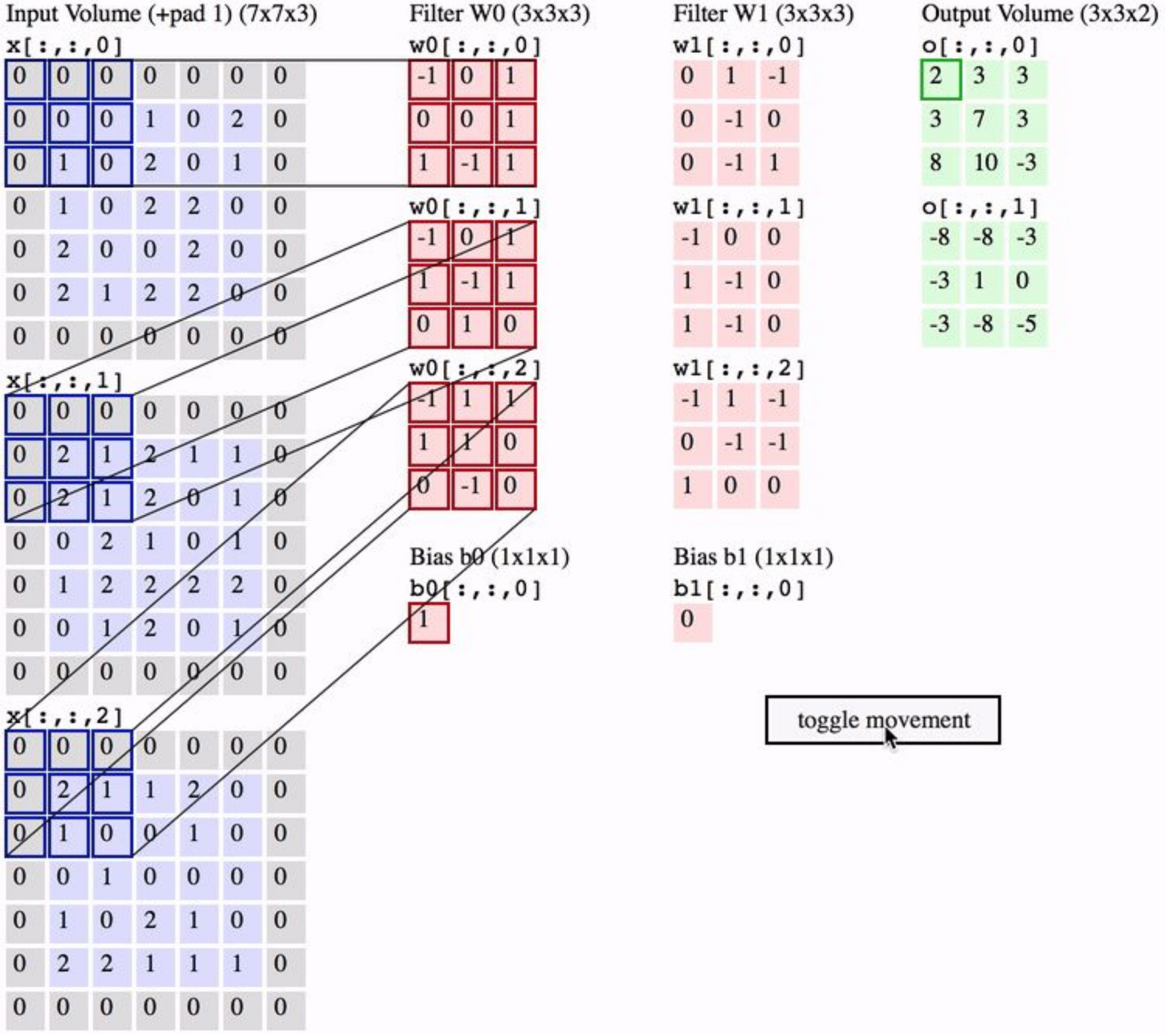
Gx

Sobel Y

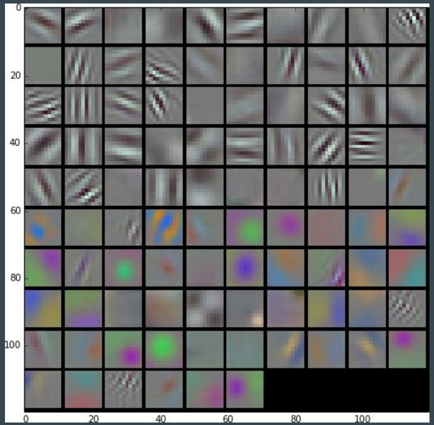
| | | |
|---|---|---|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

Gy

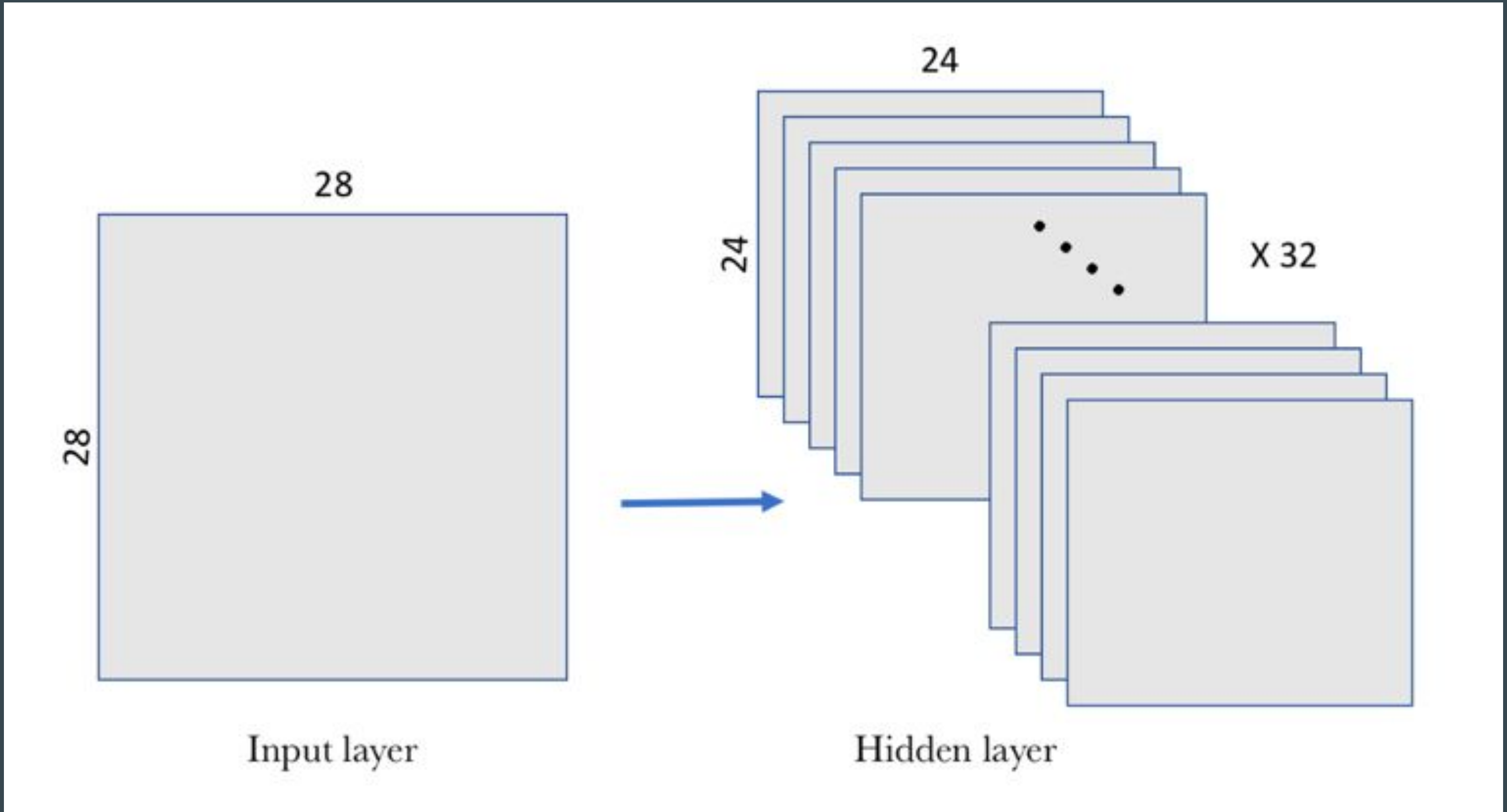

28
5
5
28
24
24
hidden layer
Input layer

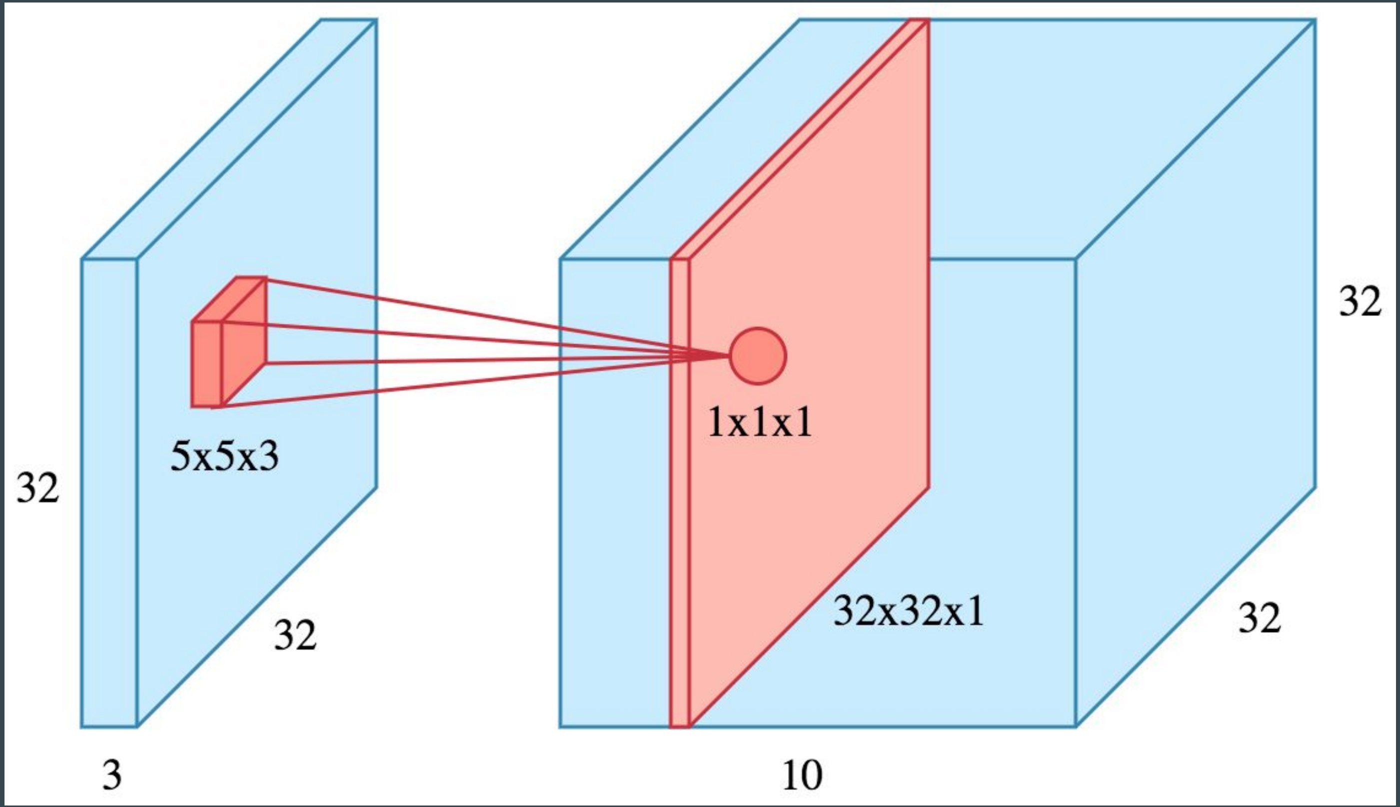

Input Volume (+pad 1) (7x7x3)
x[:,:,0]
0 0 0 0 0 0 0
0 0 0 1 0 2 0
0 1 0 2 0 1 0
0 1 0 2 2 0 0
0 2 0 0 2 0 0
0 2 1 2 2 0 0
0 0 0 0 0 0 0
x[:,:,1]
0 0 0 0 0 0 0
0 2 1 2 1 1 0
0 2 1 2 0 1 0
0 0 2 1 0 1 0
0 1 2 2 2 2 0
0 0 1 2 0 1 0
0 0 0 0 0 0 0
x[:,:,2]
0 0 0 0 0 0 0
0 2 1 1 2 0 0
0 1 0 0 1 0 0
0 0 1 0 0 0 0
0 1 0 2 1 0 0
0 2 2 1 1 1 0
0 0 0 0 0 0 0
Filter W0 (3x3x3)
w0[:,:,0]
-1 0 1
0 0 1
1 -1 1
w0[:,:,1]
-1 0 1
1 -1 1
0 1 0
w0[:,:,2]
-1 1 1
1 1 0
0 -1 0
Bias b0 (1x1x1)
b0[:,:,0]
1
Filter W1 (3x3x3)
w1[:,:,0]
0 1 -1
0 -1 0
0 -1 1
w1[:,:,1]
-1 0 0
1 -1 0
1 -1 0
w1[:,:,2]
-1 1 -1
0 -1 -1
1 0 0
Bias b1 (1x1x1)
b1[:,:,0]
0
Output Volume (3x3x2)
o[:,:,0]
2 3 3
3 7 3
8 10 -3
o[:,:,1]
-8 -8 -3
-3 1 0
-3 -8 -5
toggle movement

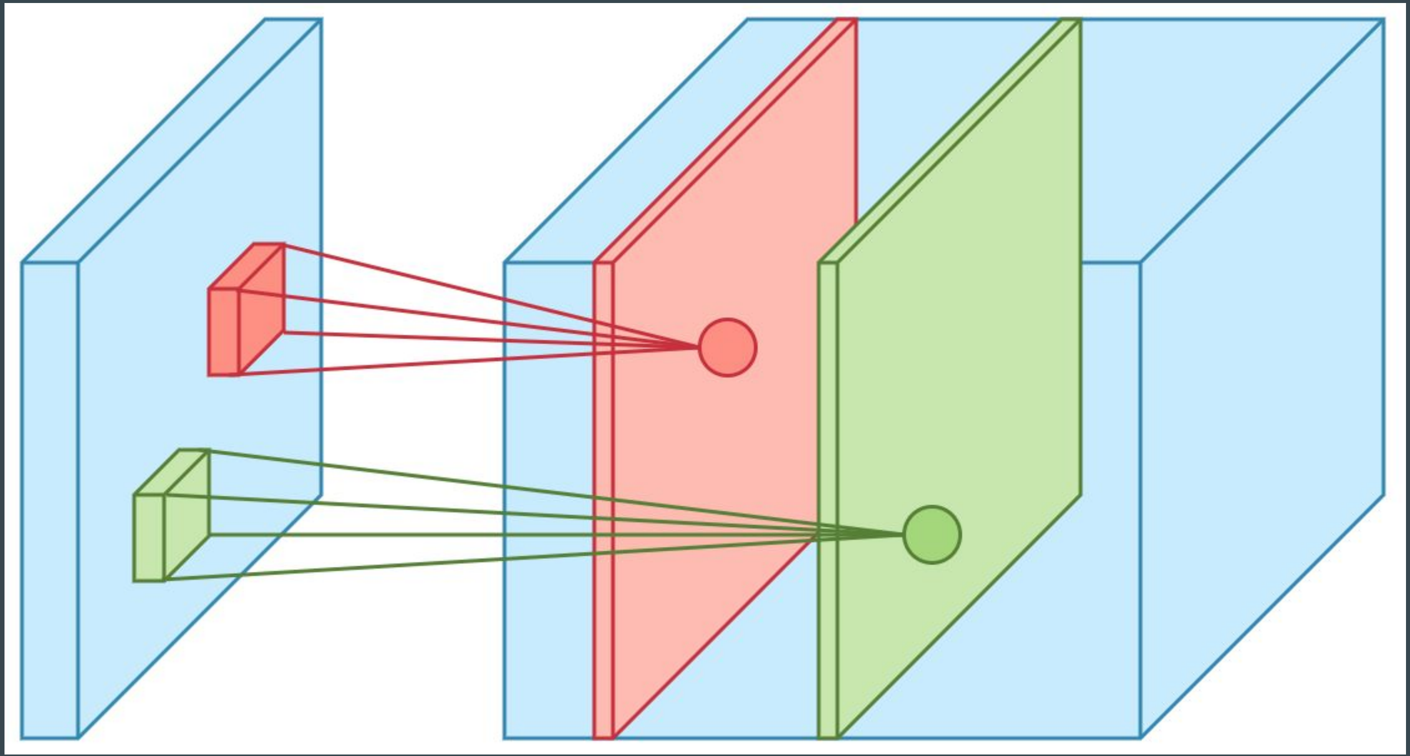
# Learning Features




Alexnet Filters


28
28
24
24
X 32
Input layer
Hidden layer


32
5x5x3
32
3
1x1x1
32
32x32x1
32
10



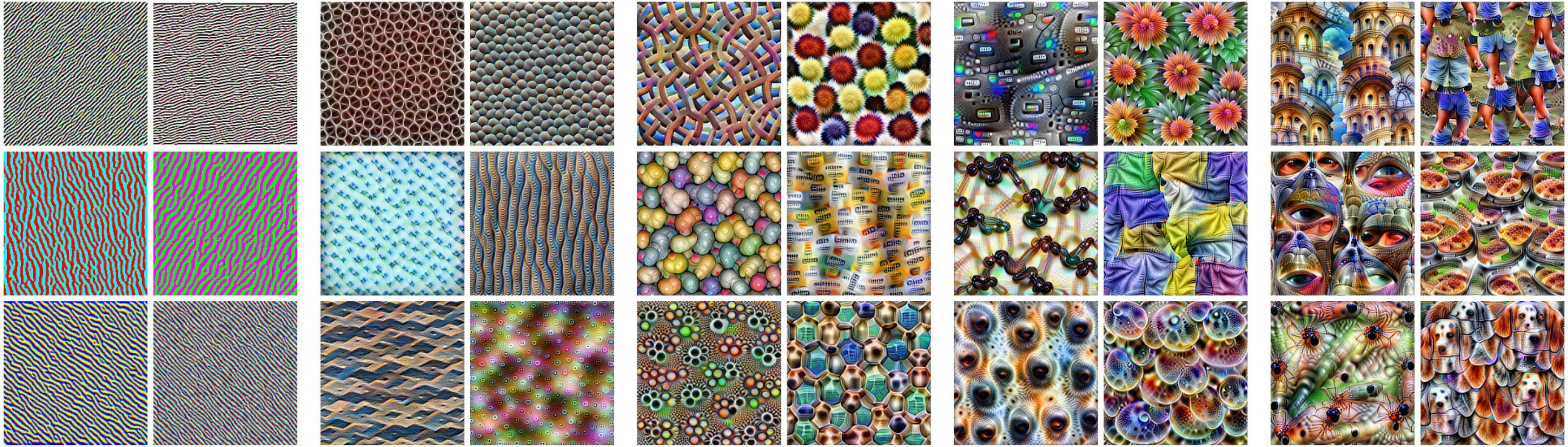
Input Layer

Hidden Layer

# What Do the Layers See?

## Feature Visualization

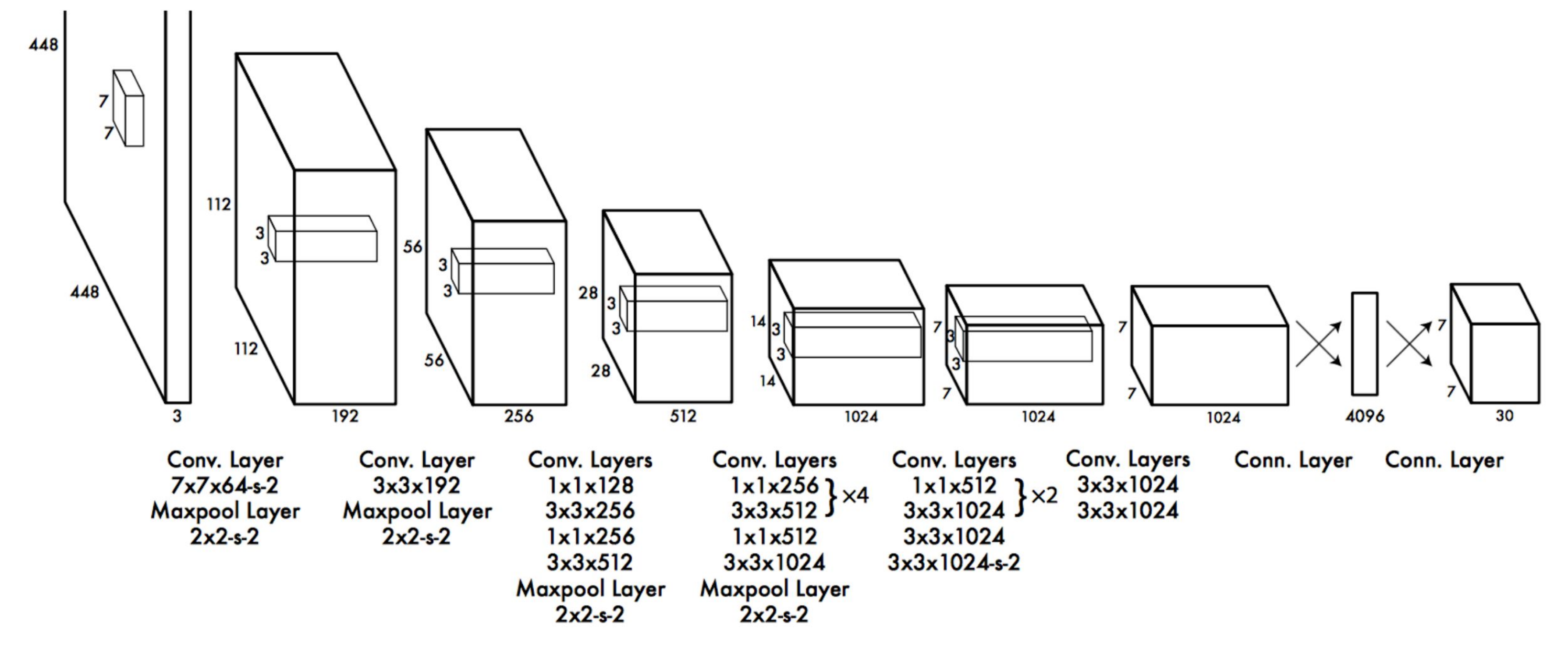
How neural networks build up their understanding of images



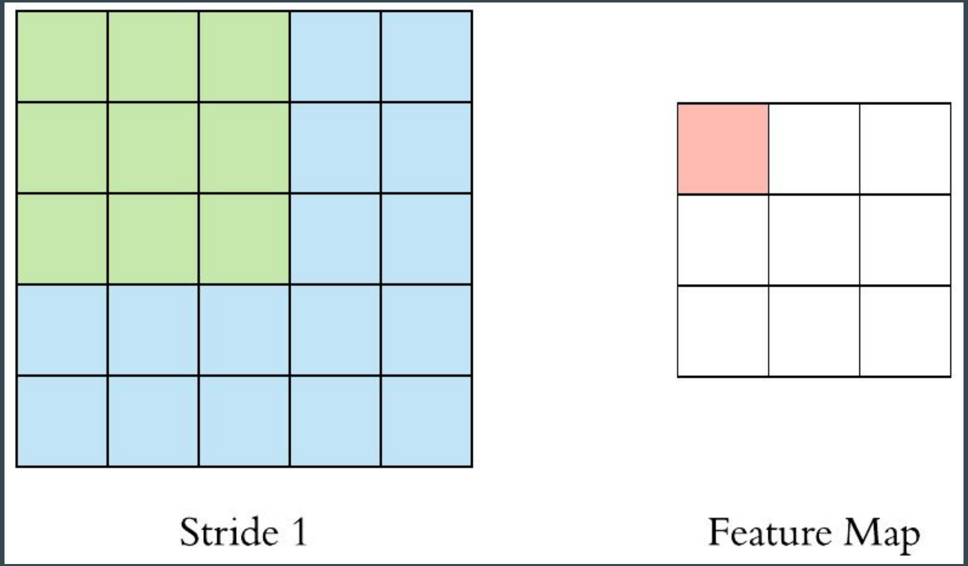
**Edges** (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

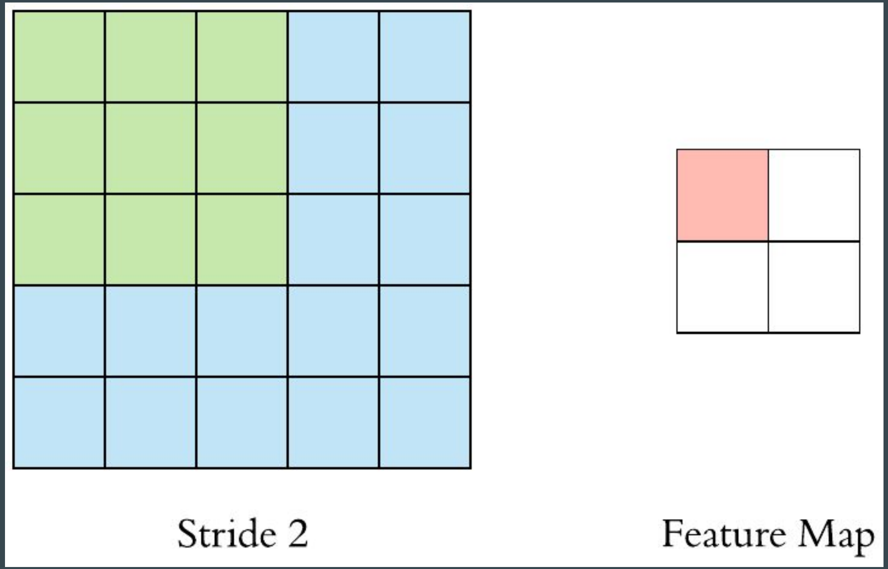
Feature visualization allows us to see how GoogLeNet [1], trained on the ImageNet [2] dataset, builds up its understanding of images over many layers. Visualizations of all channels are available in the appendix.

# Convolutions on the hidden layers

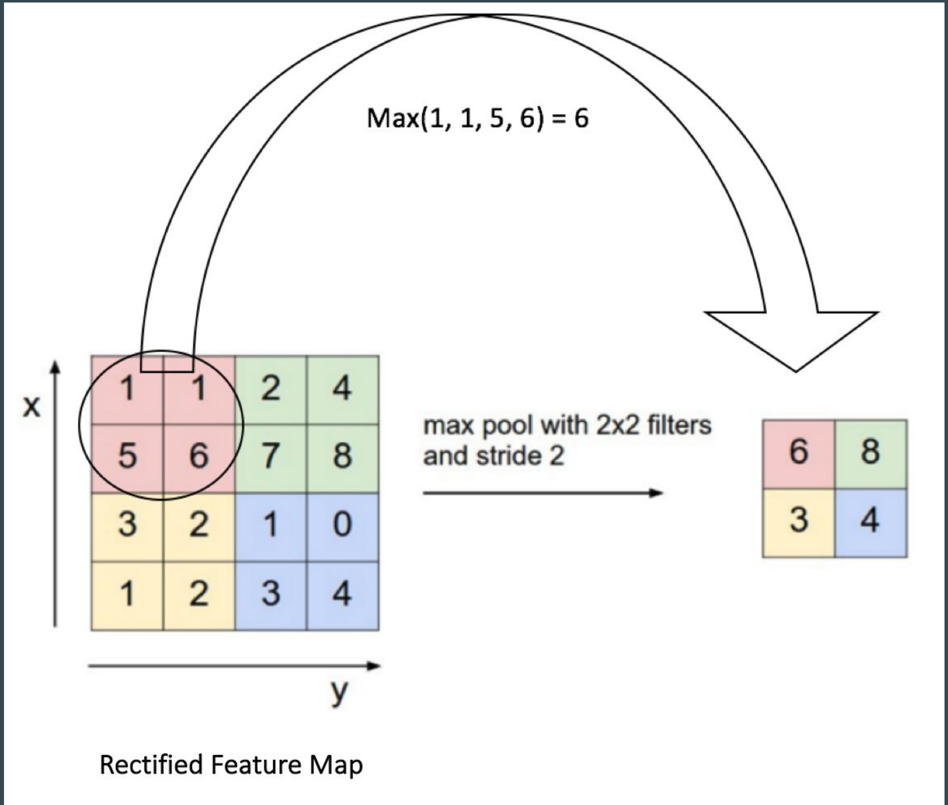


# Strides



# Max Pooling

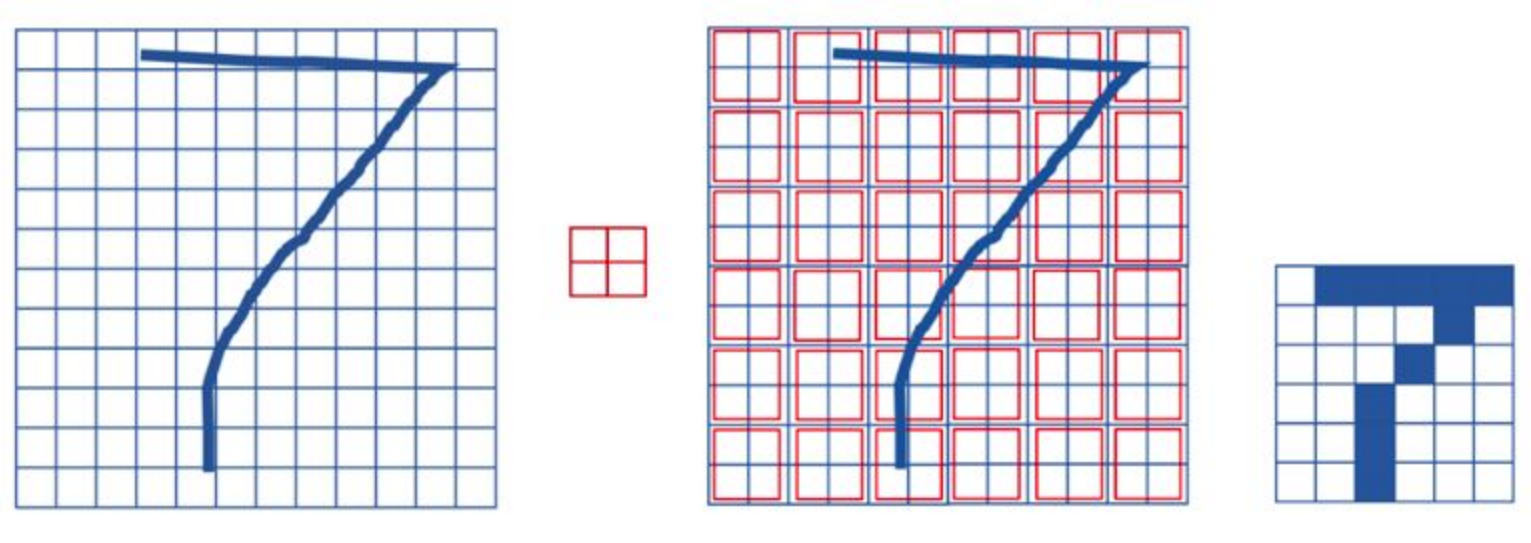



Reduces the dimensionality without losing too much information

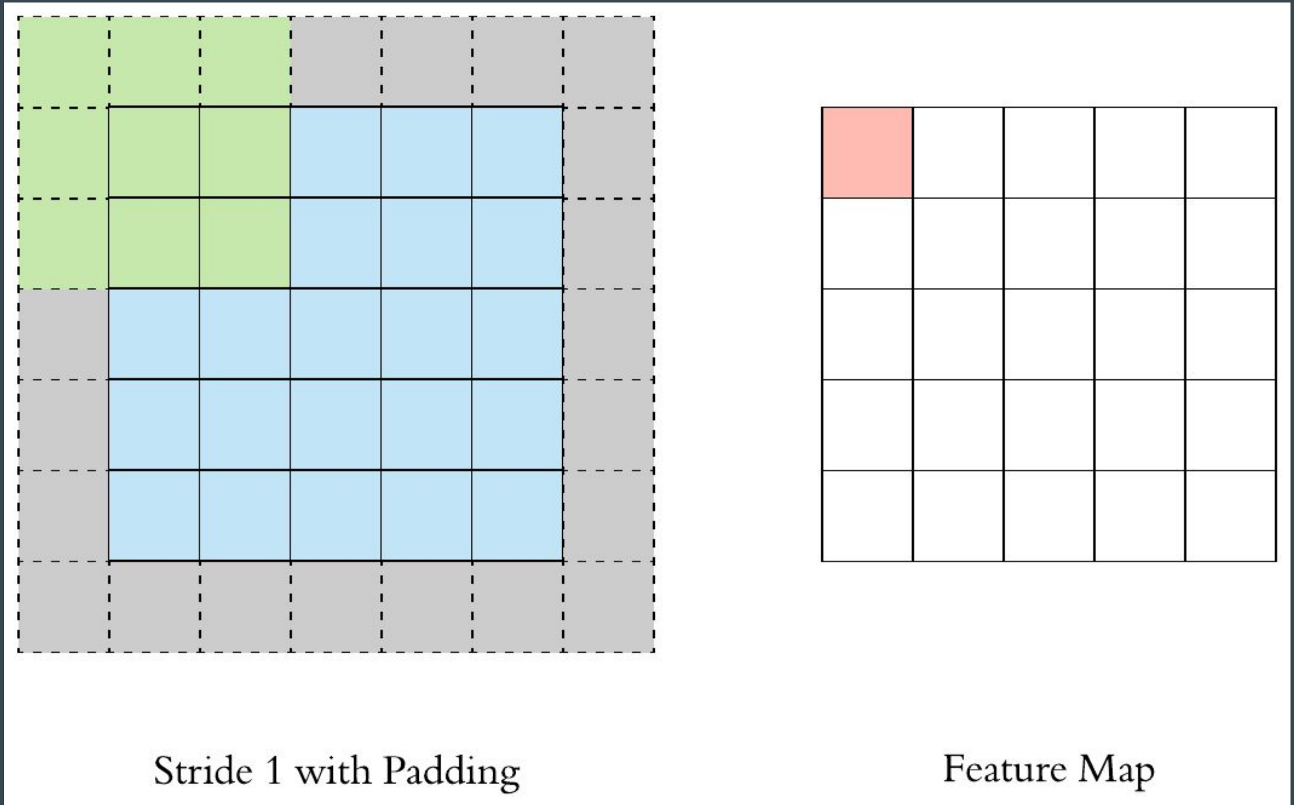
Reduces the number of parameters to train

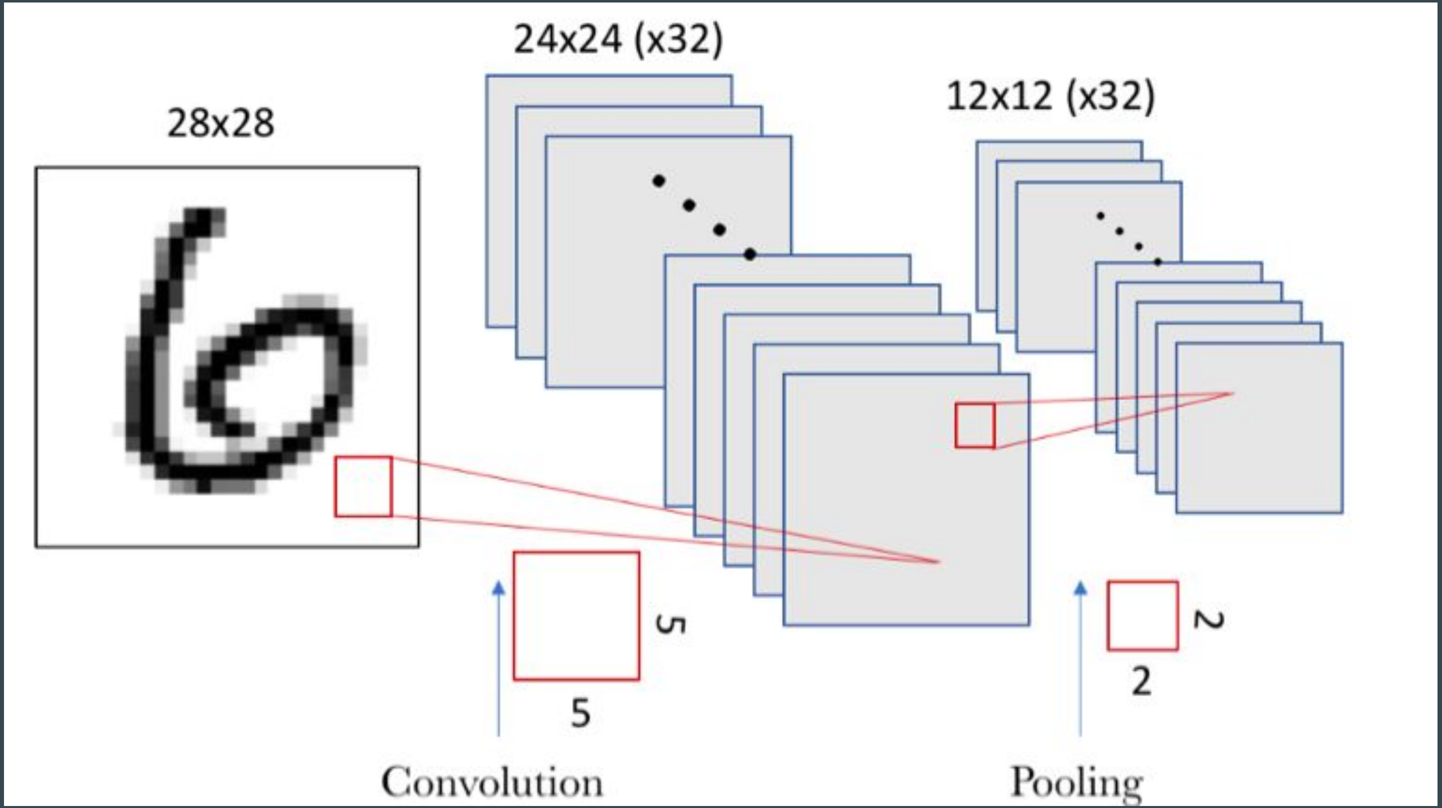
Makes the network invariant to small transformations, distortions and translations

# Max Pooling

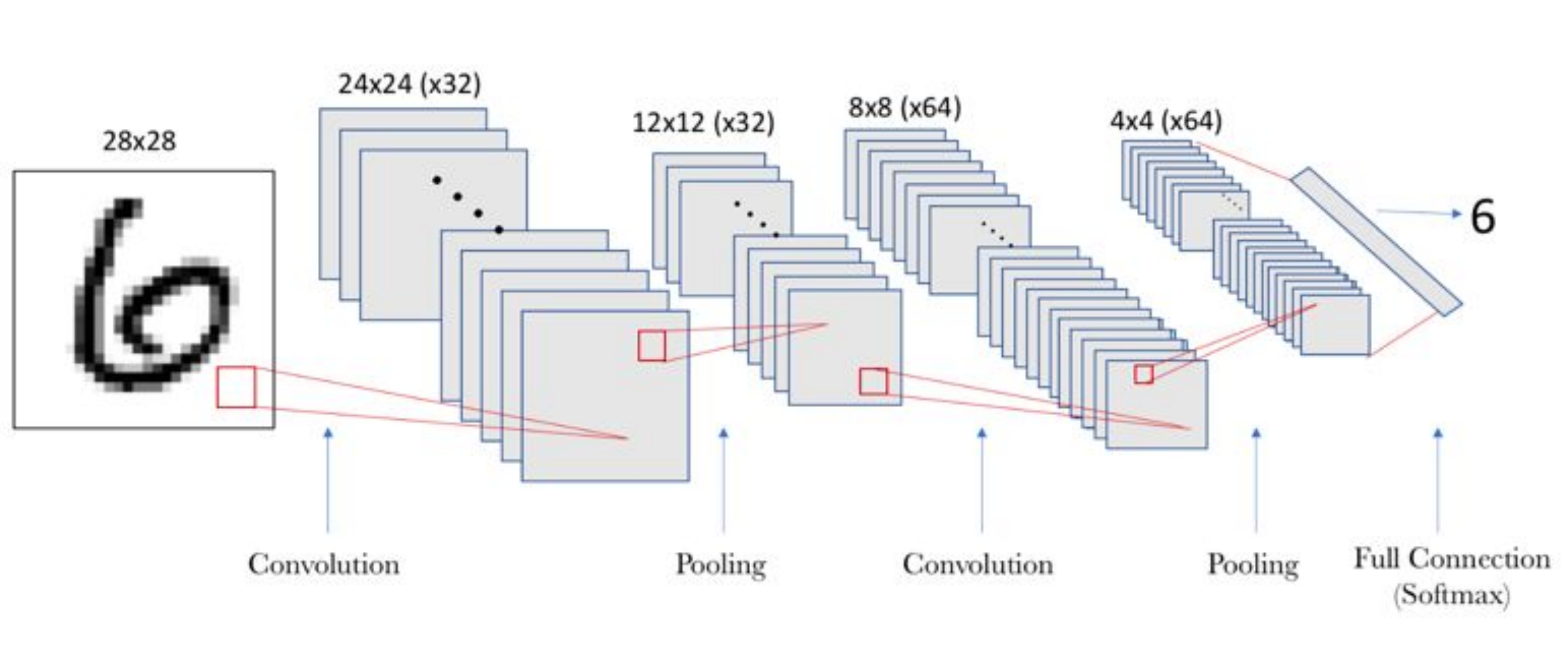


# Padding

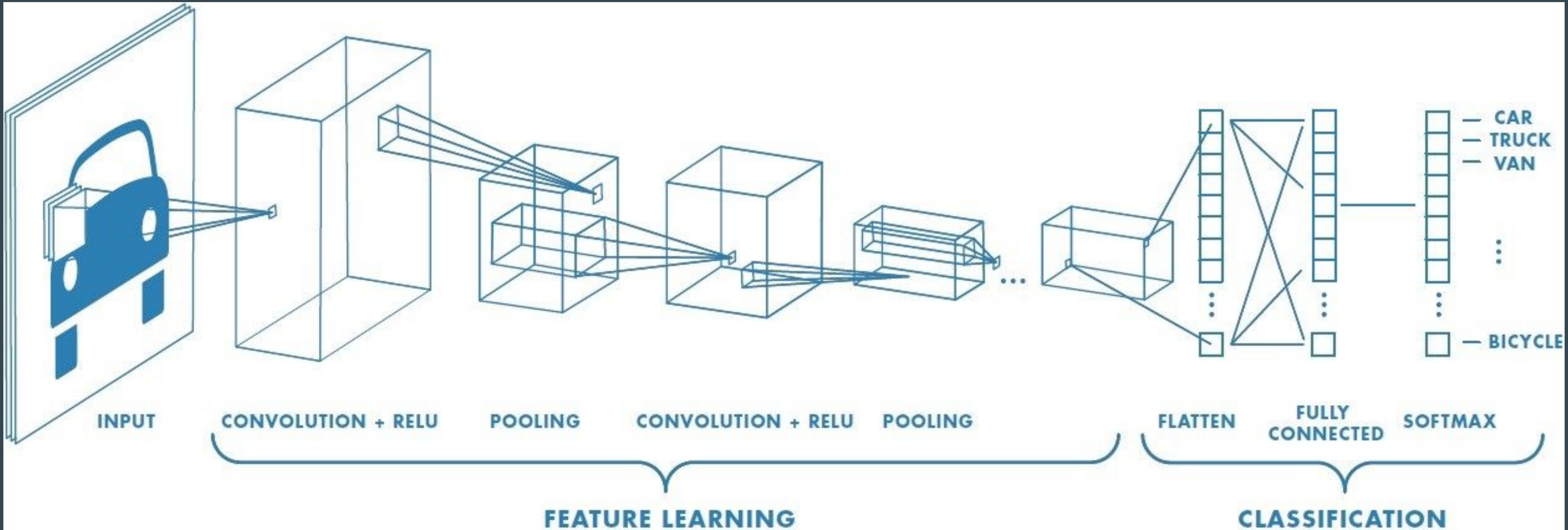


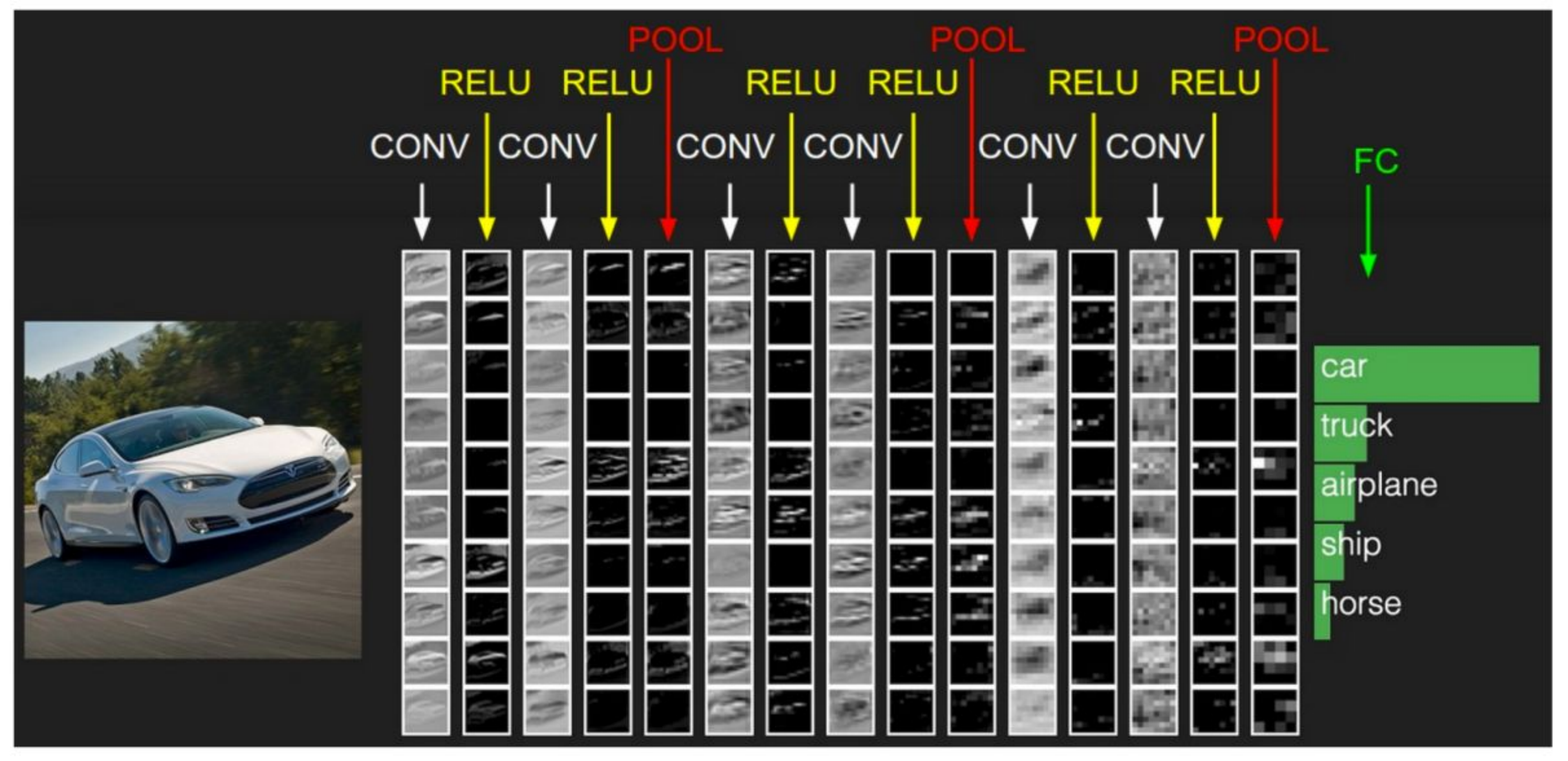

24x24 (x32)
12x12 (x32)
28x28
5
5
2
2
Convolution
Pooling

# Fully connected layer

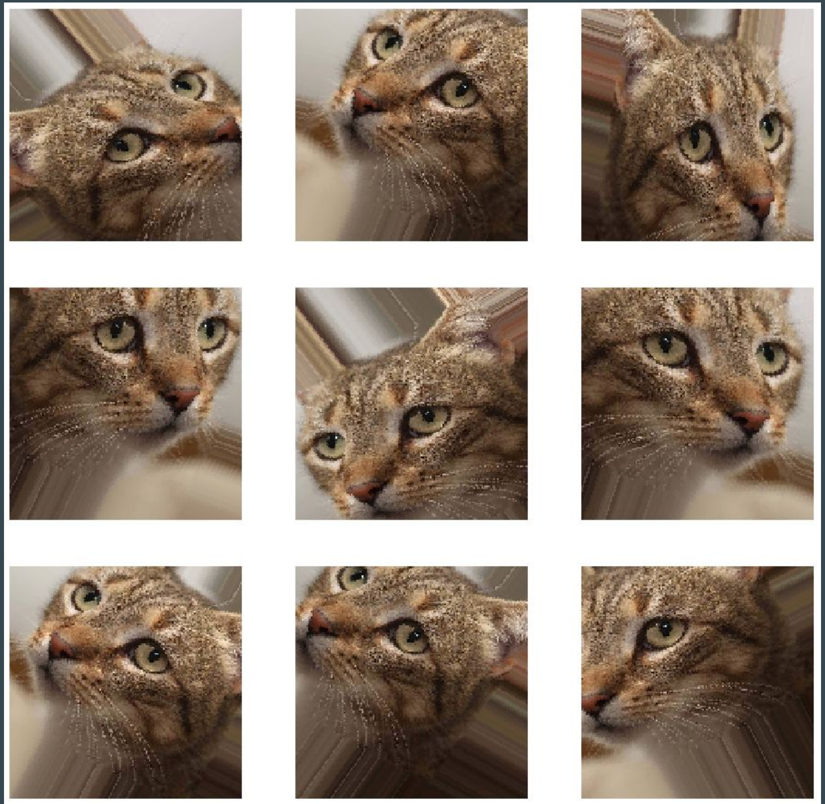


# Piecing it all together




POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

# Data Augmentation



Artificially increases data size

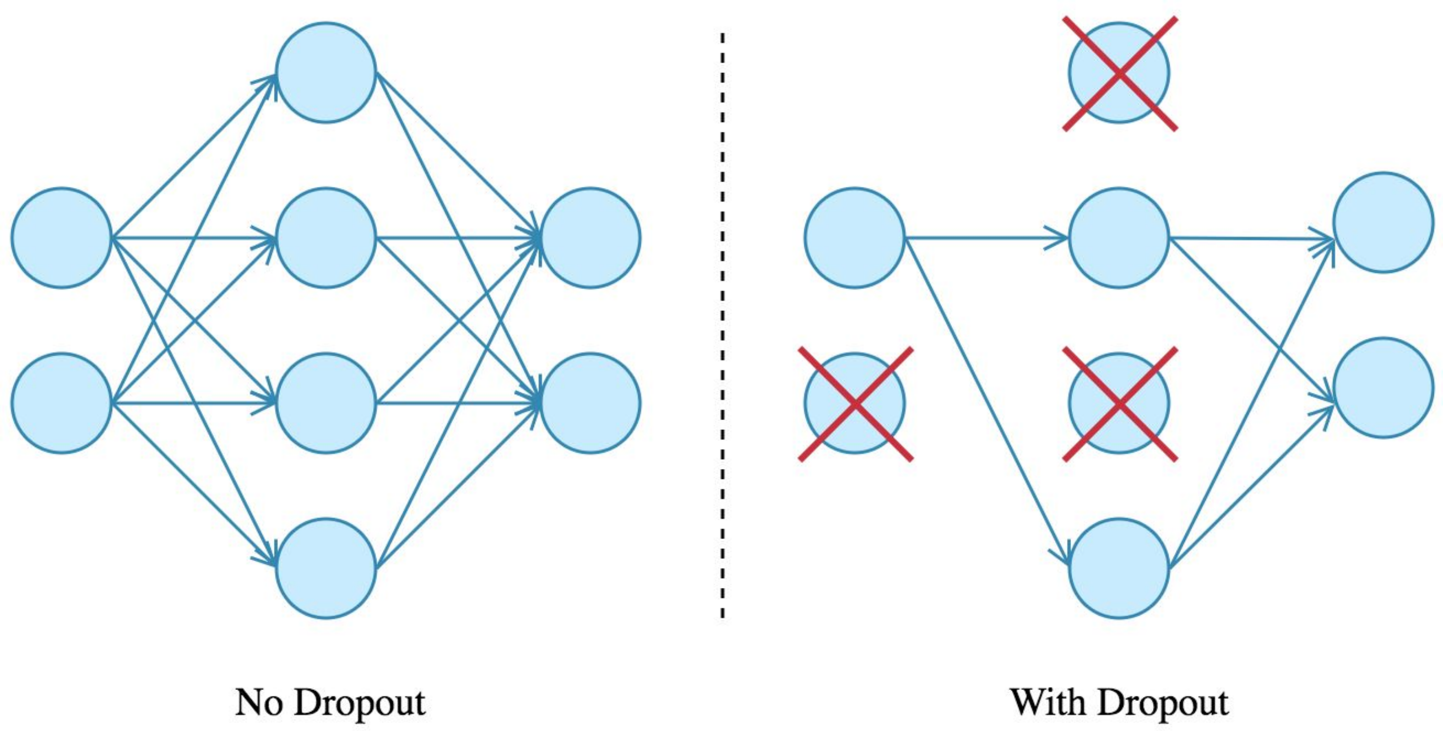
Prevents overfitting

# Dropout

Used for regularisation

Prevents overfitting

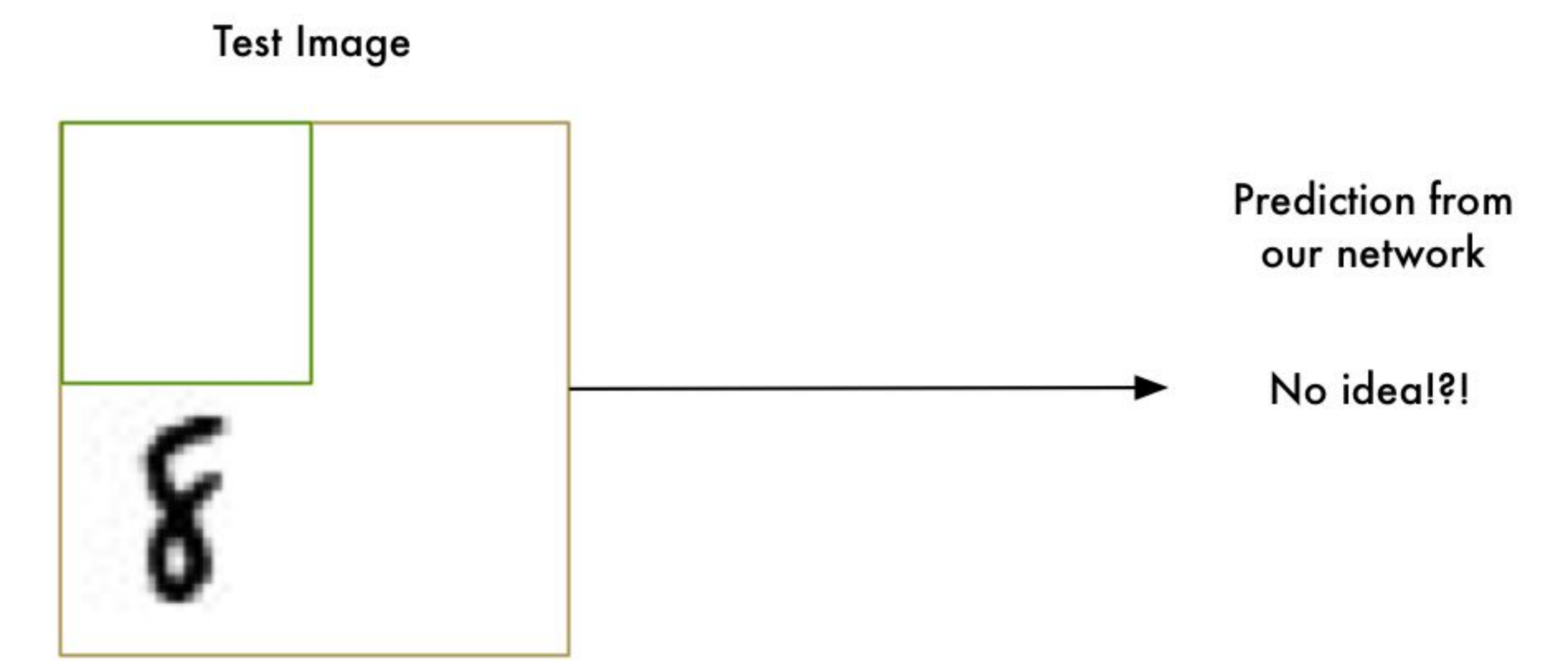
Can be applied to input and hidden layers - not final layer



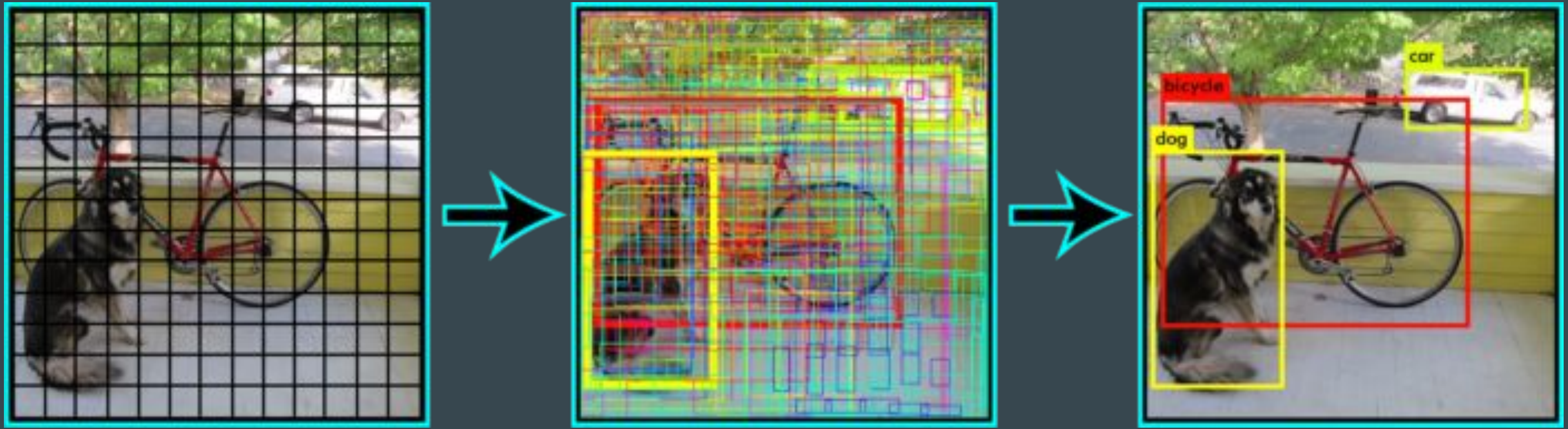
# Example

Online Demo

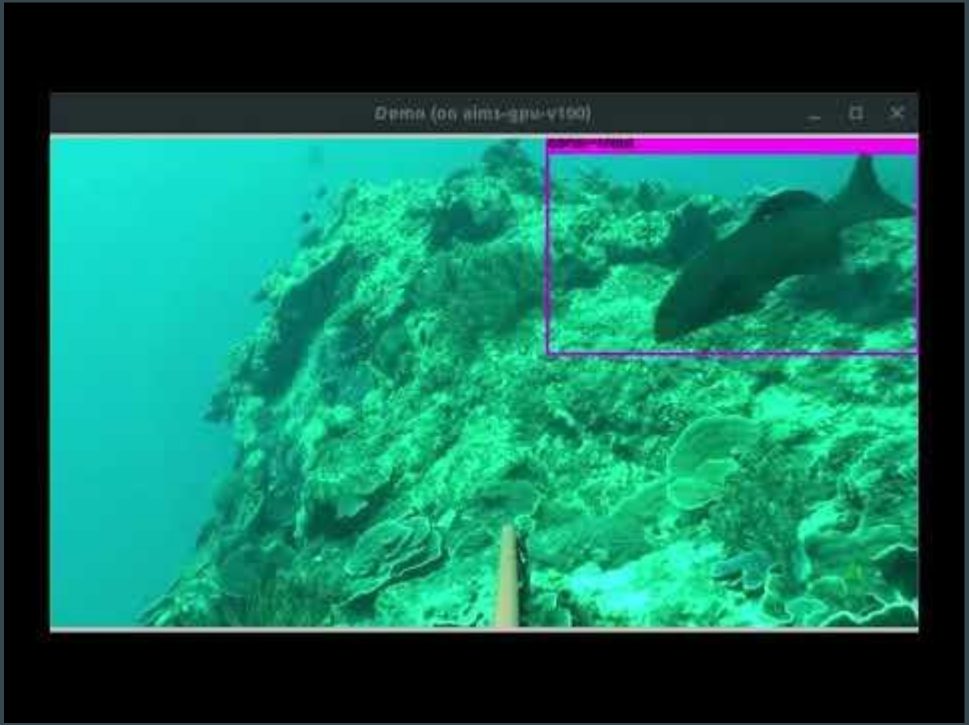
# Object Detection



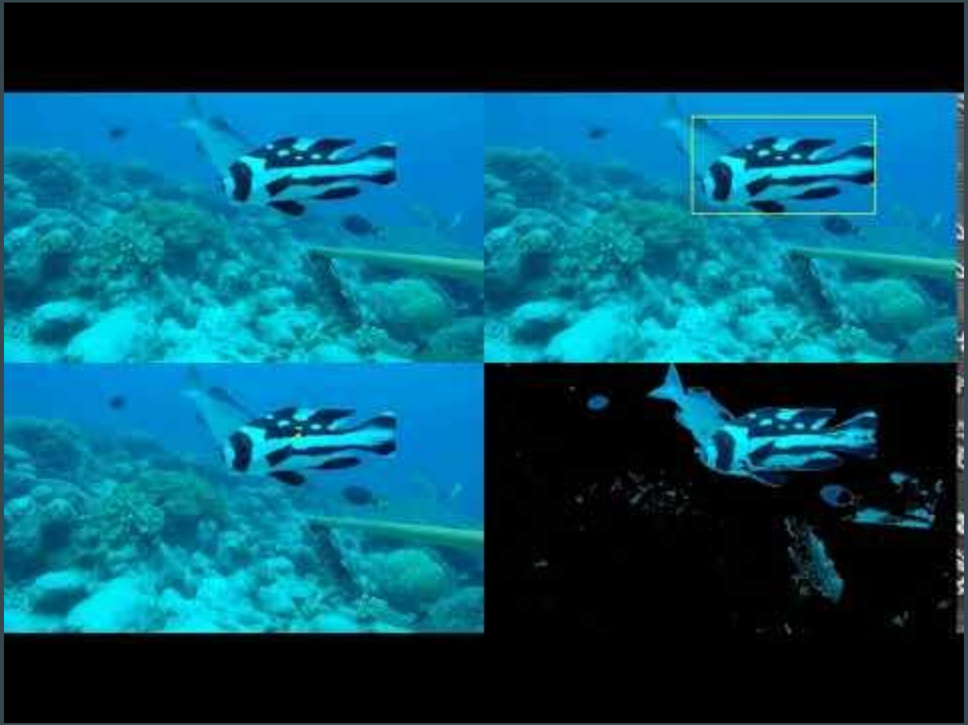
# You Only Look Once - YOLO



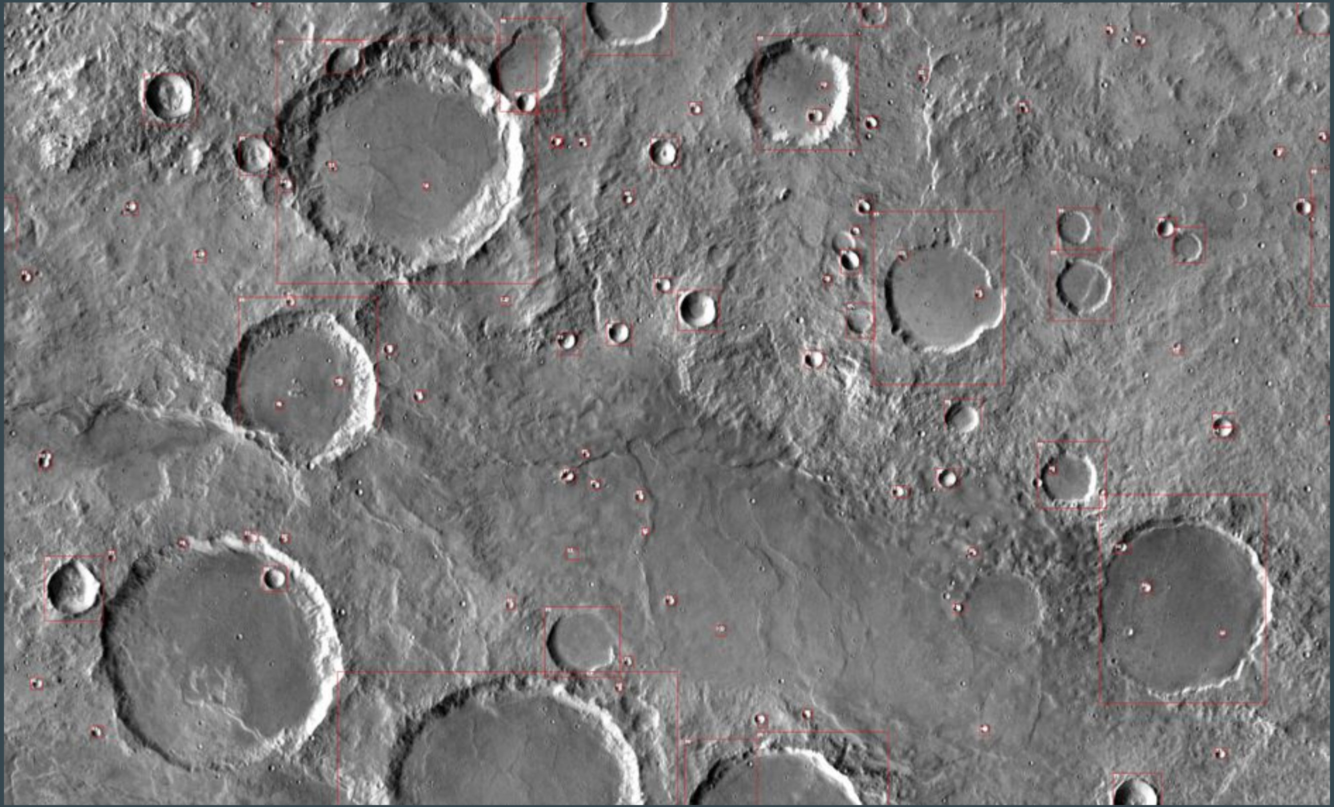
# Examples: Transfer Learning - object detection



# Examples: Image segmentation



# Examples: Counting craters to estimate the age of planetary surfaces



**Research Team:** A/Prof. Gretchen Benedix, A/Prof. Jonathan Paxman, Dr. Martin Towner, Dr. Anthony Lagain, Mr. Chris Norman, Prof. Tele Tan, Prof. Phil Bland

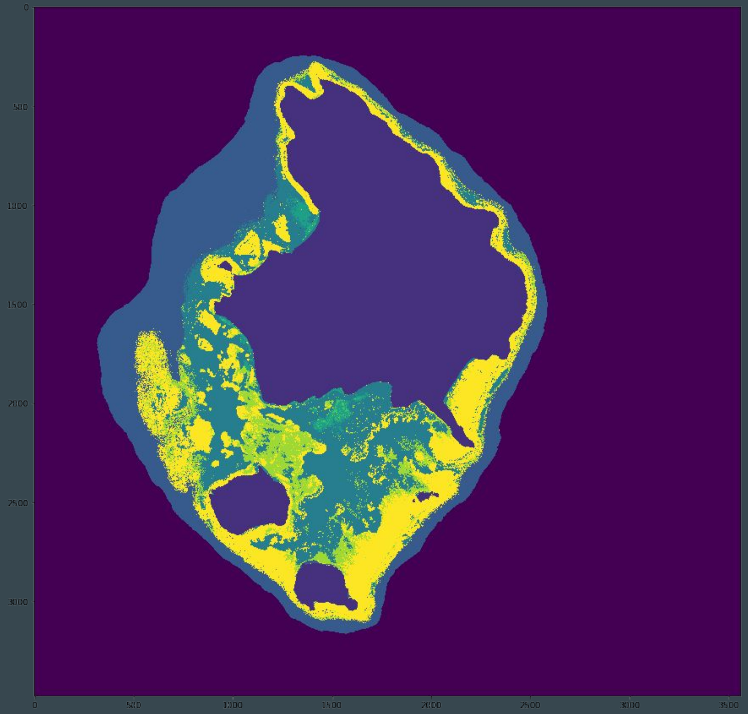
**CIC Specialists:** Dr. Kevin Chai, Shiv Meka

# Examples Rooftop segmentation to estimate urban sprawl

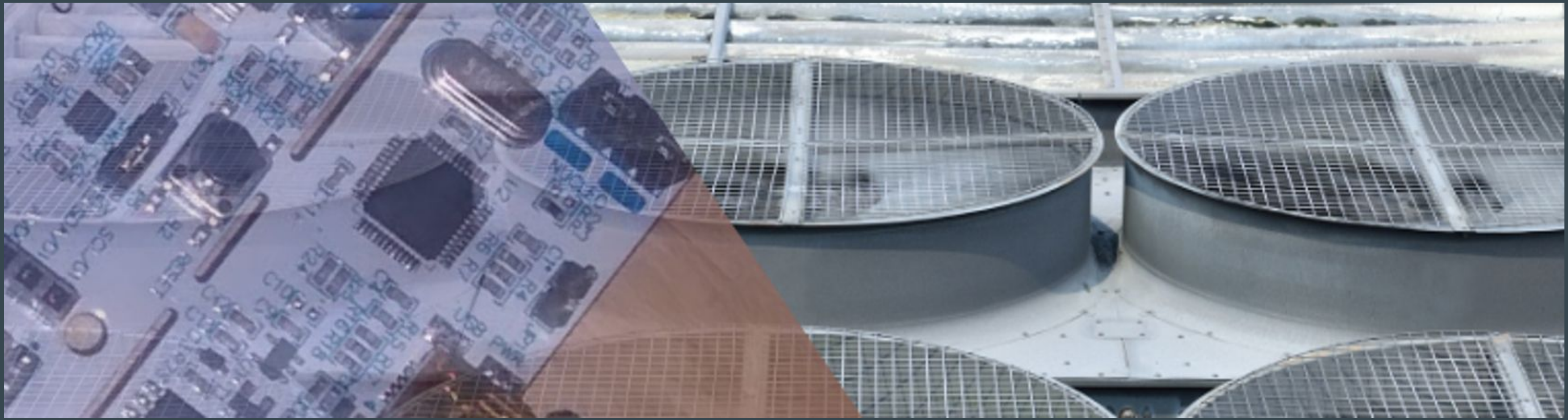
**Research Team:** Peiyu Li, Kexiang Xu, Dr. Mohammad Swapan, Dr. Cecilia Xia

**CIC Specialist:** Shiv Meka

# Examples: Benthic Habitat Mapping



# Detecting faults in Fin Fans from acoustic sensors



**Team:** Dr. Kristofer McKee, Dr. Amir Amin, Prof. Ian Howard, Jack Wiltshire (Cisco), Nathan Jombwe (Cisco)
**CIC specialist:** Shiv Meka

# Web links

- https://towardsdatascience.com/convolutional-neural-networks-for-all-part-i-cdd282ee7947
- https://medium.com/@ageitgey/machine-learning-is-fun-part-3-deep-learning-and-convolutional-neural-networks-f40359318721
- https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2
- http://neuralnetworksanddeeplearning.com/chap5.html
- http://mathworld.wolfram.com/Convolution.html
- https://distill.pub/2017/feature-visualization/