Computer Vision

Convolutional Neural Network

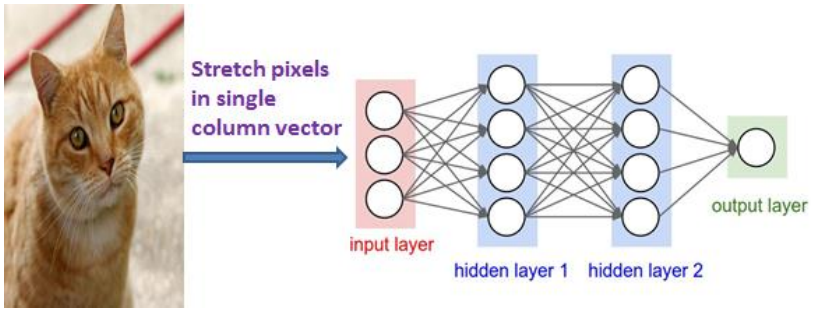
Dr. Mrinmoy Ghorai

Indian Institute of Information Technology

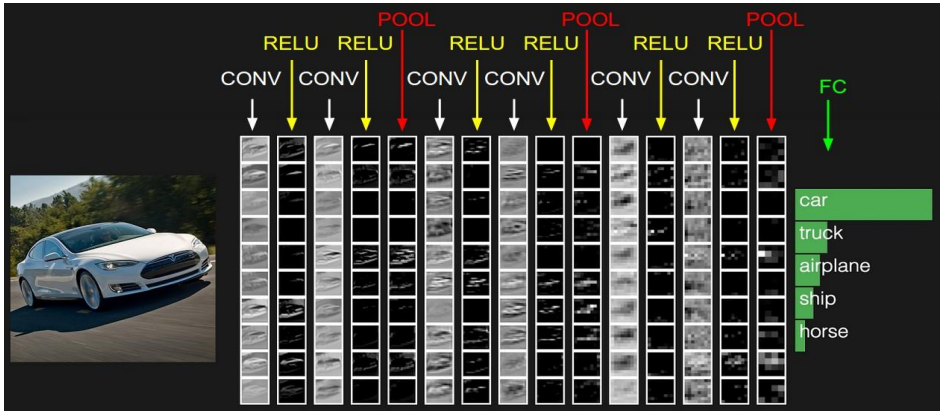
Sri City, Chittoor

This Class

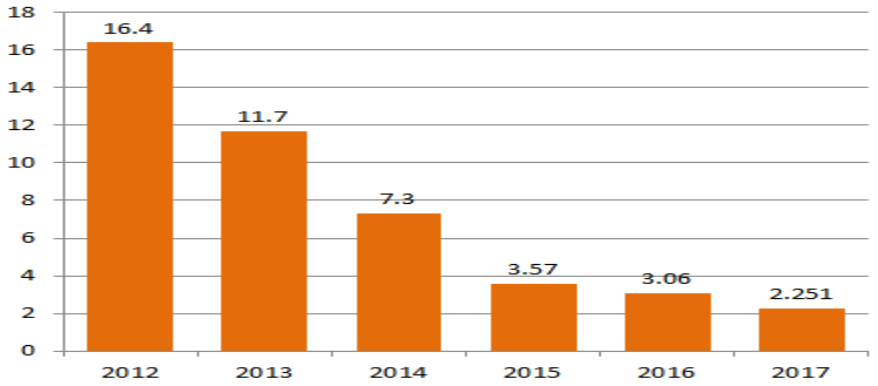
- Neural Network and Image
  - Dimensionality
  - Local relationship



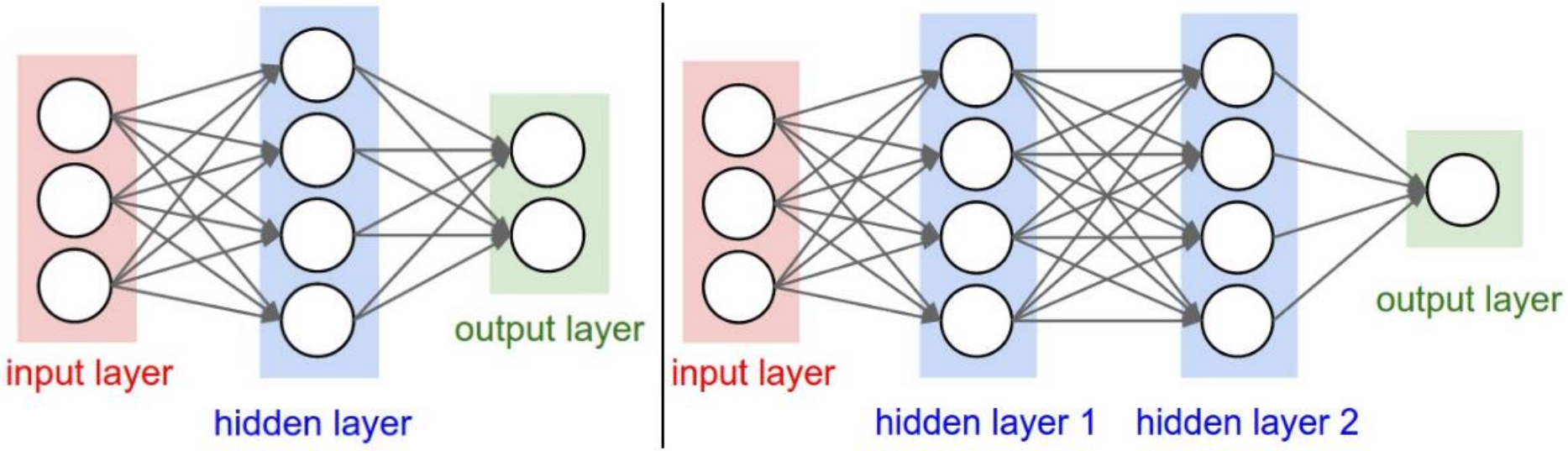
- Convolutional Neural Network (CNN)
  - Convolution Layer
  - Non-linearity Layer
  - Pooling Layer
  - Fully Connected Layer
  - Classification Layer



- ImageNet Challenge
  - Progress
  - Human Level Performance

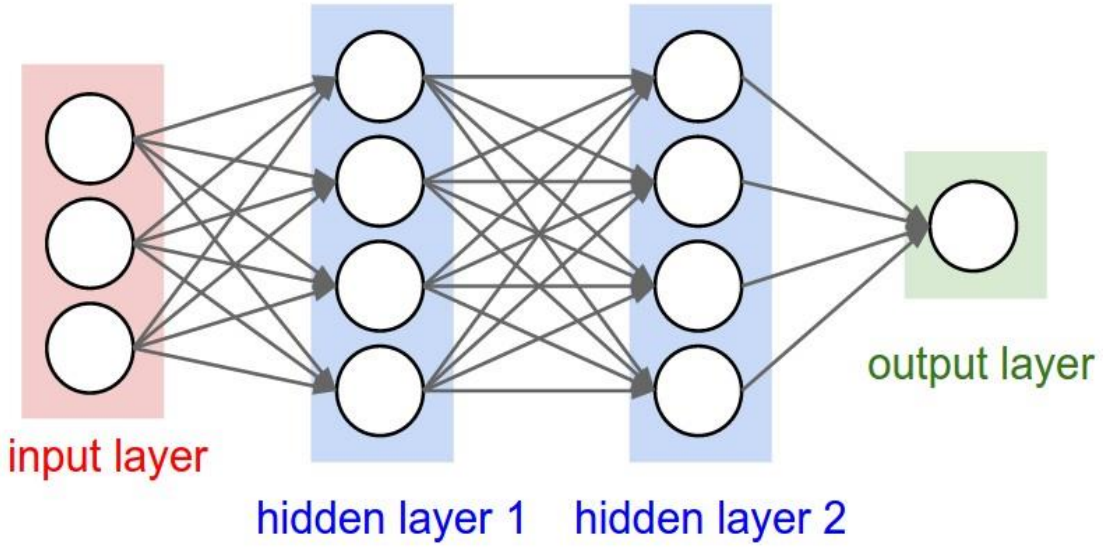


Neural Networks



Source: http://cs231n.github.io

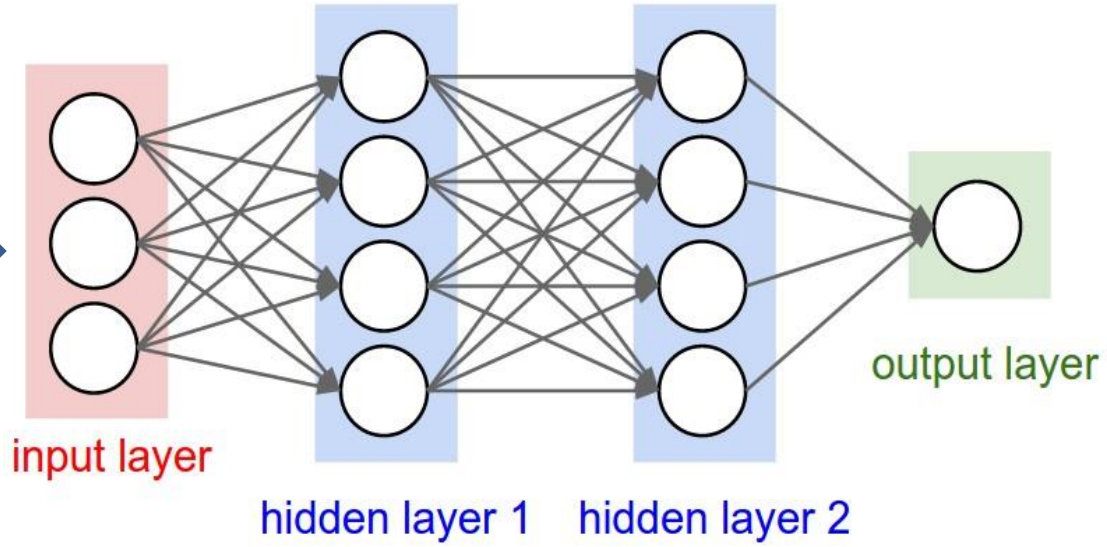
Multi-layer Neural Network & Image



How to apply NN over Image?

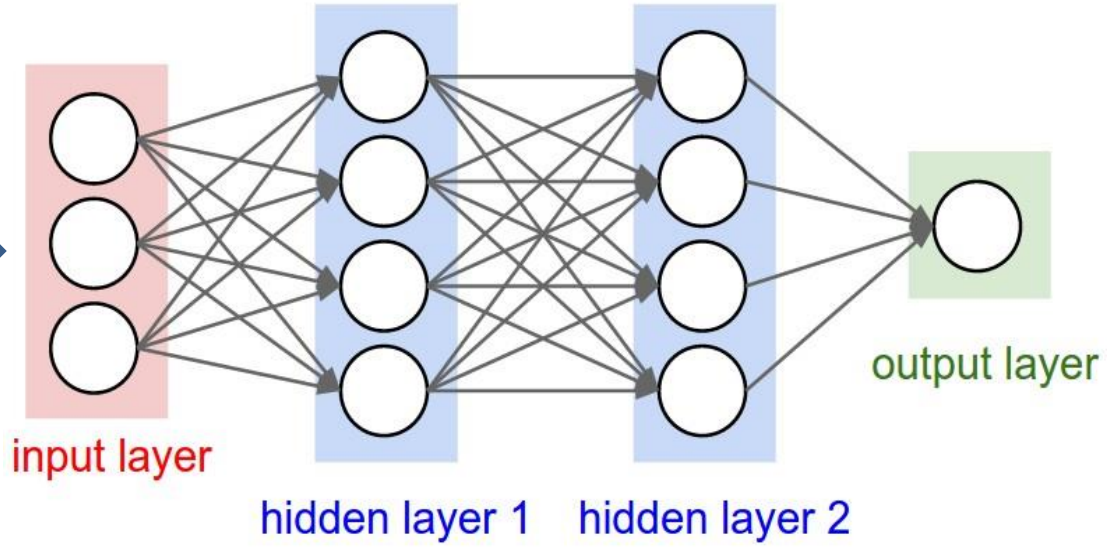
Multi-layer Neural Network & Image

Stretch pixels in single column vector



Multi-layer Neural Network & Image

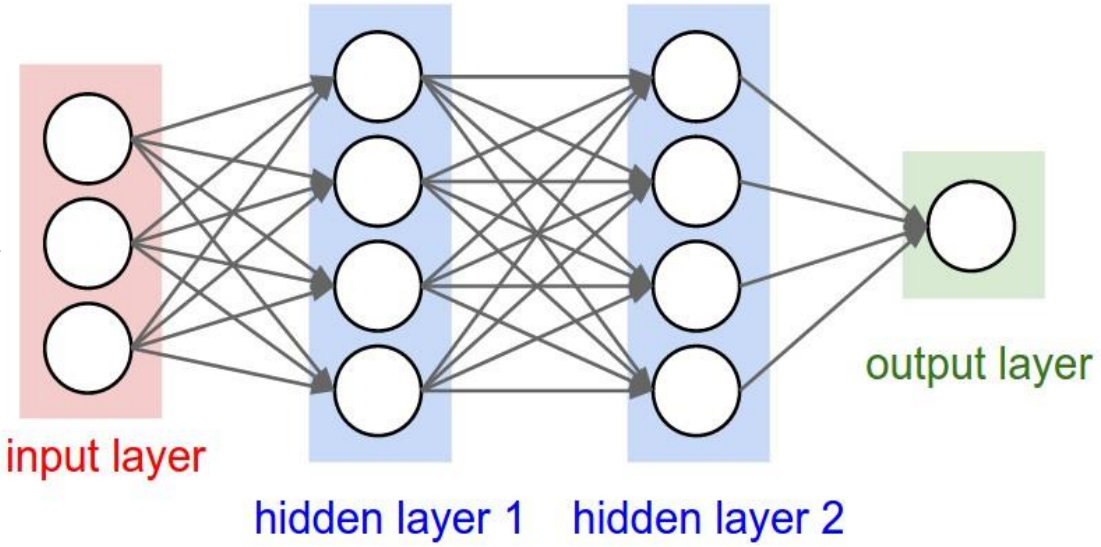
Stretch pixels in single column vector



Problems ?

Multi-layer Neural Network & Image

Stretch pixels in single column vector

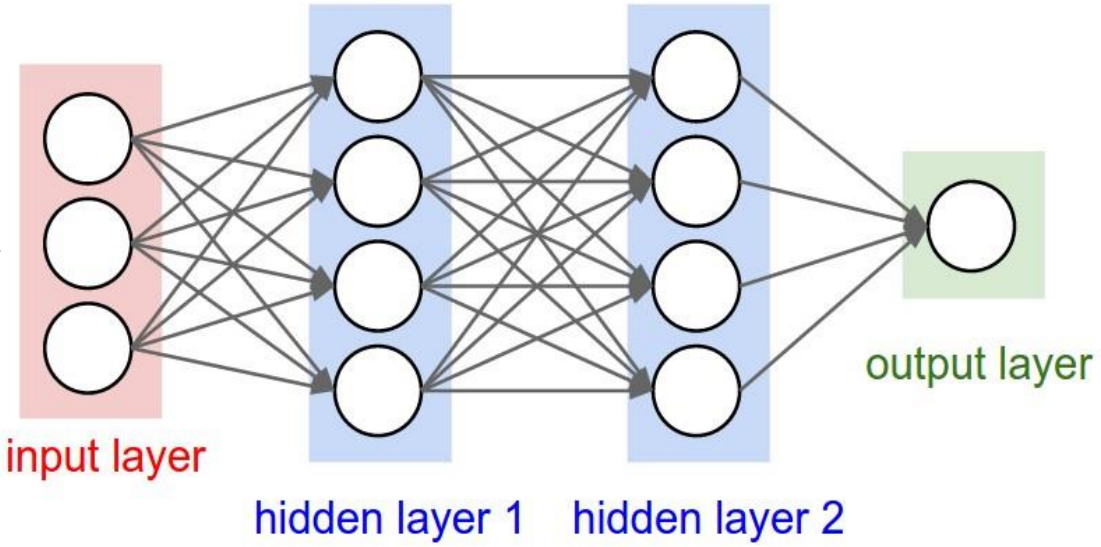


Problems:

- **High dimensionality**
- **Local relationship**

Multi-layer Neural Network & Image

Stretch pixels in single column vector



Problems:

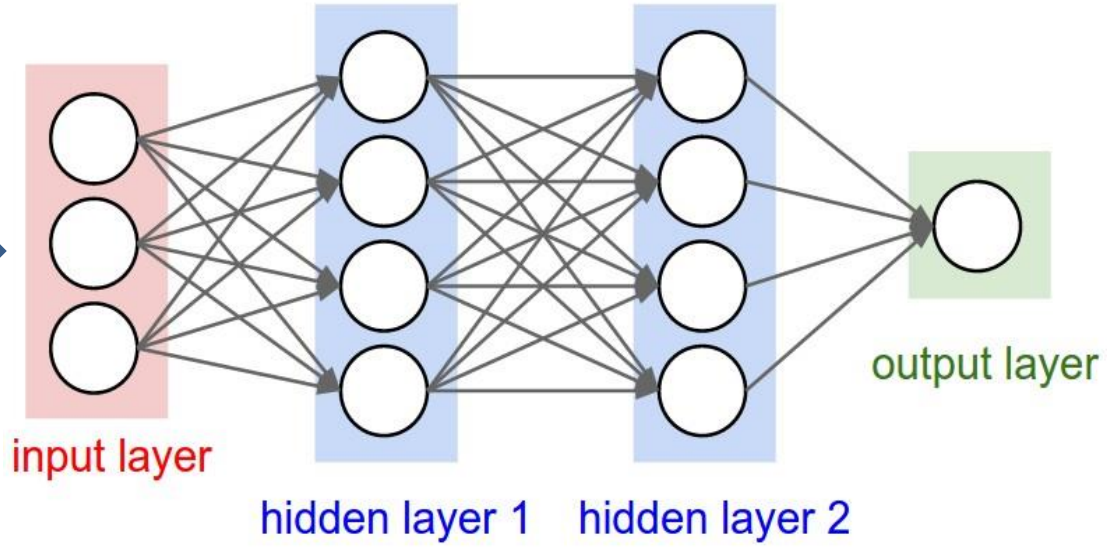
Solution ?

High dimensionality

Local relationship

Multi-layer Neural Network & Image

Stretch pixels in single column vector



Problems:

High dimensionality

Local relationship

Solution:

Convolutional Neural Network

Convolutional Neural Networks

- Also known as

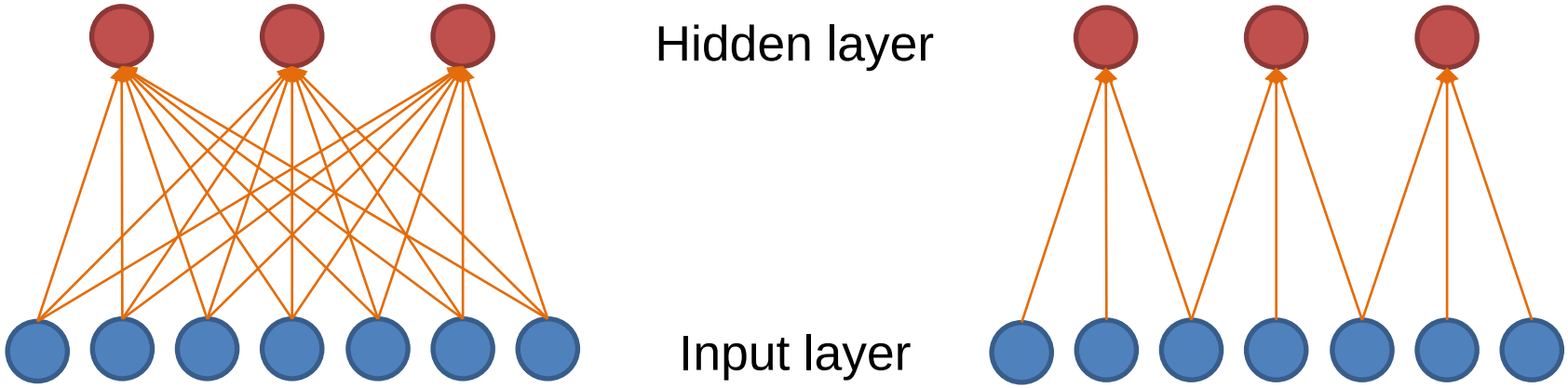
  CNN,

  ConvNet,

  DCN

- CNN = a multi-layer neural network with
  1. Local connectivity
  2. Weight sharing

CNN: Local Connectivity

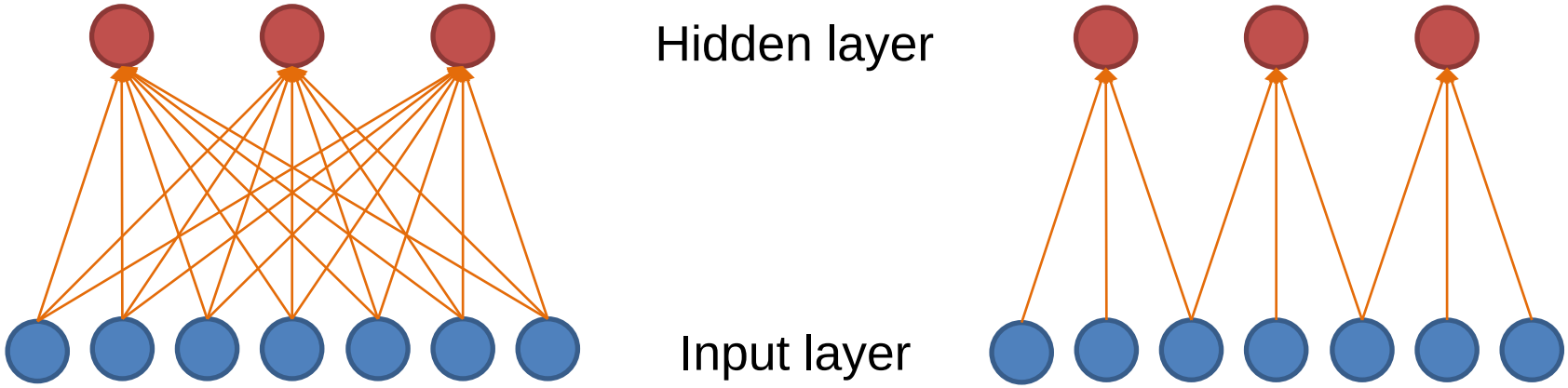


Global connectivity

Local connectivity

- # input units (neurons): 7
- # hidden units: 3

CNN: Local Connectivity

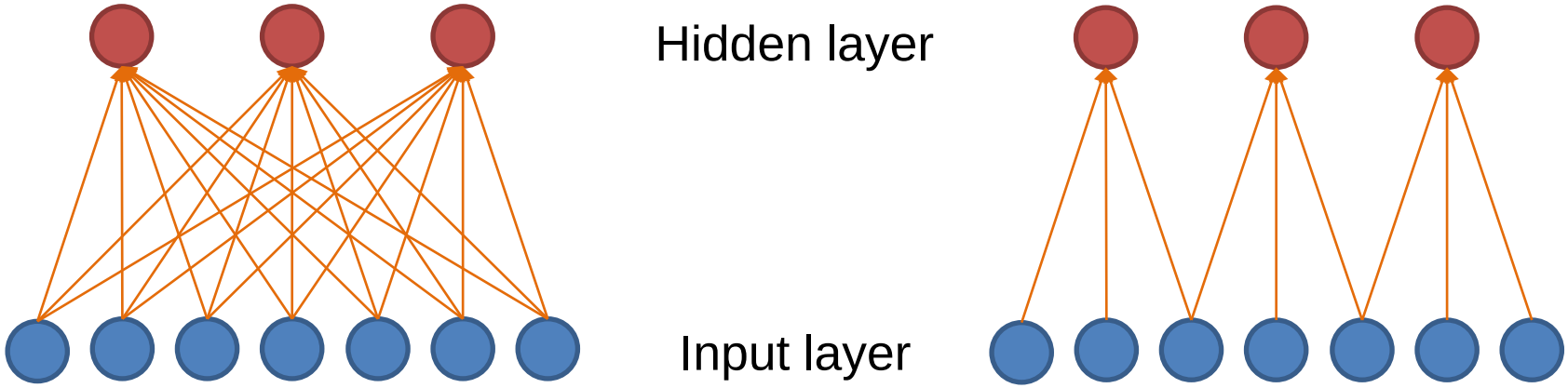


Global connectivity

Local connectivity

- # input units (neurons): 7
- # hidden units: 3
- **Number of parameters**
  - Global connectivity: ?
  - Local connectivity: ?

CNN: Local Connectivity

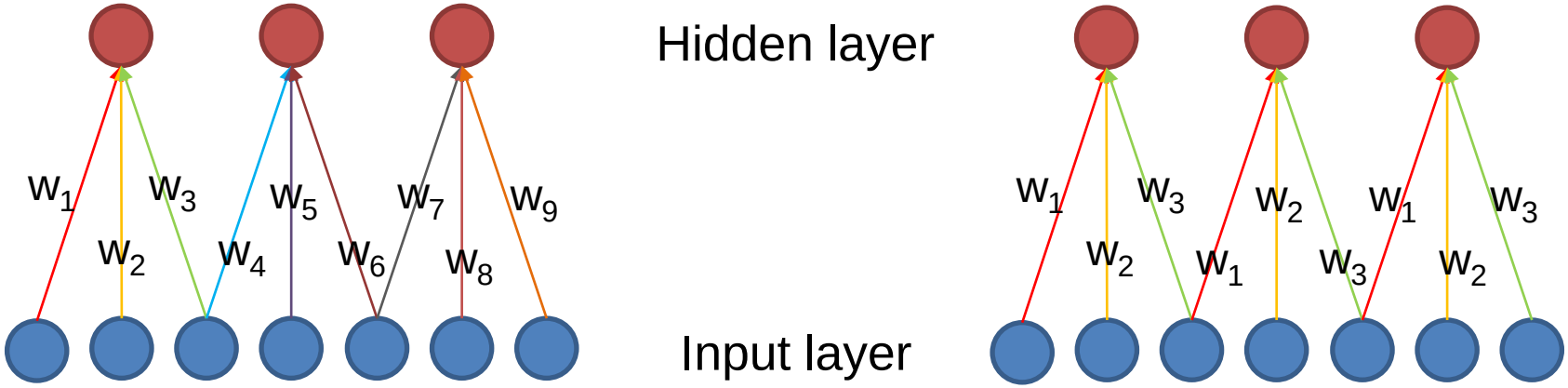


Global connectivity

Local connectivity

- # input units (neurons): 7
- # hidden units: 3
- **Number of parameters**
  - Global connectivity: **3 x 7 = 21**
  - Local connectivity: **3 x 3 = 9**

CNN: Weight Sharing

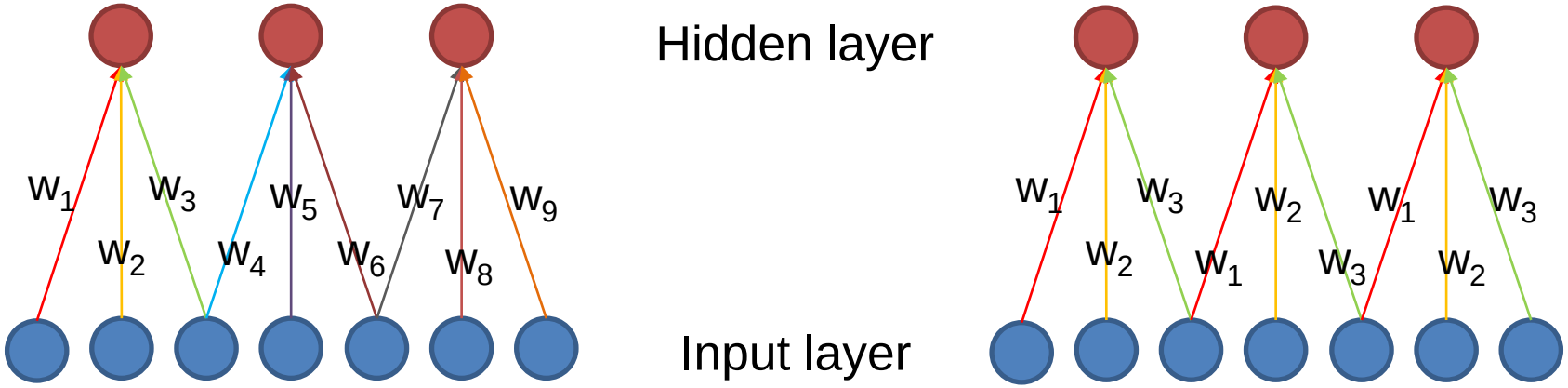


Without weight sharing

With weight sharing

- # input units (neurons): 7
- # hidden units: 3

CNN: Weight Sharing

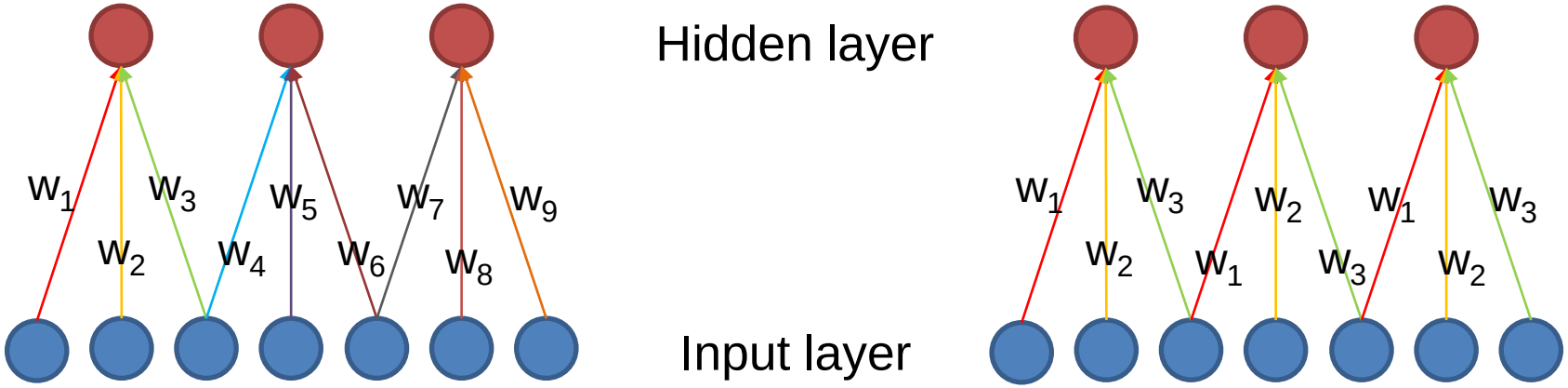


Without weight sharing

With weight sharing

- # input units (neurons): 7
- # hidden units: 3
- **Number of parameters**
  - Without weight sharing: ?
  - With weight sharing : ?

CNN: Weight Sharing

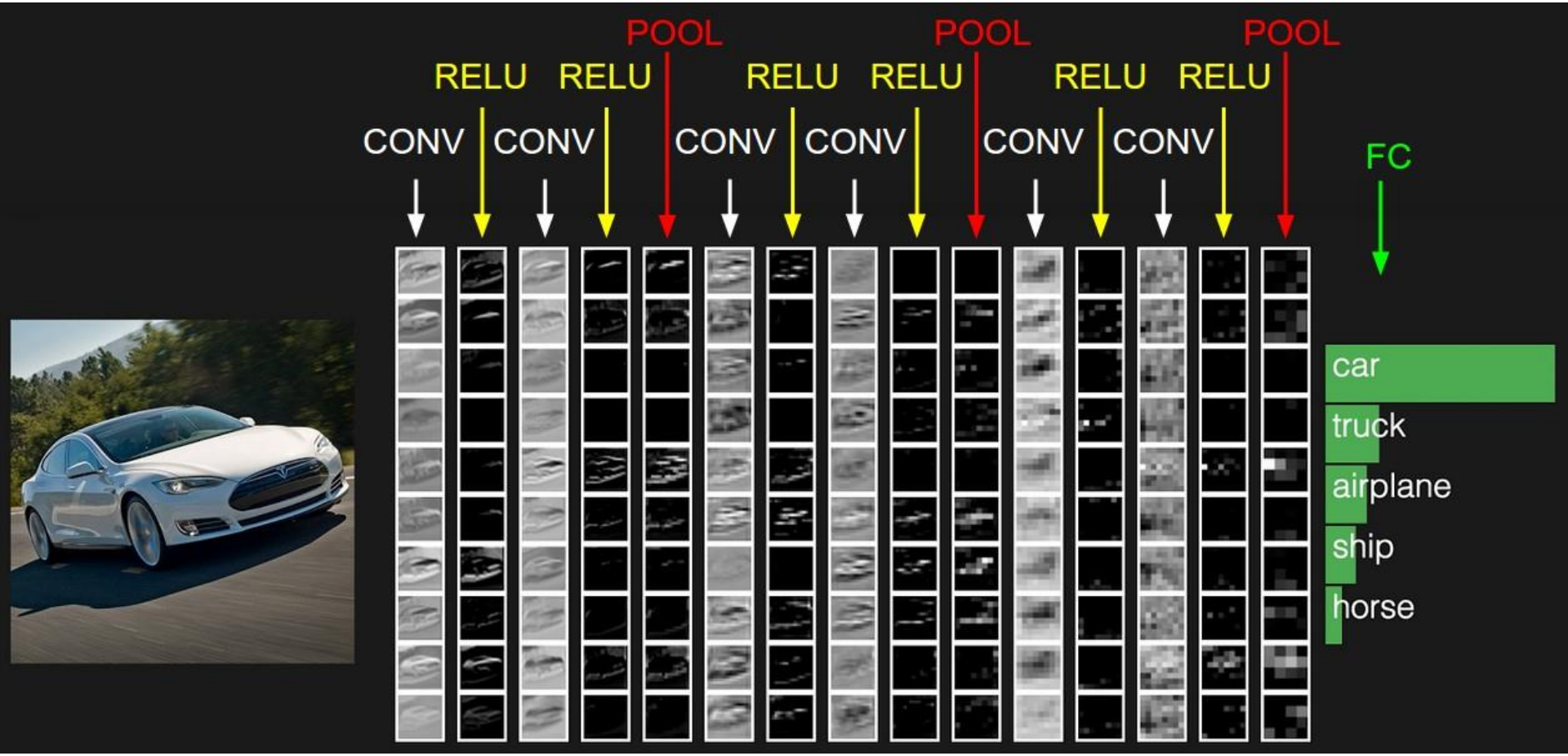


Without weight sharing

With weight sharing

- # input units (neurons): 7
- # hidden units: 3
- **Number of parameters**
  - Without weight sharing: **3 x 3 = 9**
  - With weight sharing : **3 x 1 = 3**

Convolutional Neural Networks



Source: cs231n, Stanford University

Layers used to build ConvNets

Input Layer (Input image)

Convolutional Layer

Non-linearity Layer (such as Sigmoid, Tanh, ReLU, PReLU, ELU, Swish, etc.)

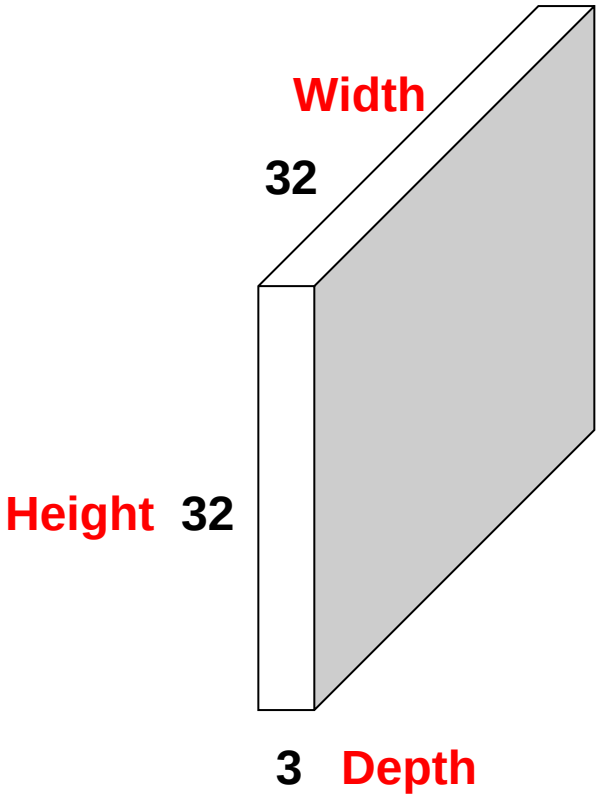
Pooling Layer (such as Max Pooling, Average Pooling, etc.)

Fully-Connected Layer

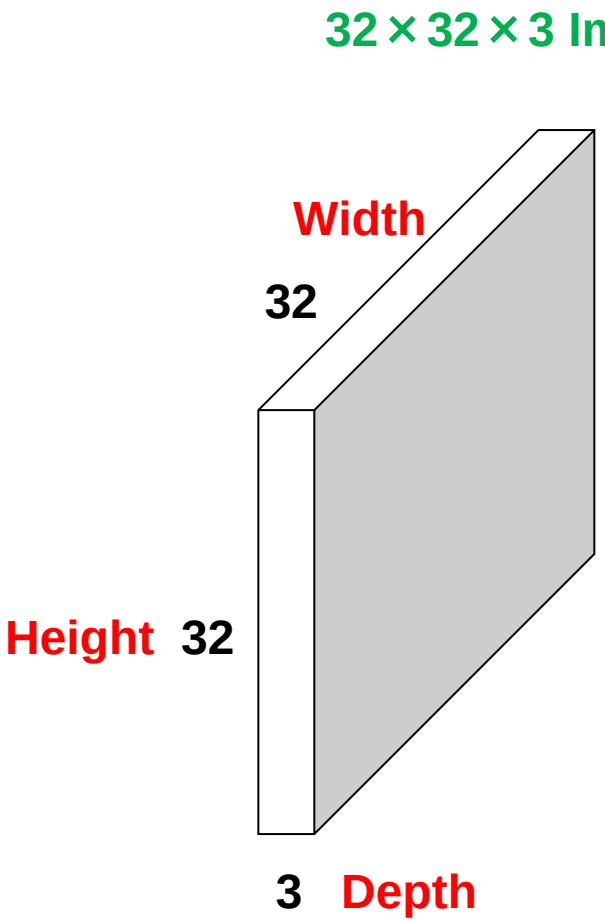
Classification Layer (Softmax, etc.)

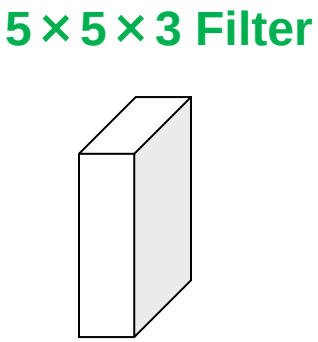
Convolutional Layer

32 × 32 × 3 Image -> preserve spatial structure



Convolutional Layer





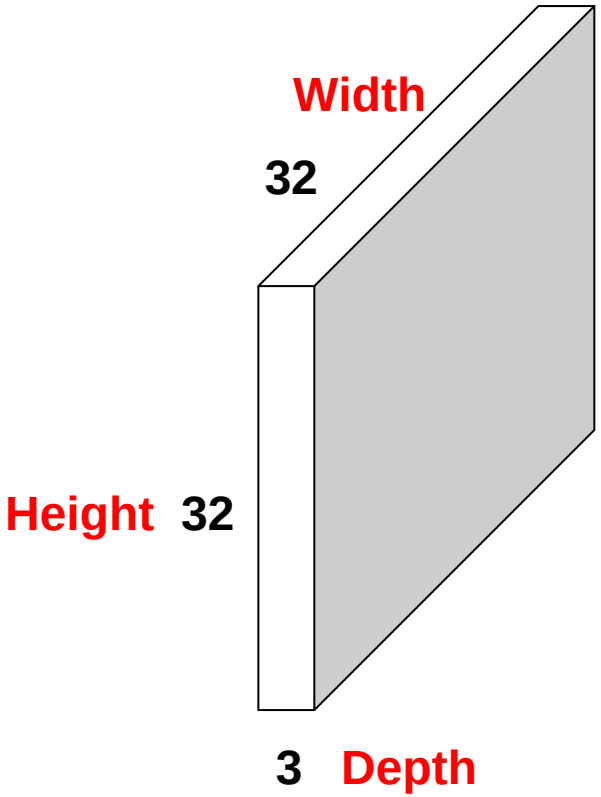
Convolve the filter with the image i.e. "slide over the image spatially, computing dot products"

Convolutional Layer

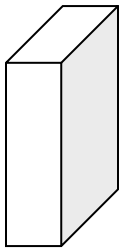
Handling multiple input channels

Filters always extend the full depth of the input volume

32 × 32 × 3 Image

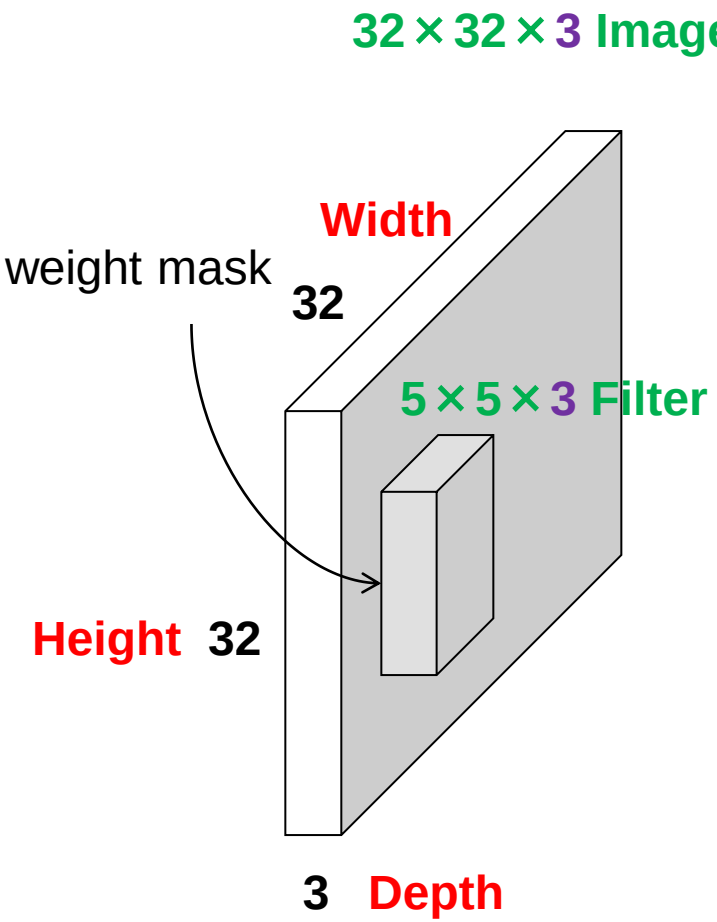


5 × 5 × 3 Filter

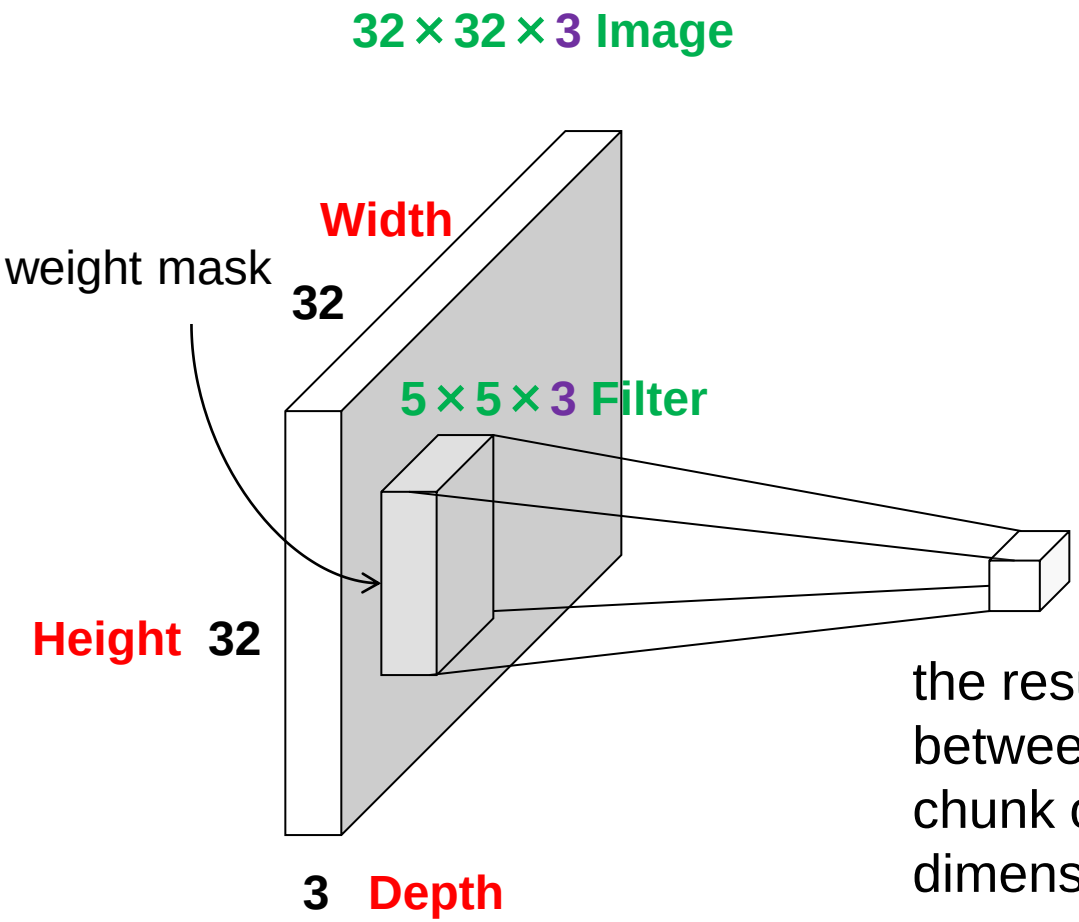


Convolve the filter with the image i.e. "slide over the image spatially, computing dot products"

Convolutional Layer



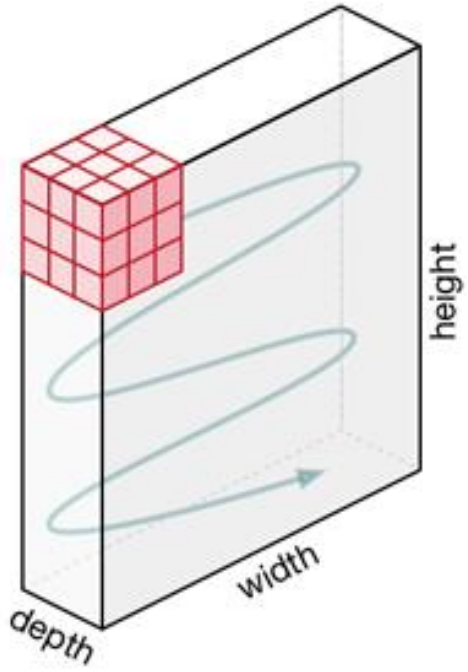
Convolutional Layer



the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T.x + b$$

Convolutional Layer



32 × 32 × 3 Image

weight mask

Width

32

5 × 5 × 3 Filter

A single value

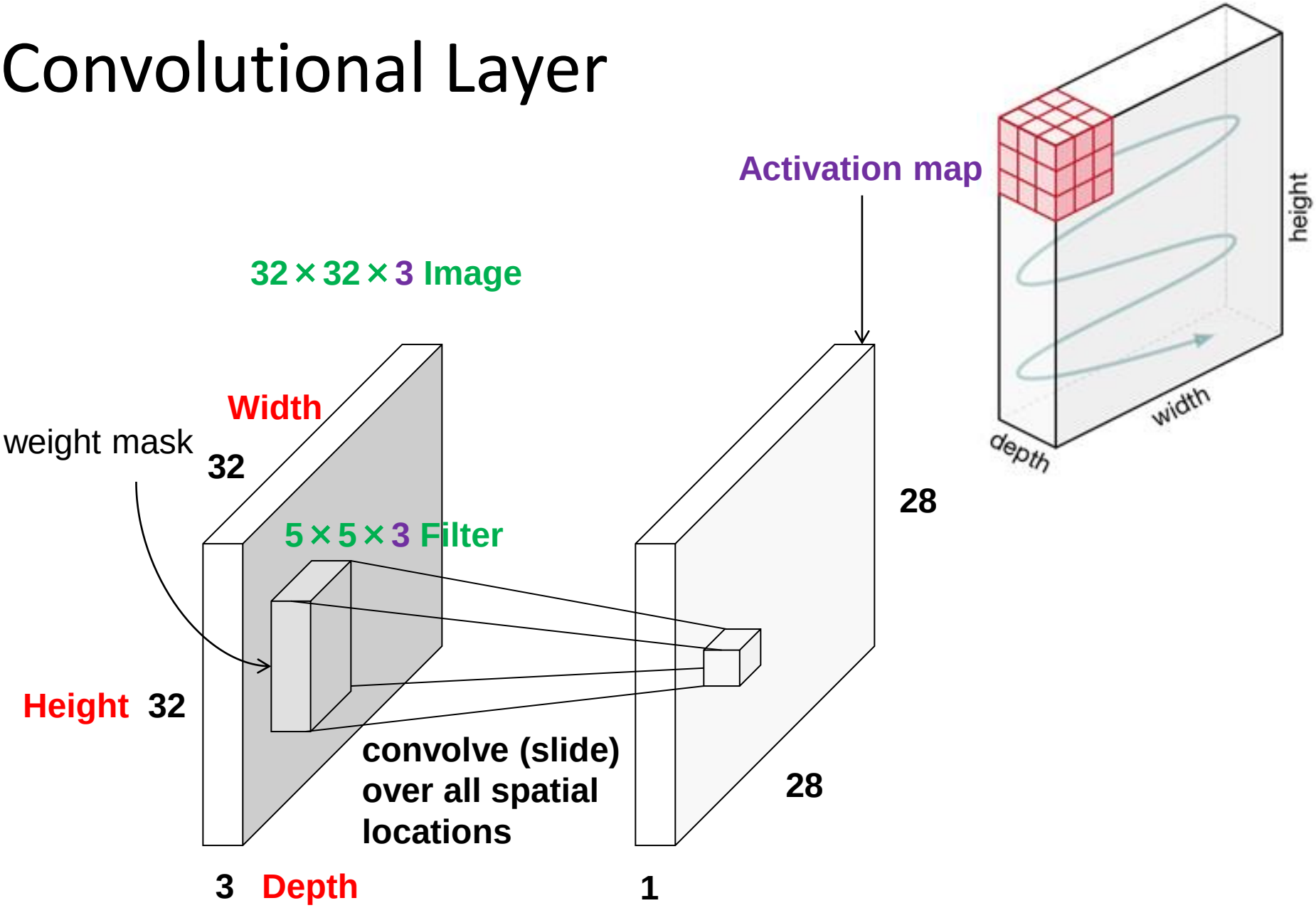
Height 32

3 Depth

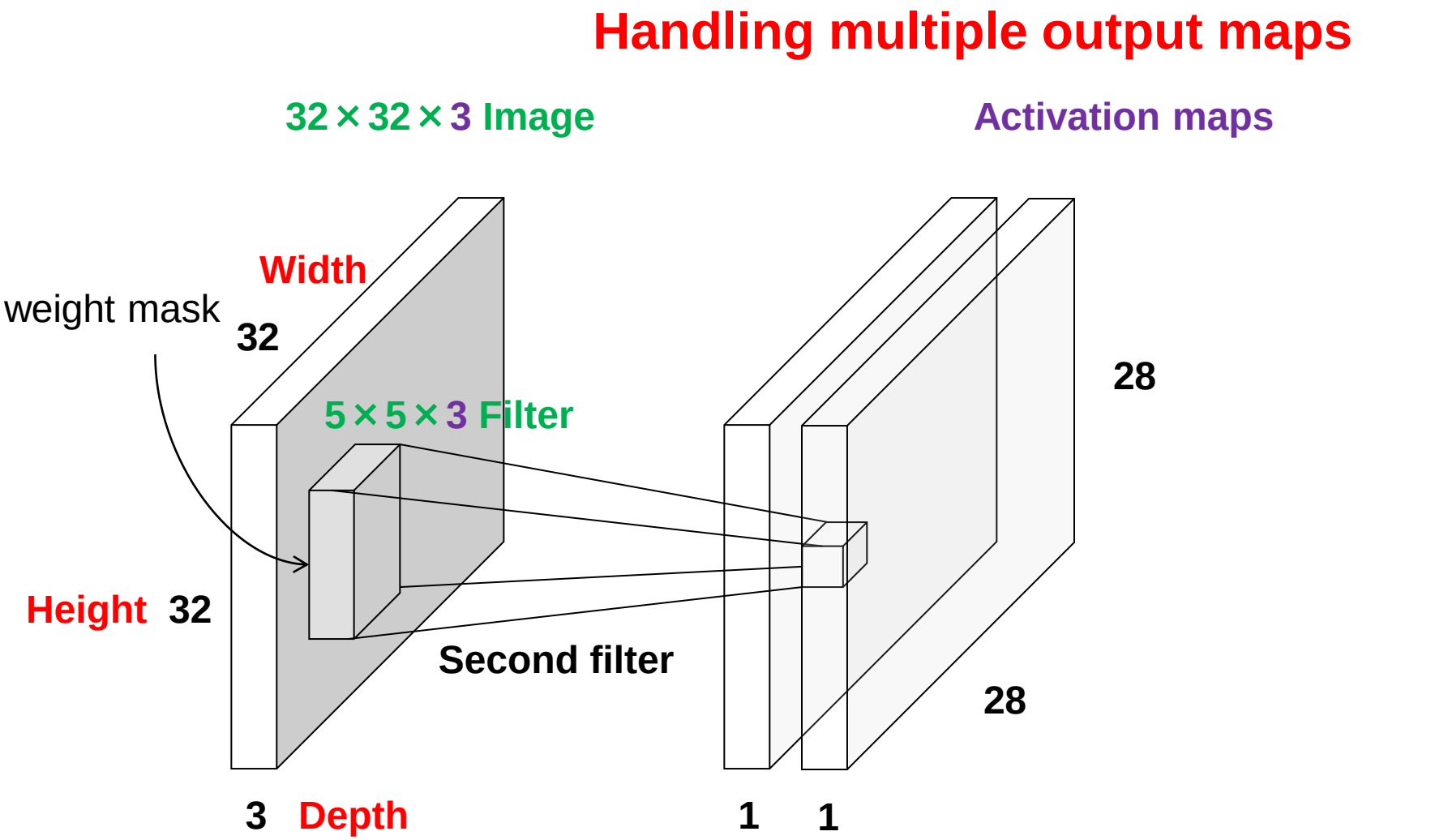
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T.x + b$$

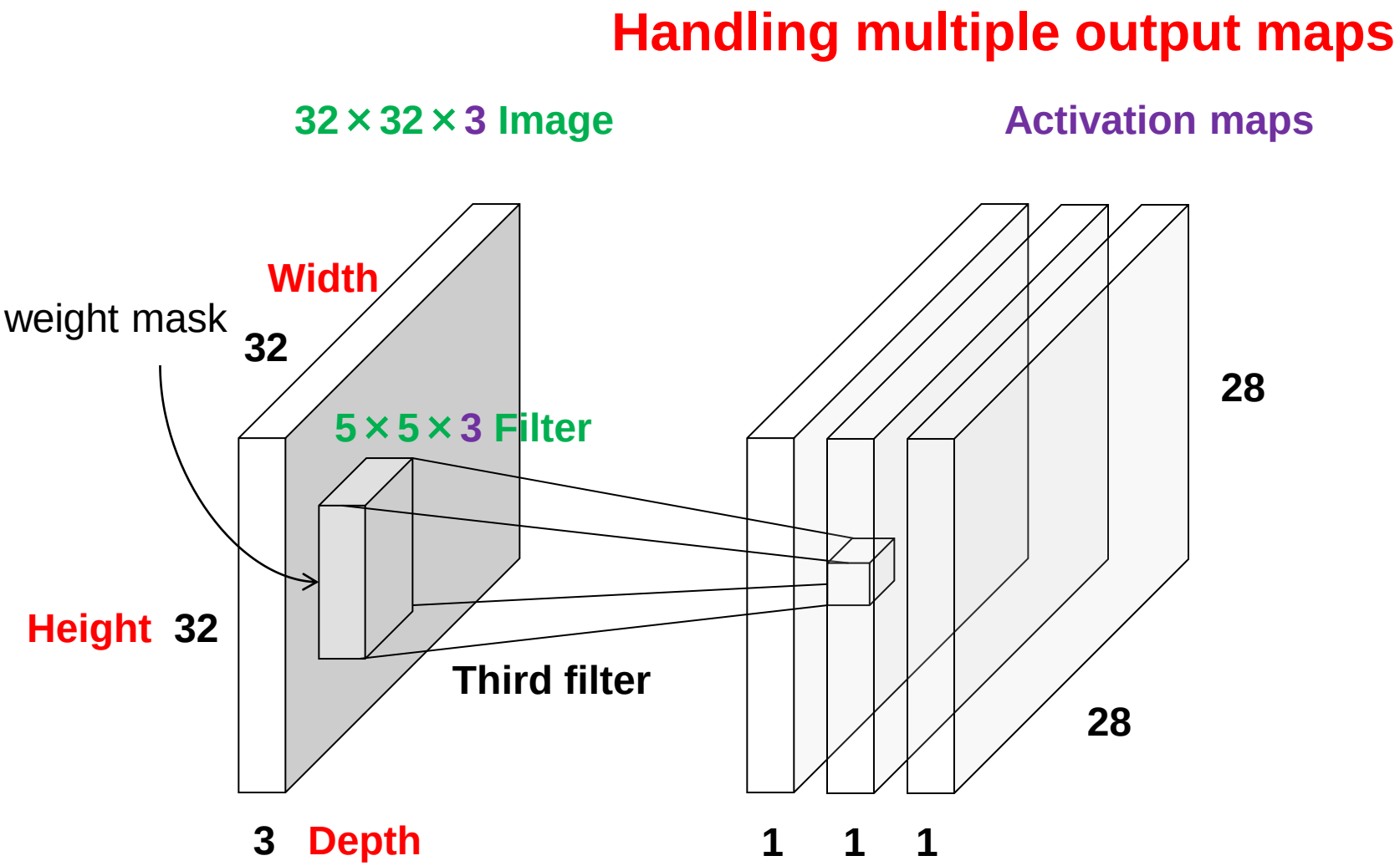
Convolutional Layer



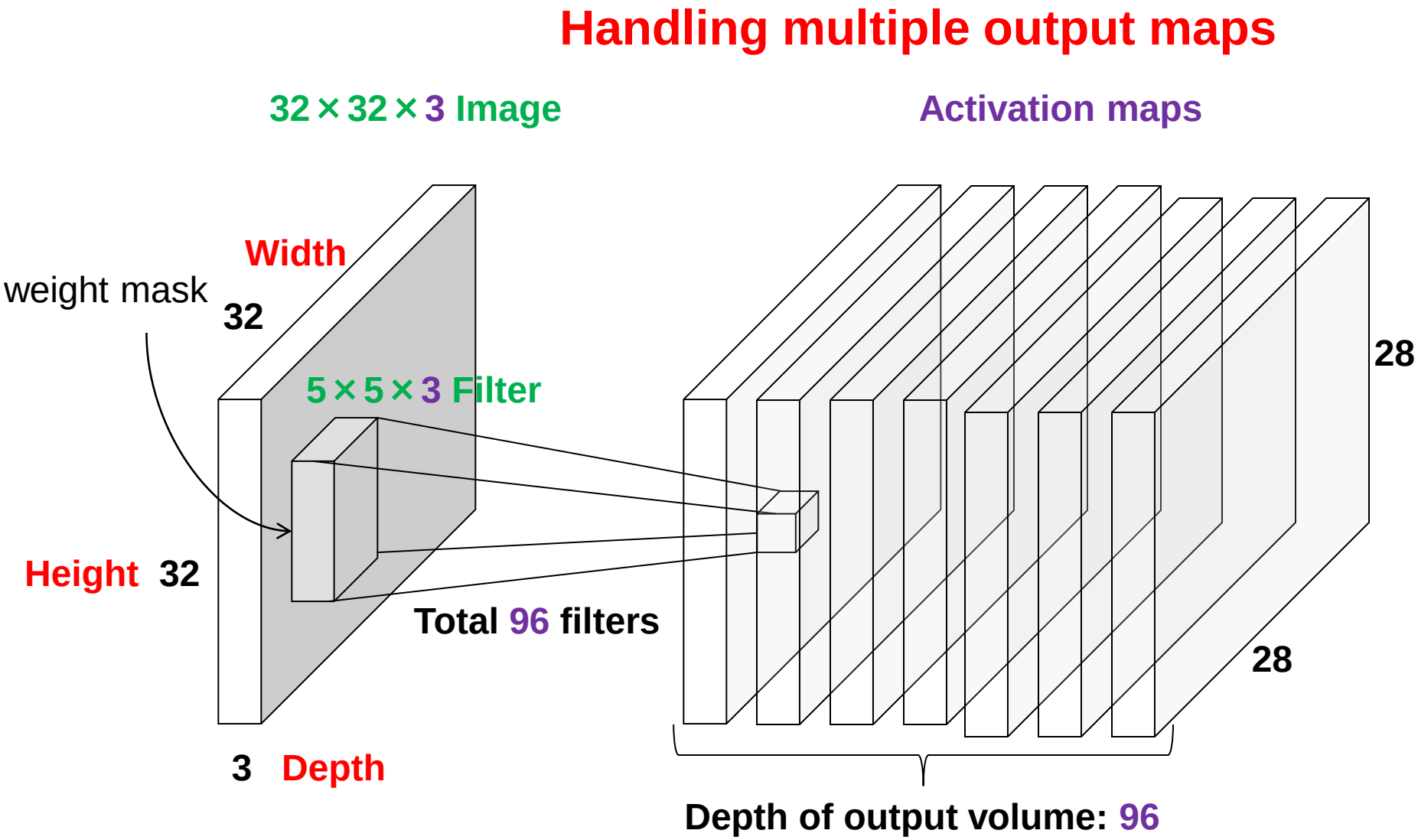
Convolutional Layer



Convolutional Layer



Convolutional Layer



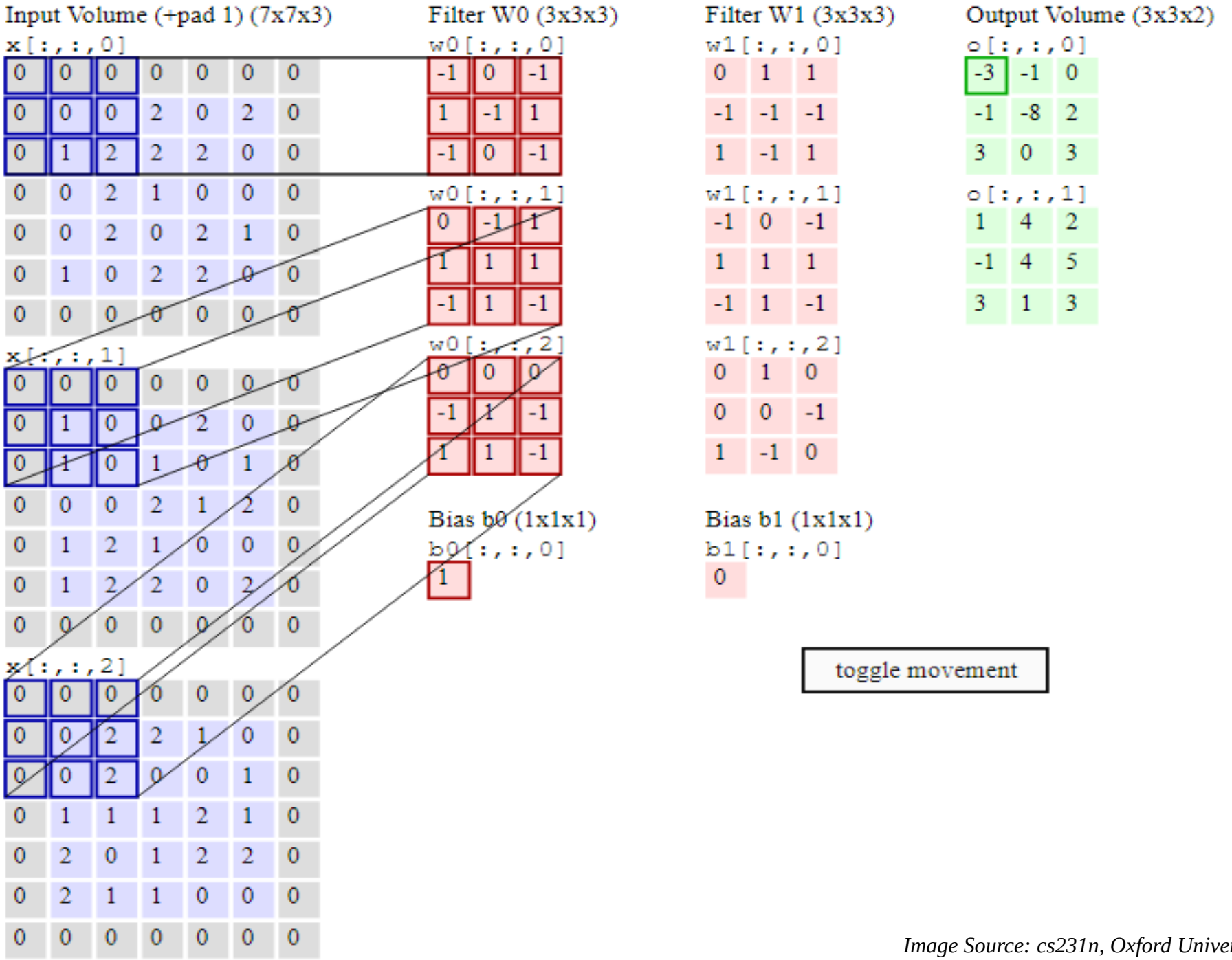


Image Source: cs231n, Oxford University

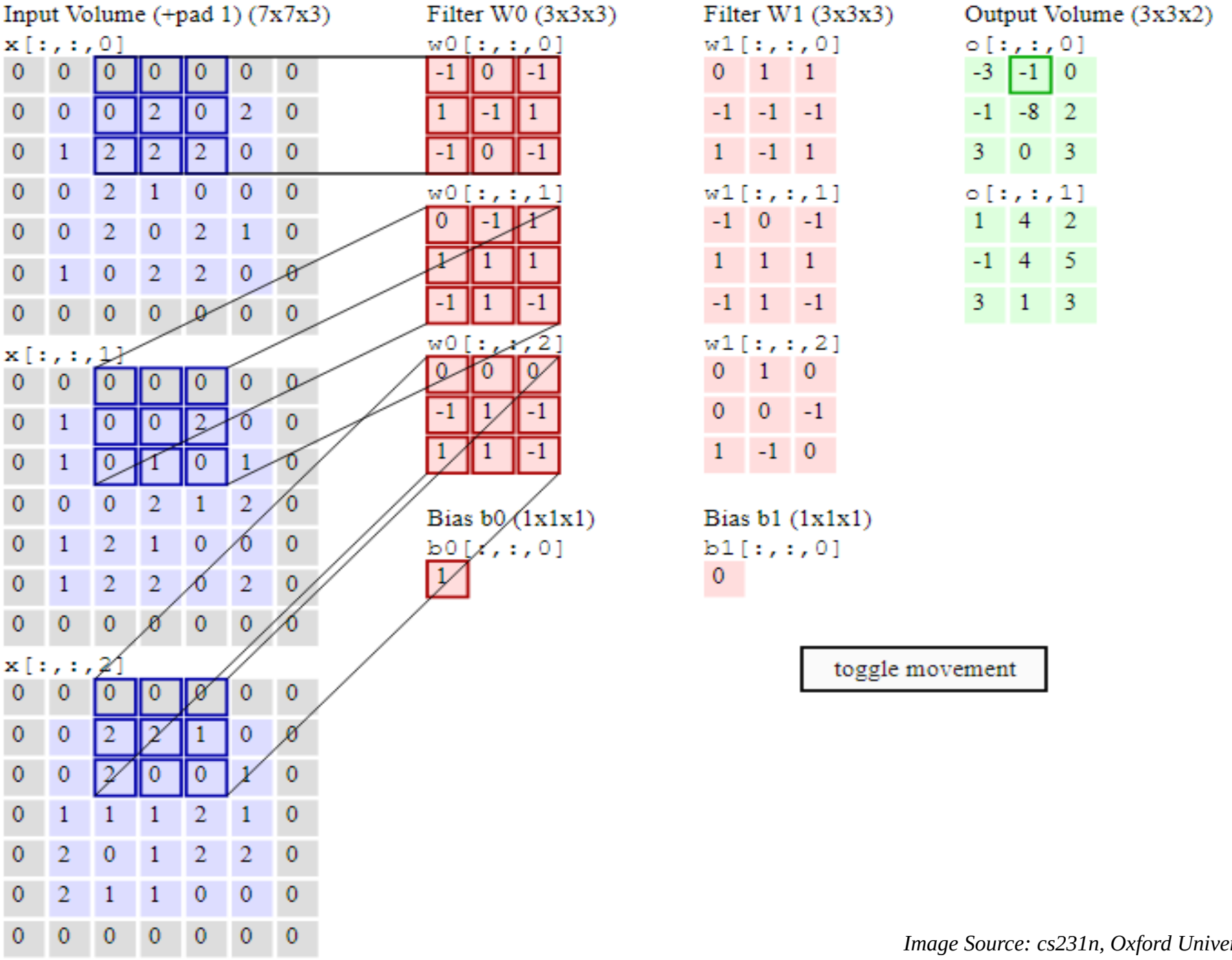


Image Source: cs231n, Oxford University

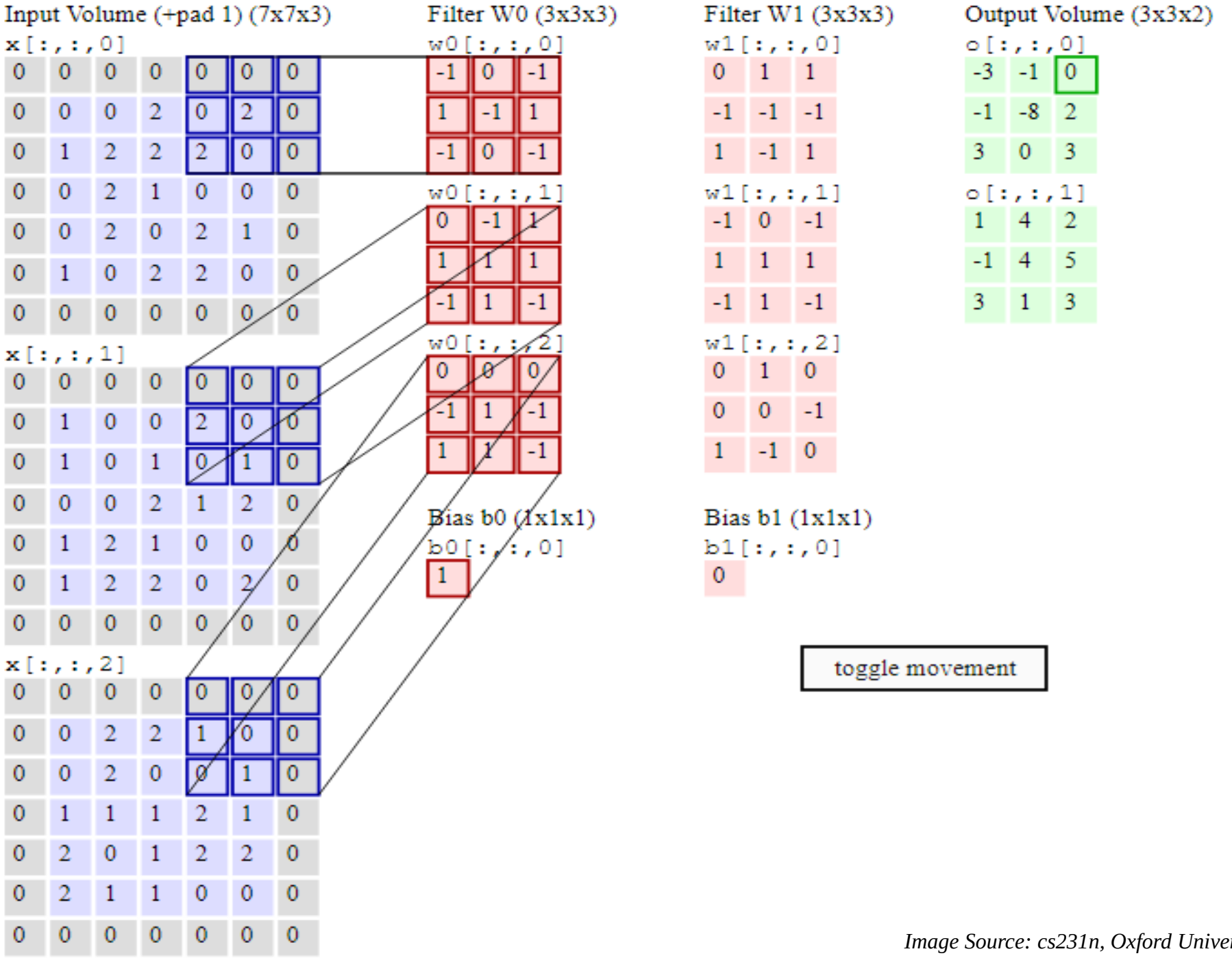
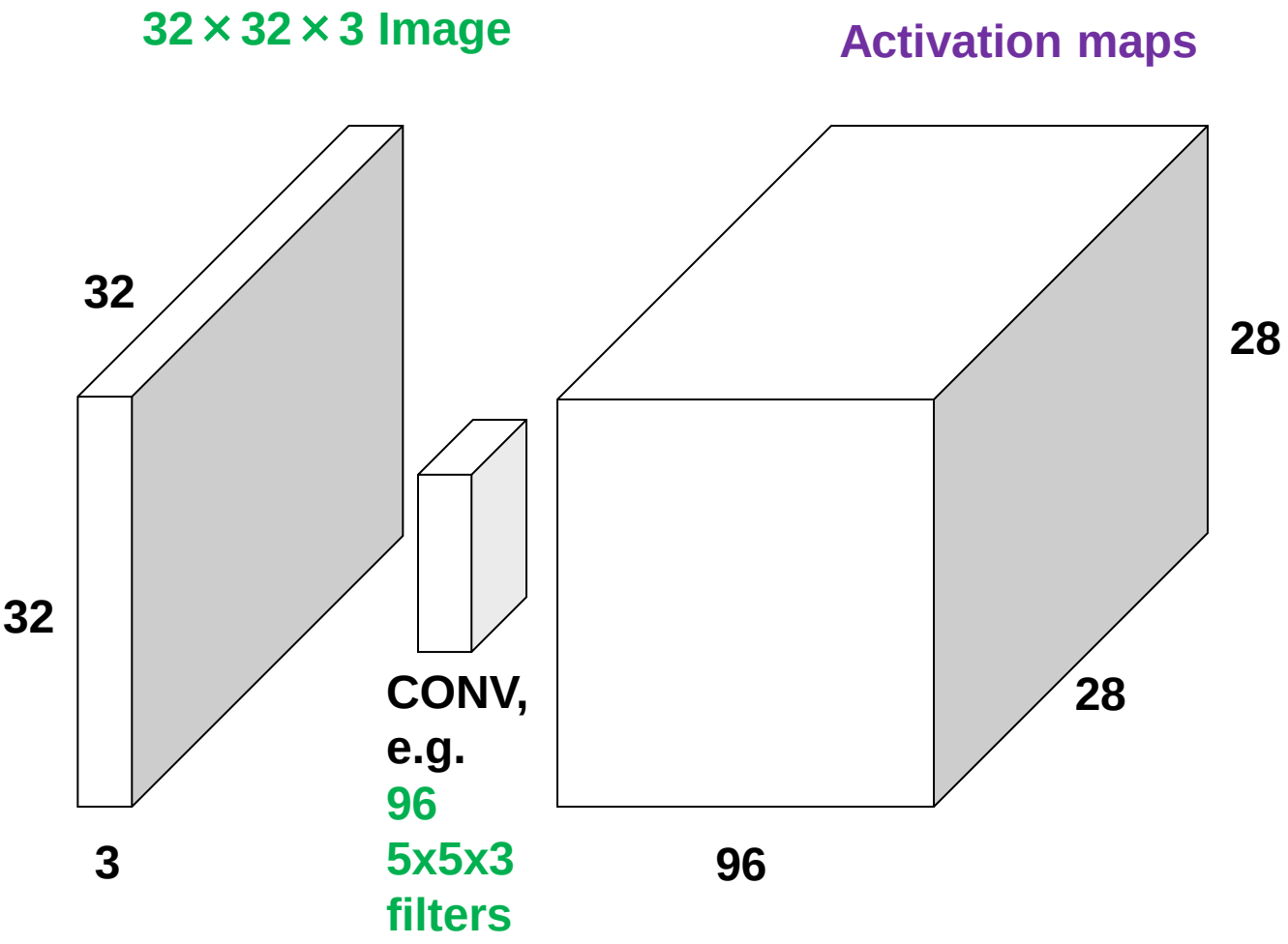


Image Source: cs231n, Oxford University

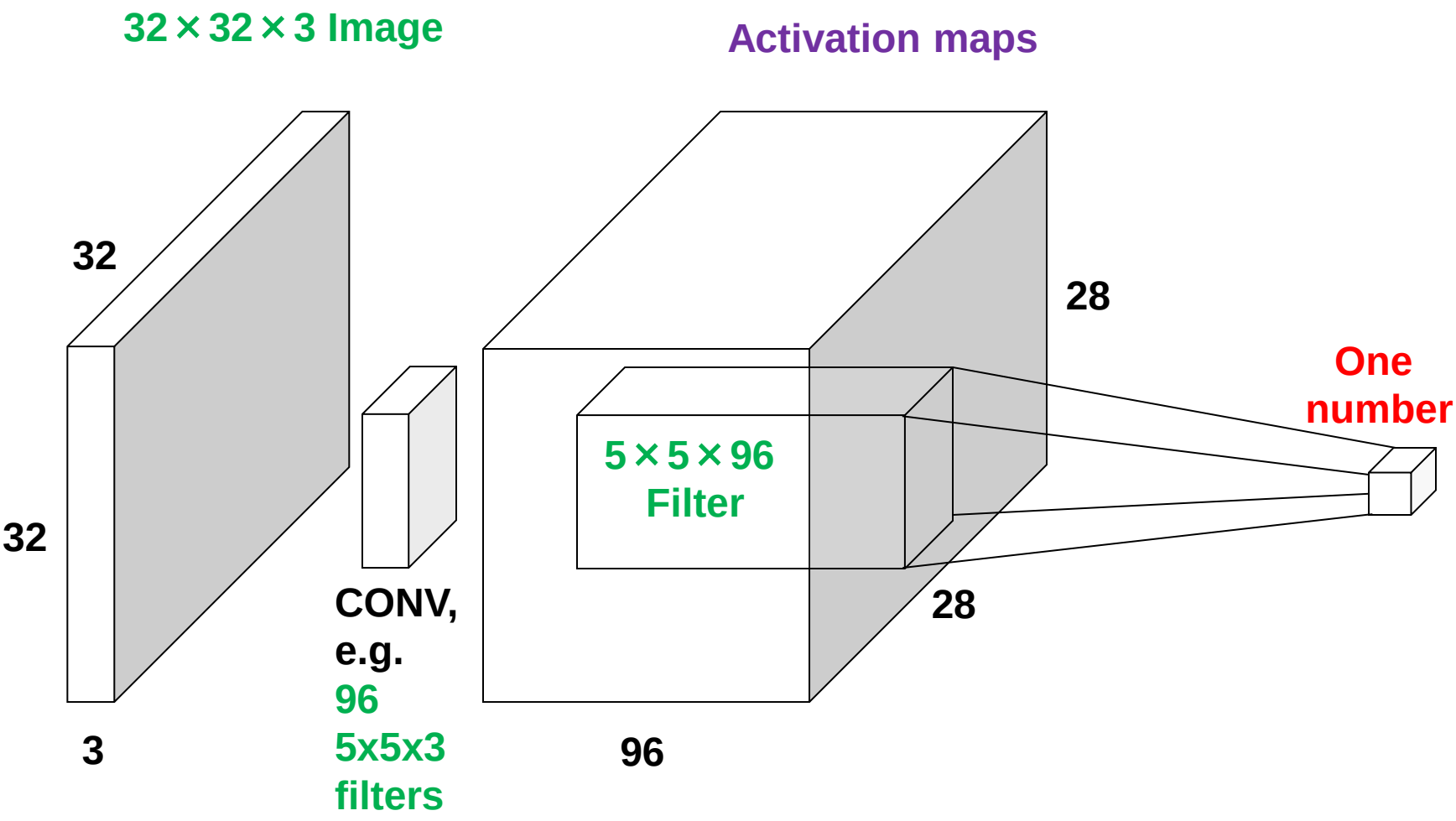
Convolutional Layer

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



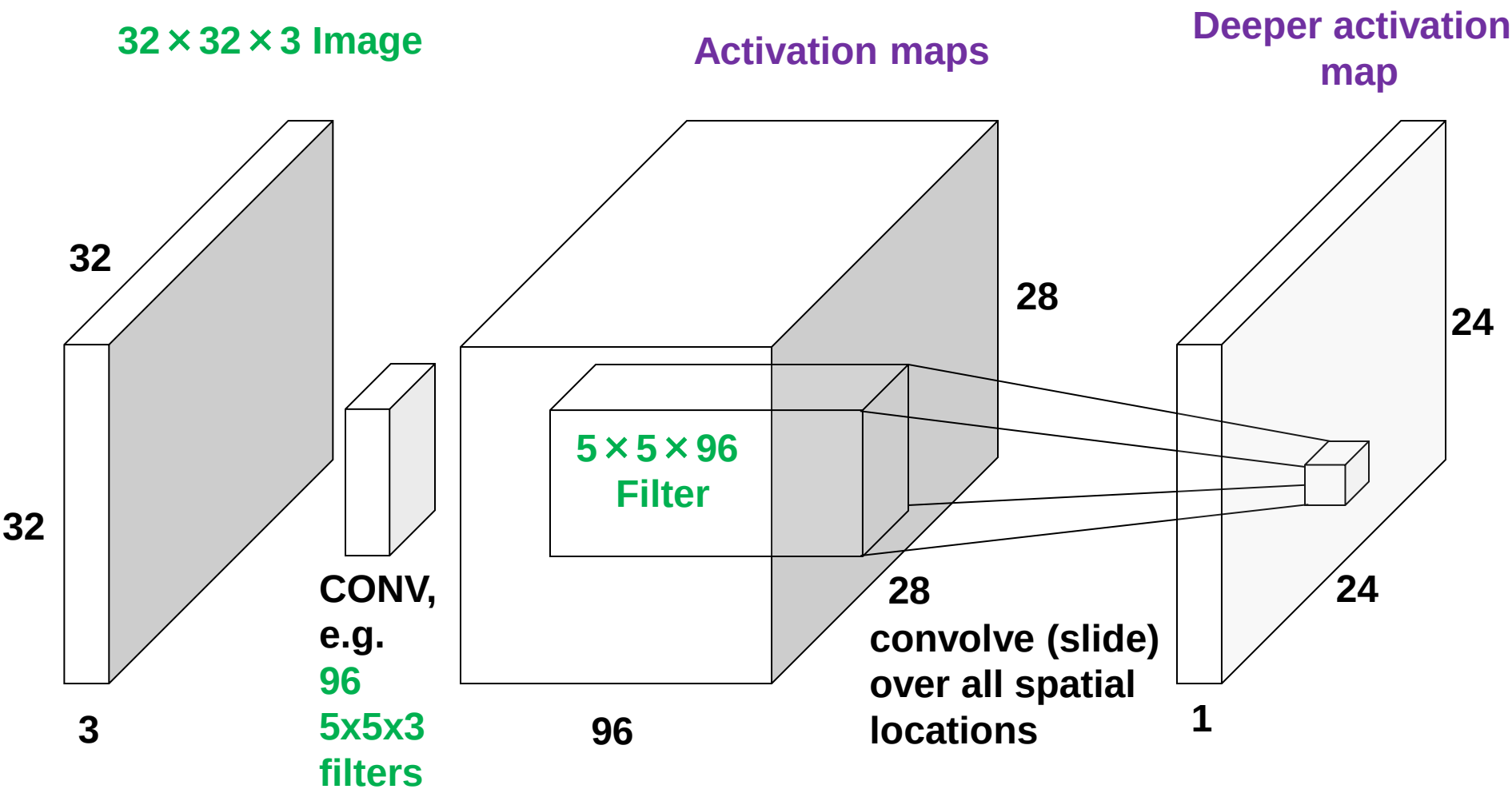
Convolutional Layer

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



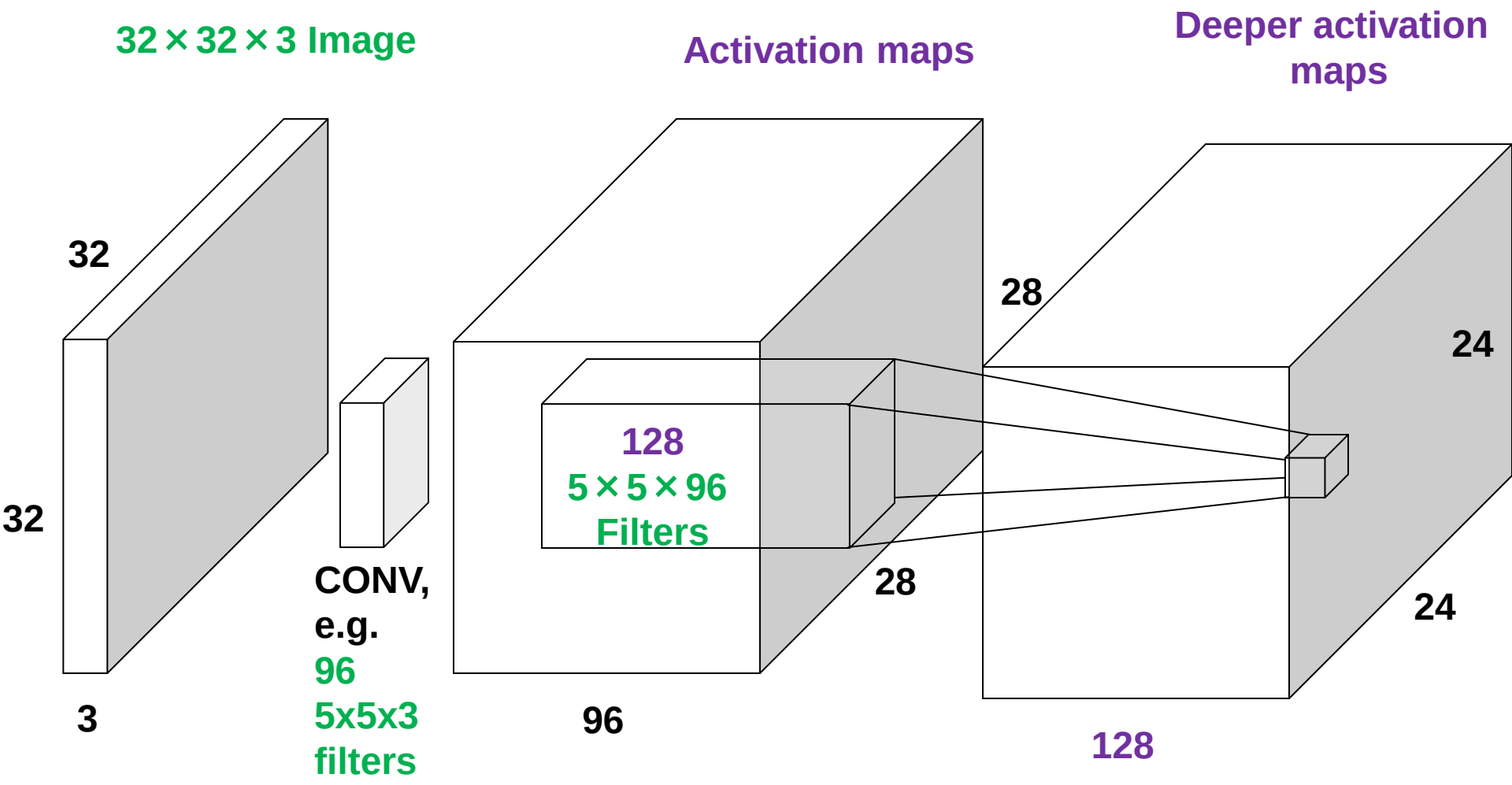
Convolutional Layer

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



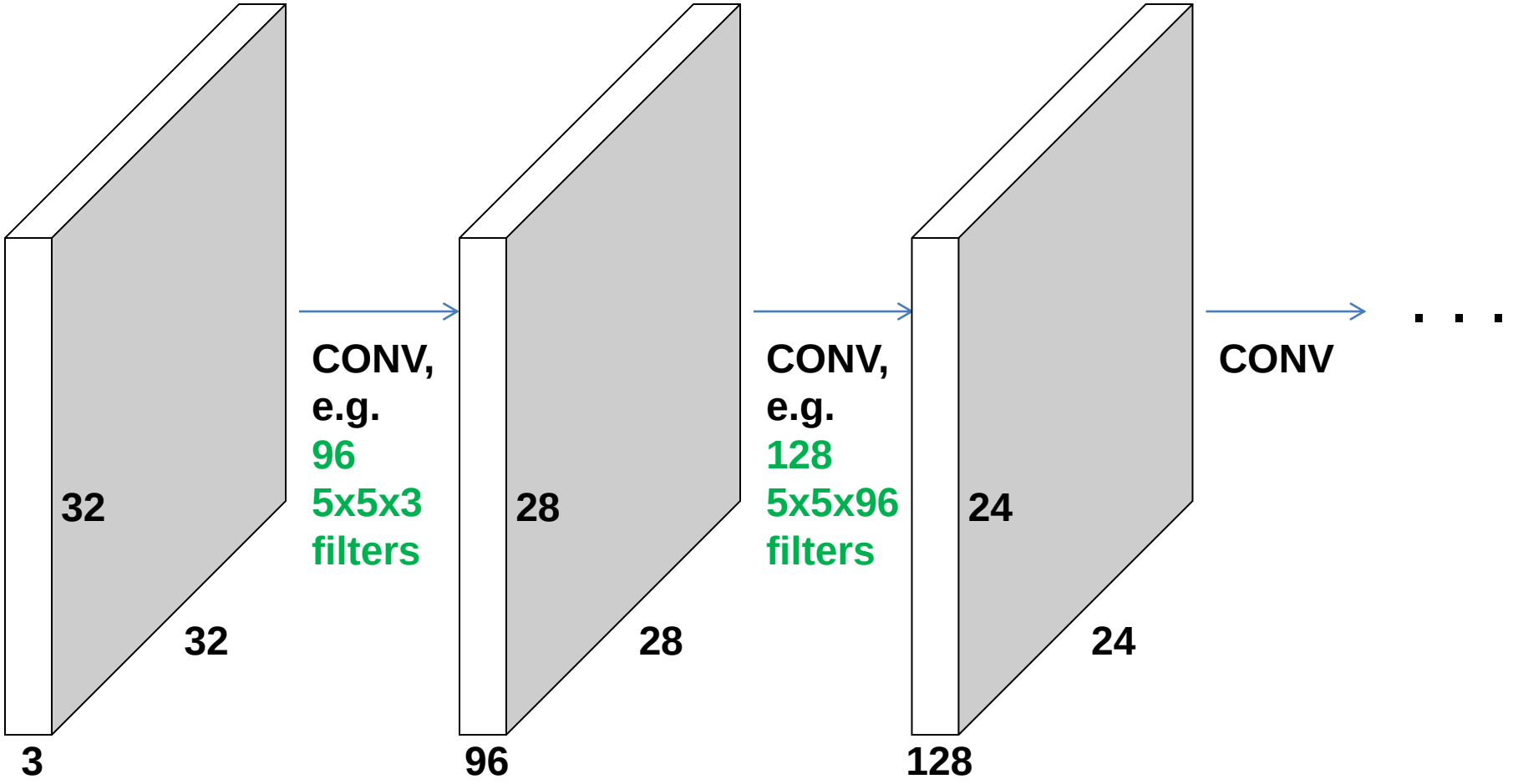
Convolutional Layer

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Multilayer Convolution

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Any Convolution Layer

- Local connectivity
- Weight sharing
- Handling multiple input channels
- Handling multiple output maps

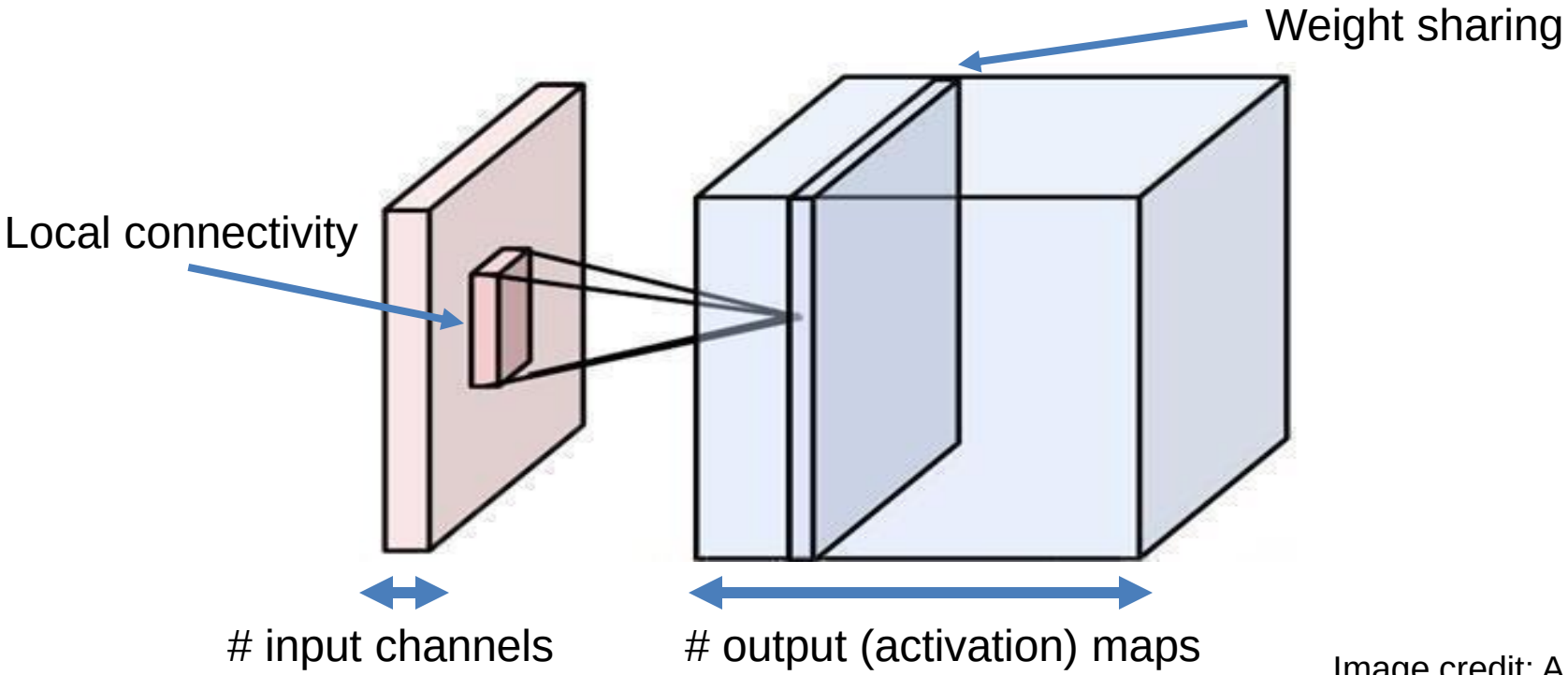
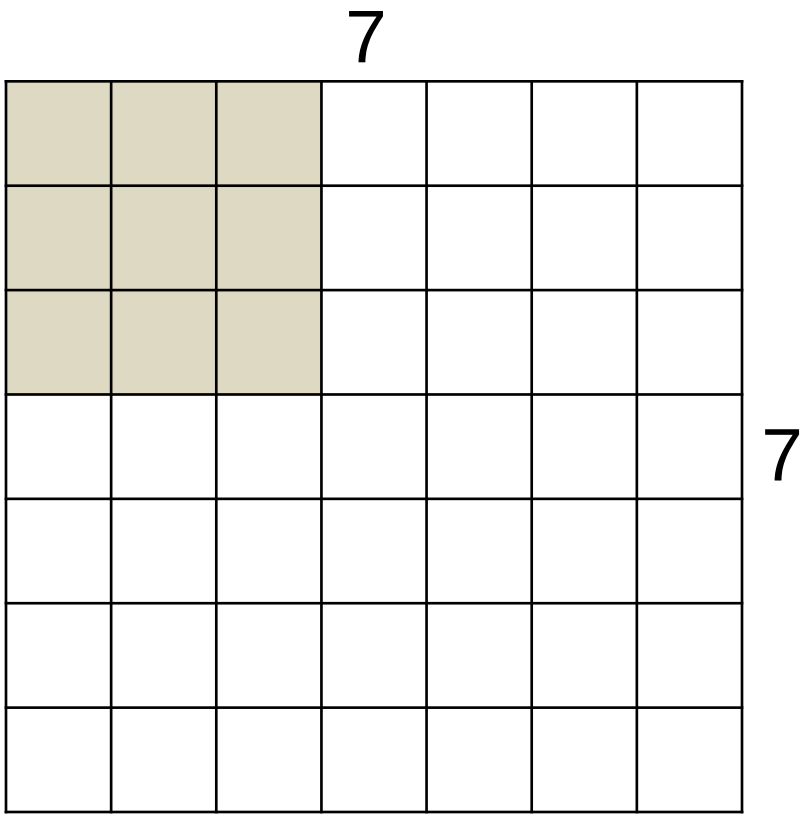


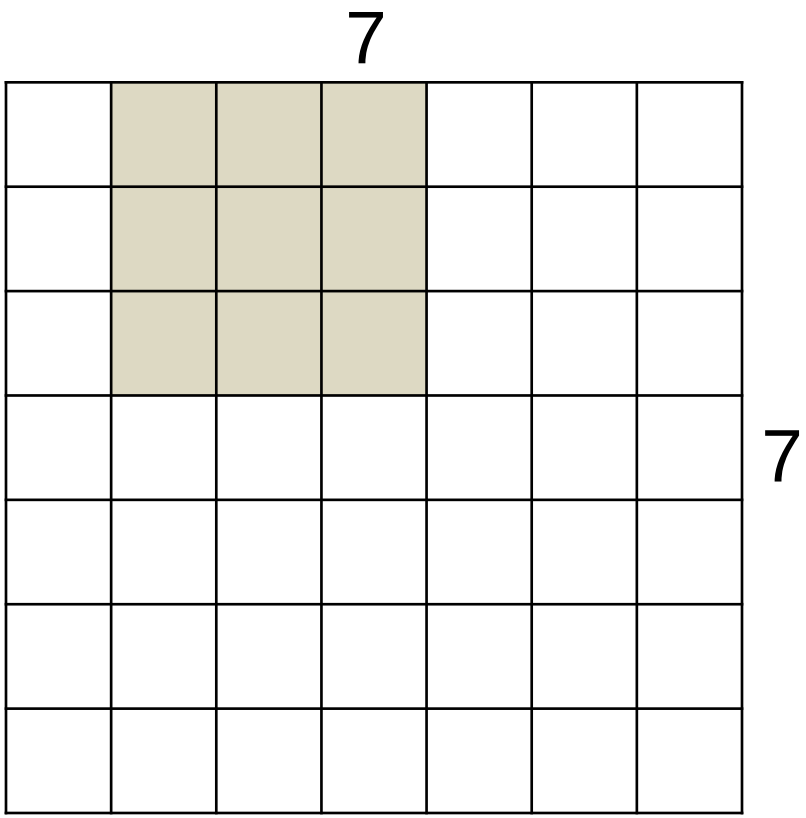
Image credit: A. Karpathy

A closer look at spatial dimensions



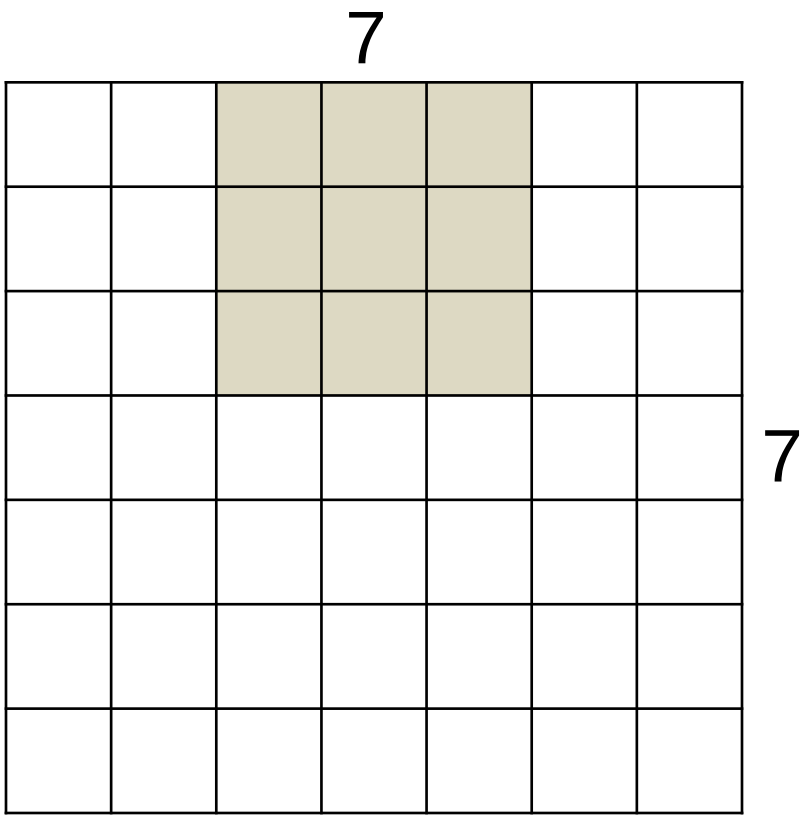
7 × 7 input (spatially)
assume 3 × 3 filter

A closer look at spatial dimensions



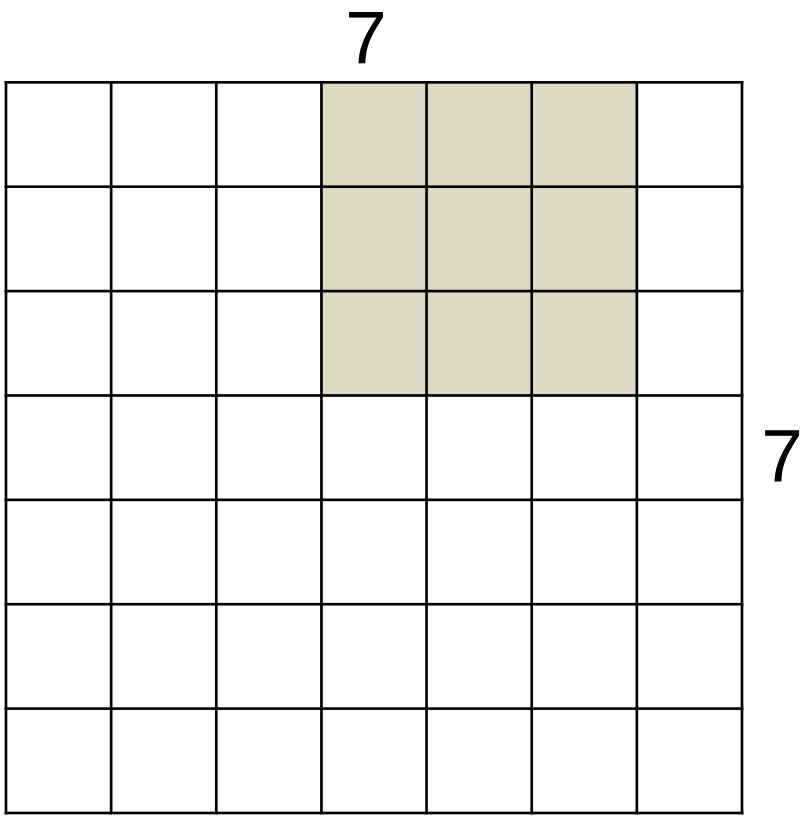
7×7 input (spatially)
assume 3×3 filter

A closer look at spatial dimensions



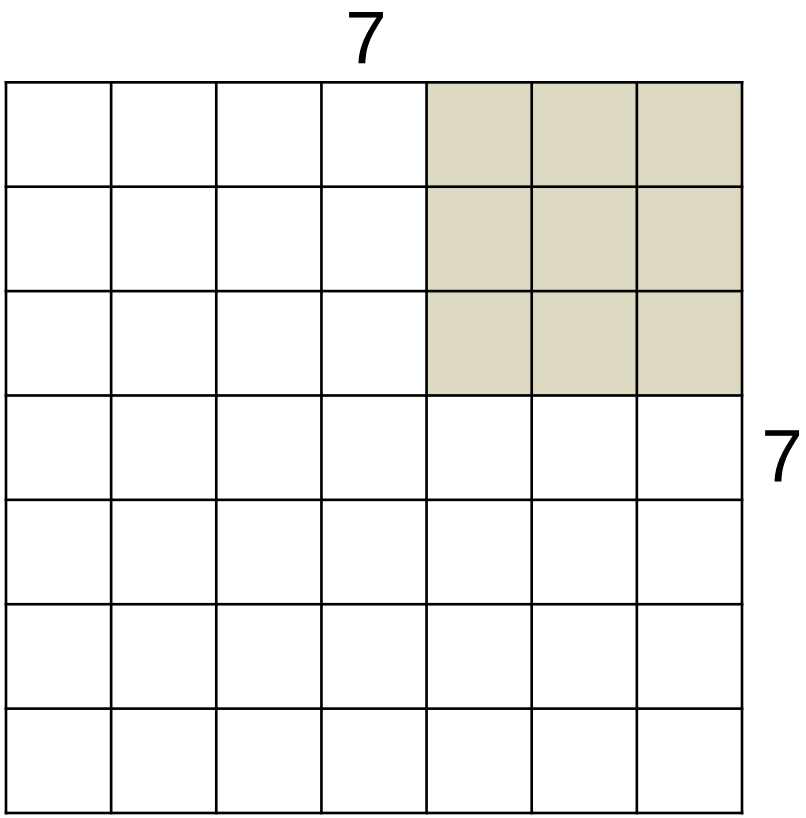
7×7 input (spatially)
assume 3×3 filter

A closer look at spatial dimensions



7×7 input (spatially)
assume 3×3 filter

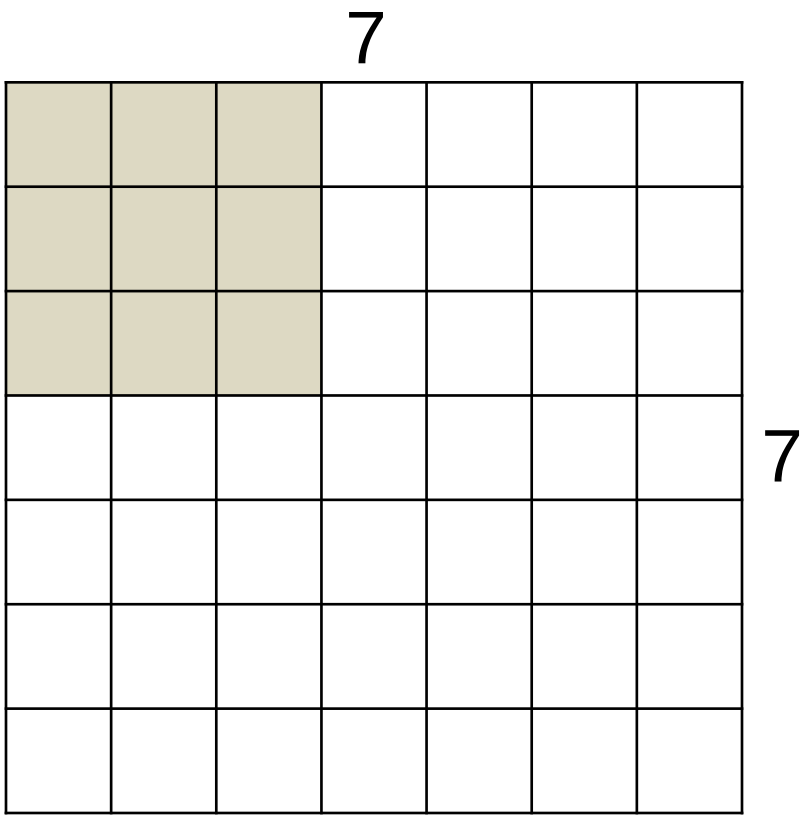
A closer look at spatial dimensions



7 × 7 input (spatially)
assume 3 × 3 filter

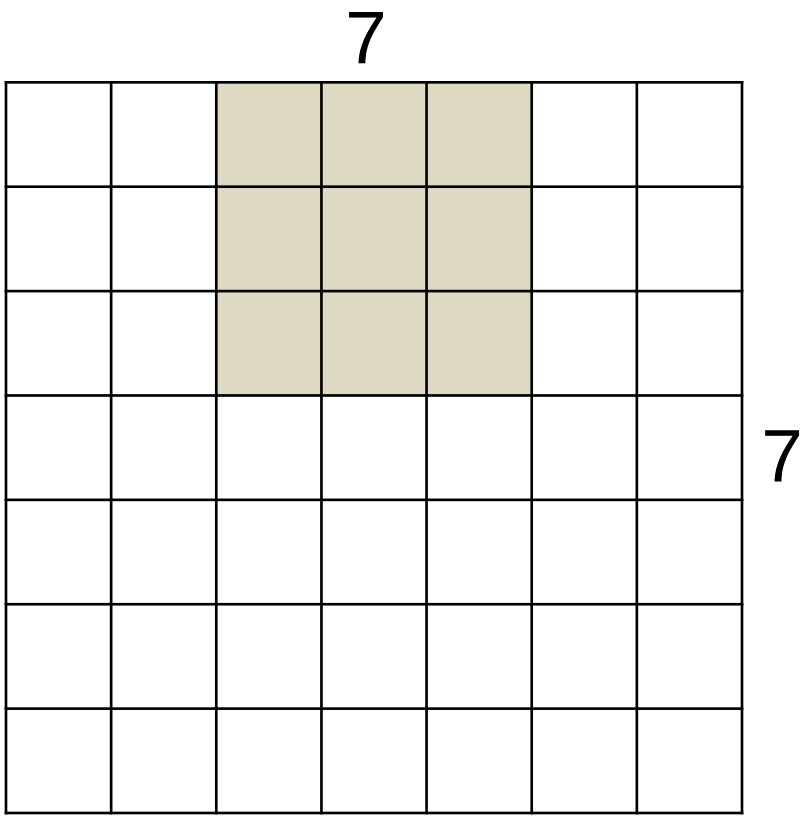
5 × 5 output

A closer look at spatial dimensions



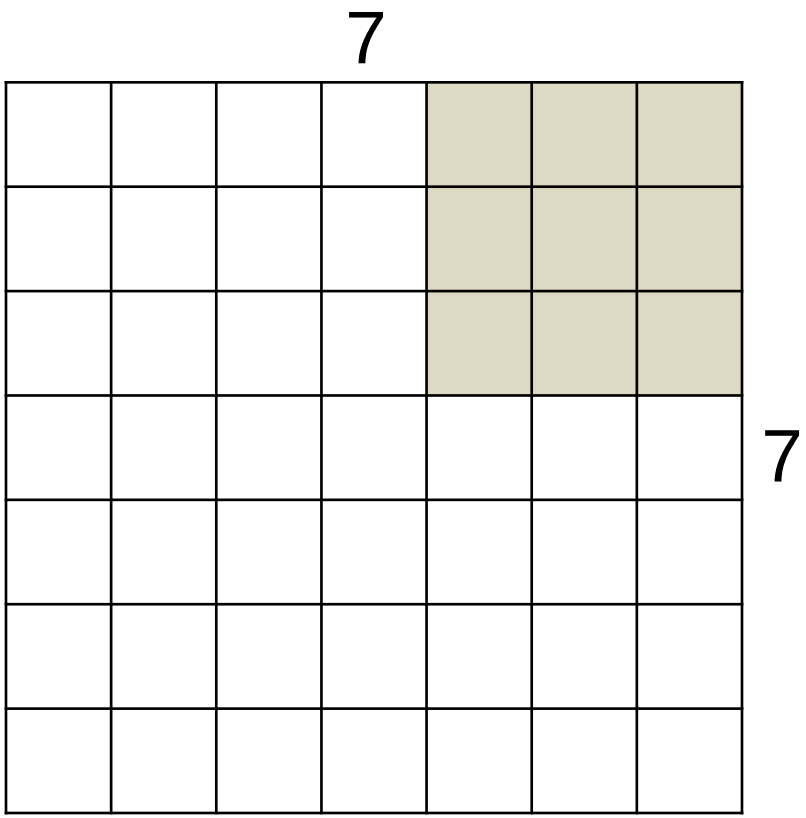
7 × 7 input (spatially)
assume 3 × 3 filter
applied with **stride 2**

A closer look at spatial dimensions



7 × 7 input (spatially)
assume 3 × 3 filter
applied with **stride 2**

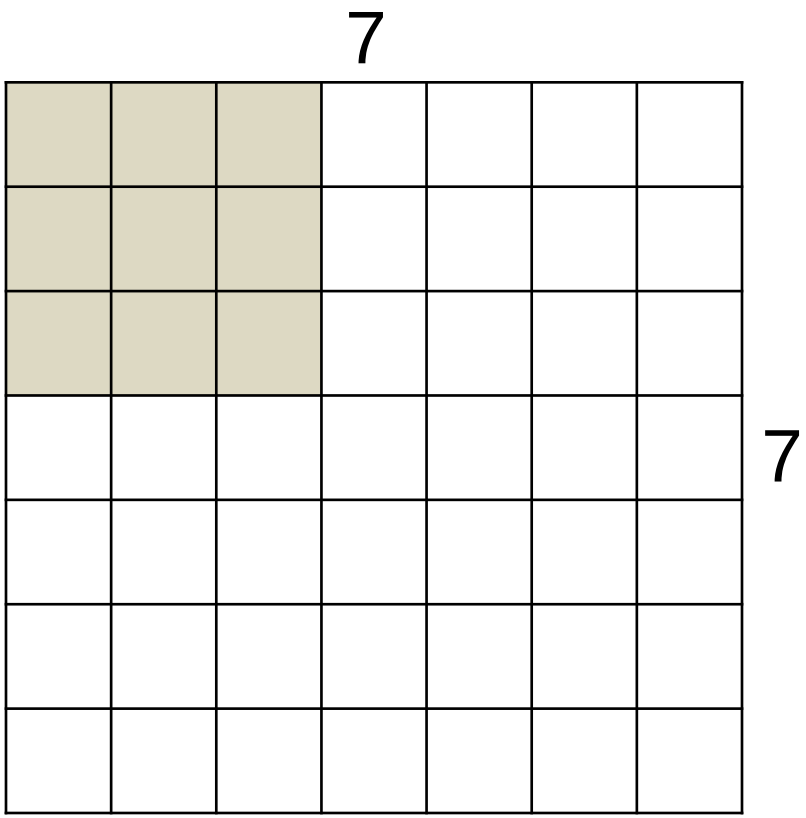
A closer look at spatial dimensions



7 × 7 input (spatially)
assume 3 × 3 filter
applied with **stride 2**

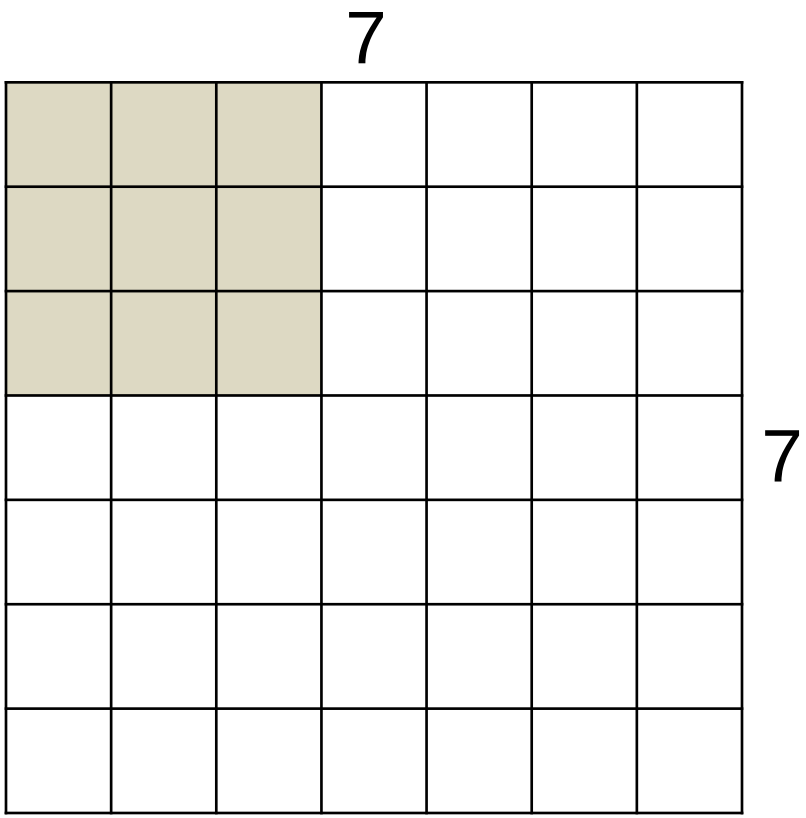
3 × 3 output

A closer look at spatial dimensions



7 × 7 input (spatially)
assume 3 × 3 filter
applied with **stride 3**

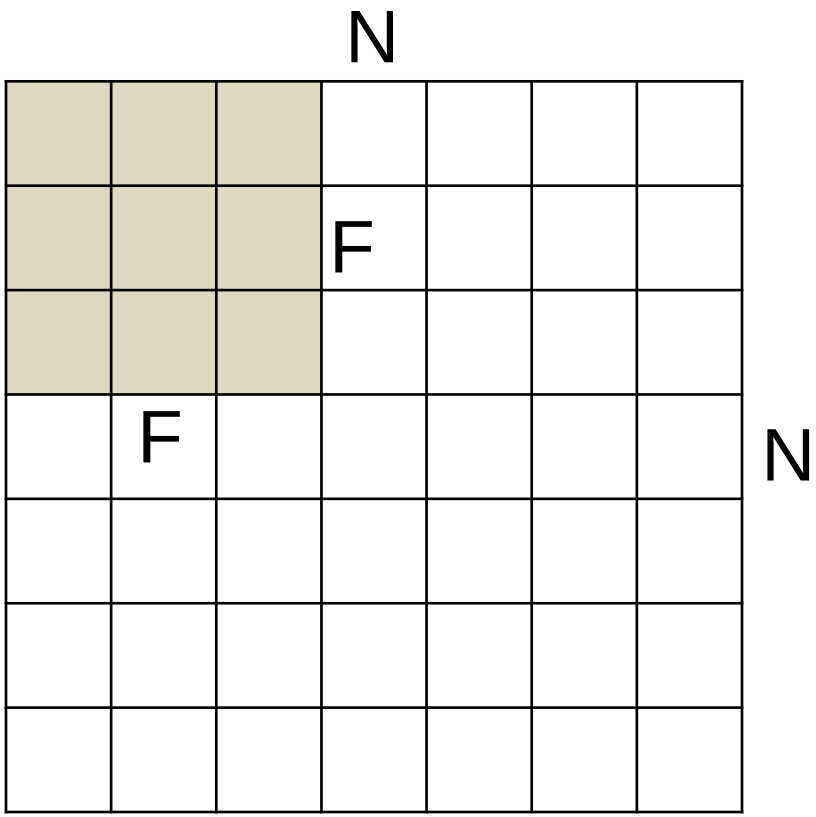
A closer look at spatial dimensions



7 × 7 input (spatially)
assume 3 × 3 filter
applied with **stride 3**

doesn't fit!
cannot apply 3x3 filter on 7x7 input with stride 3.

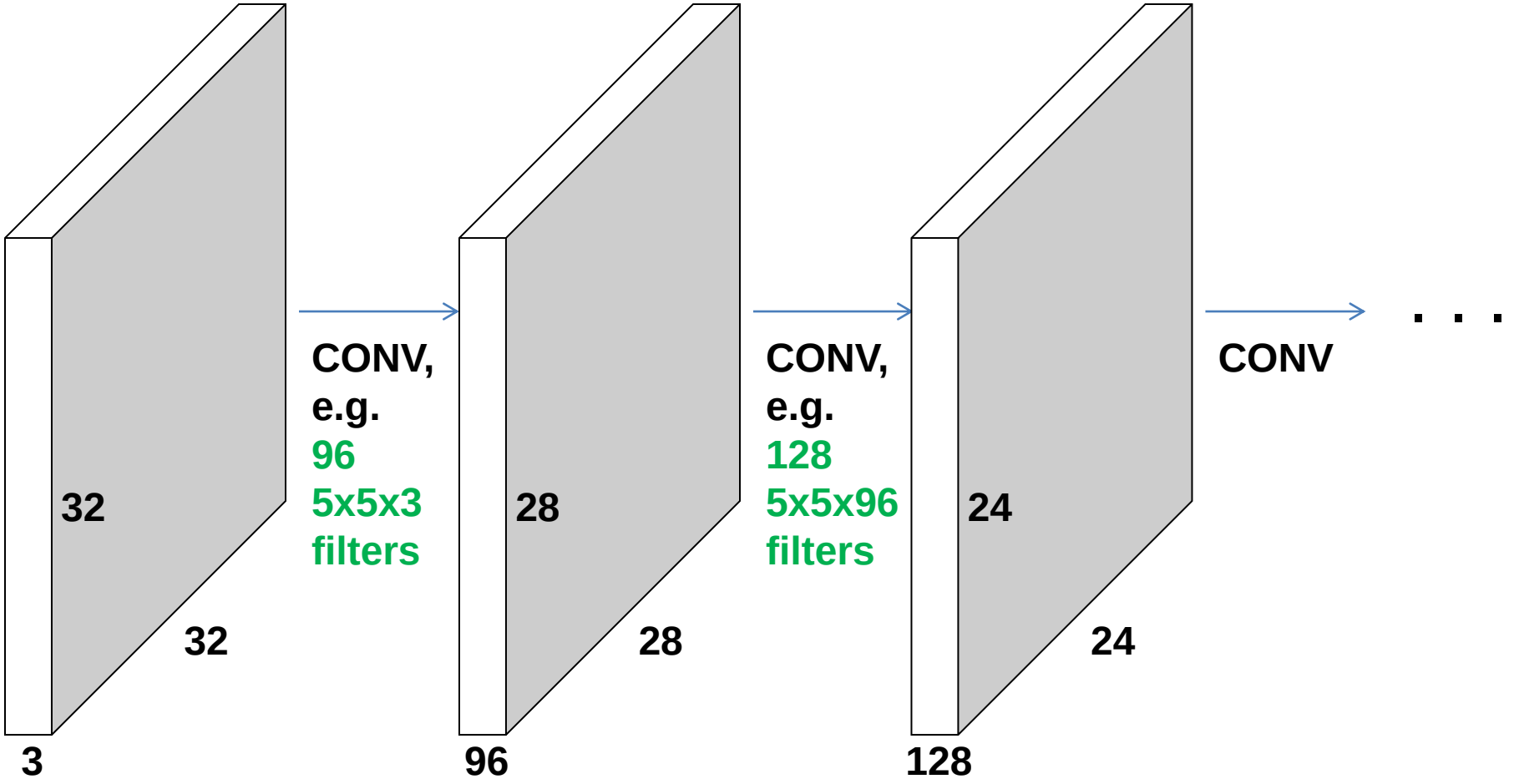
A closer look at spatial dimensions



Output size
(N - F) / stride + 1

e.g. N = 7, F = 3
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33

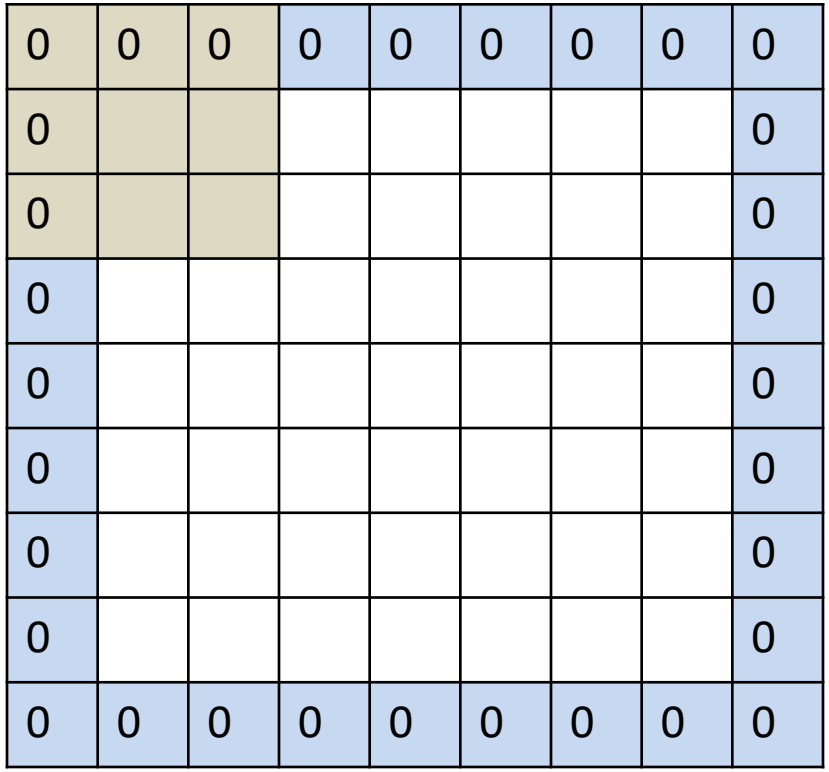
A closer look at spatial dimensions



E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.

Source: cs231n, Stanford University

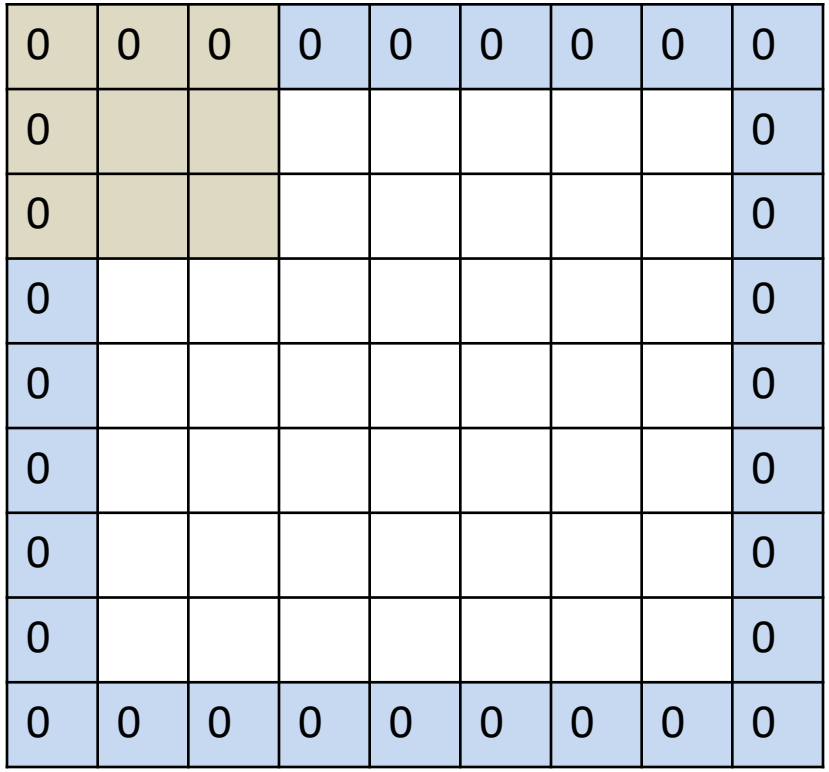
In practice: common to zero pad



e.g. **input 7 × 7** (spatially)
3 × 3 filter, applied with **stride 1**
pad with 1 pixel border

What is the output dimension?

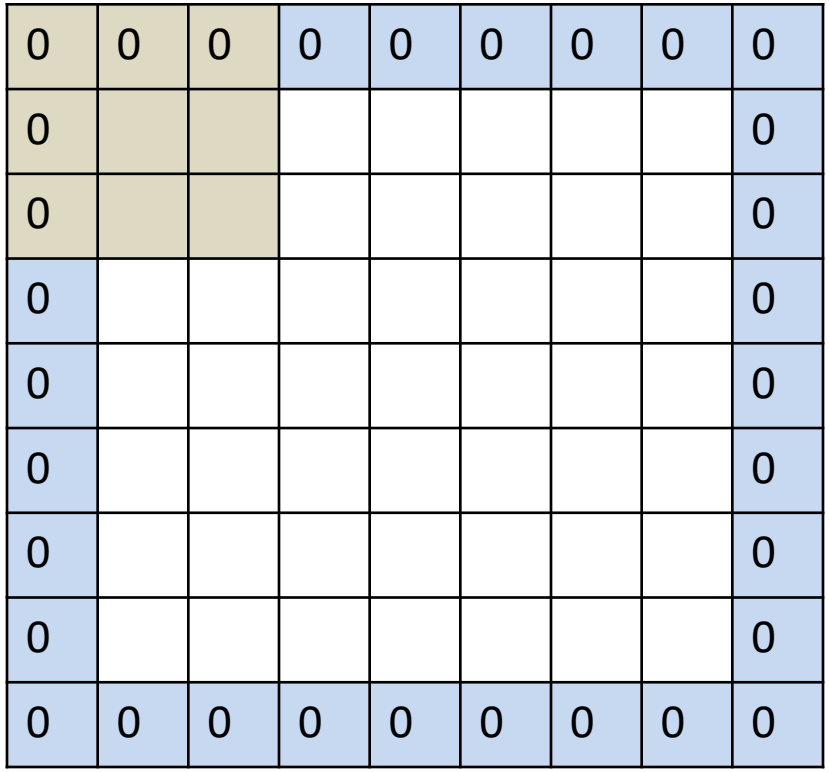
In practice: common to zero pad



e.g. **input 7 × 7** (spatially)
3 × 3 filter, applied with **stride 1**
pad with 1 pixel border

7 × 7 Output

In practice: common to zero pad

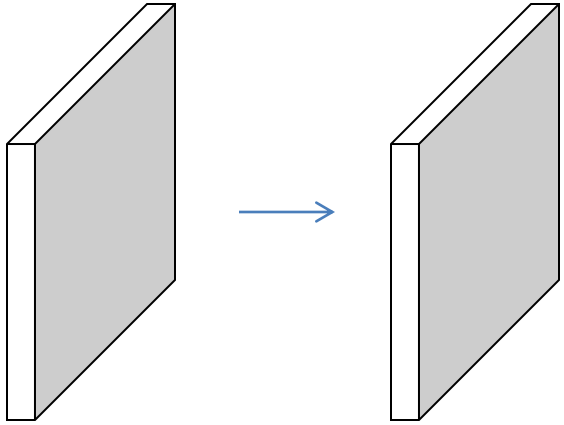


e.g. **input 7×7** (spatially)
3×3 filter, applied with **stride 1**
pad with 1 pixel border

7×7 Output
in general, common to see CONV layers with stride 1, filters of size F×F, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g.
F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

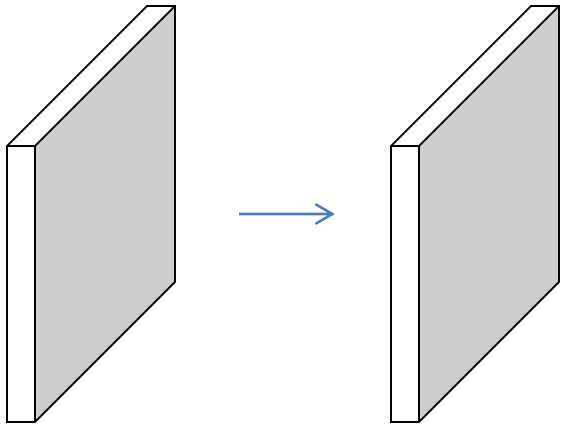
Example

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Output volume size: ?

Example

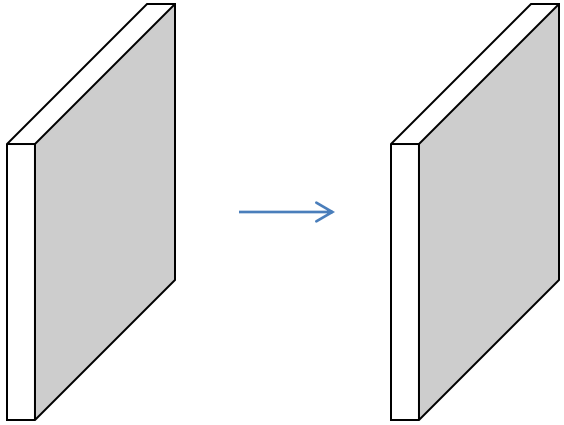


Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10

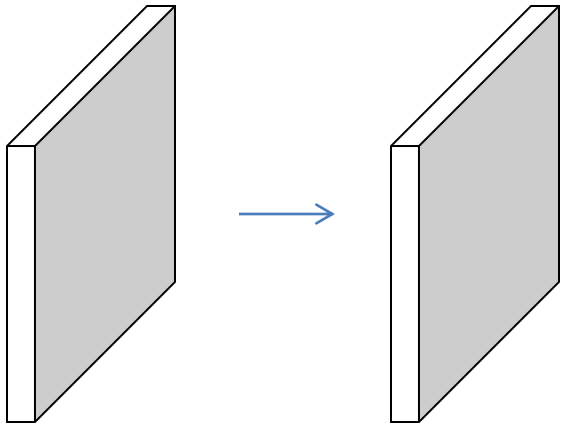
Example

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Number of parameters in this layer?

Example



Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?

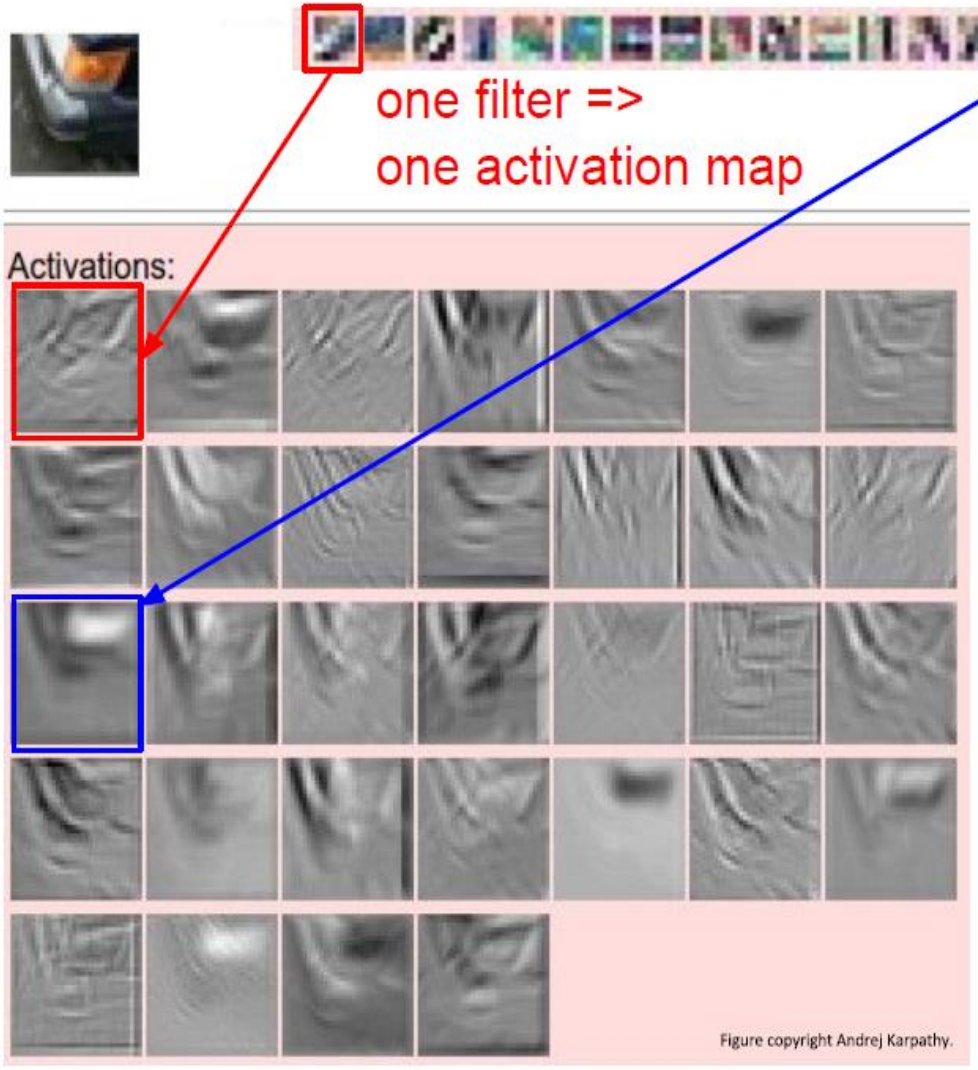
each filter has
5*5*3 + 1 = 76 params (+1 for bias)
=> 76*10 = **760**

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.

Source: cs231n, Stanford University

Convolution as feature extraction



example 5x5 filters
(32 total)

We call the layer convolutional because it is related to convolution of two signals:

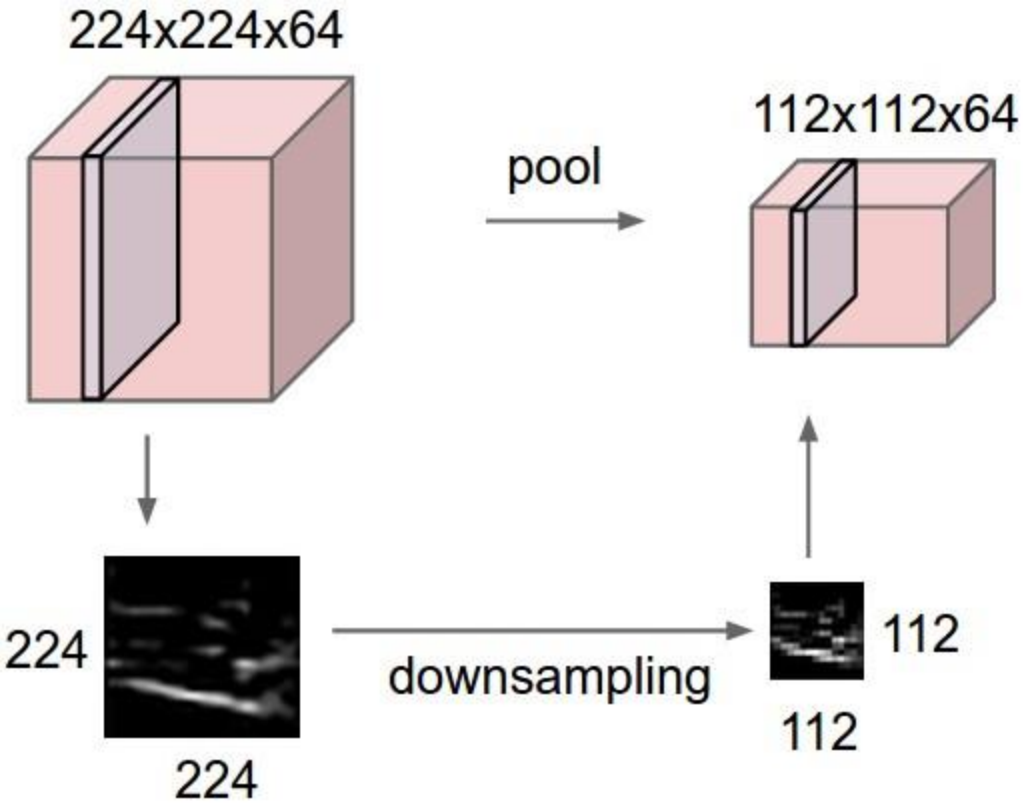
$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

elementwise multiplication and sum of a filter and the signal (image)

Source: cs231n, Stanford University

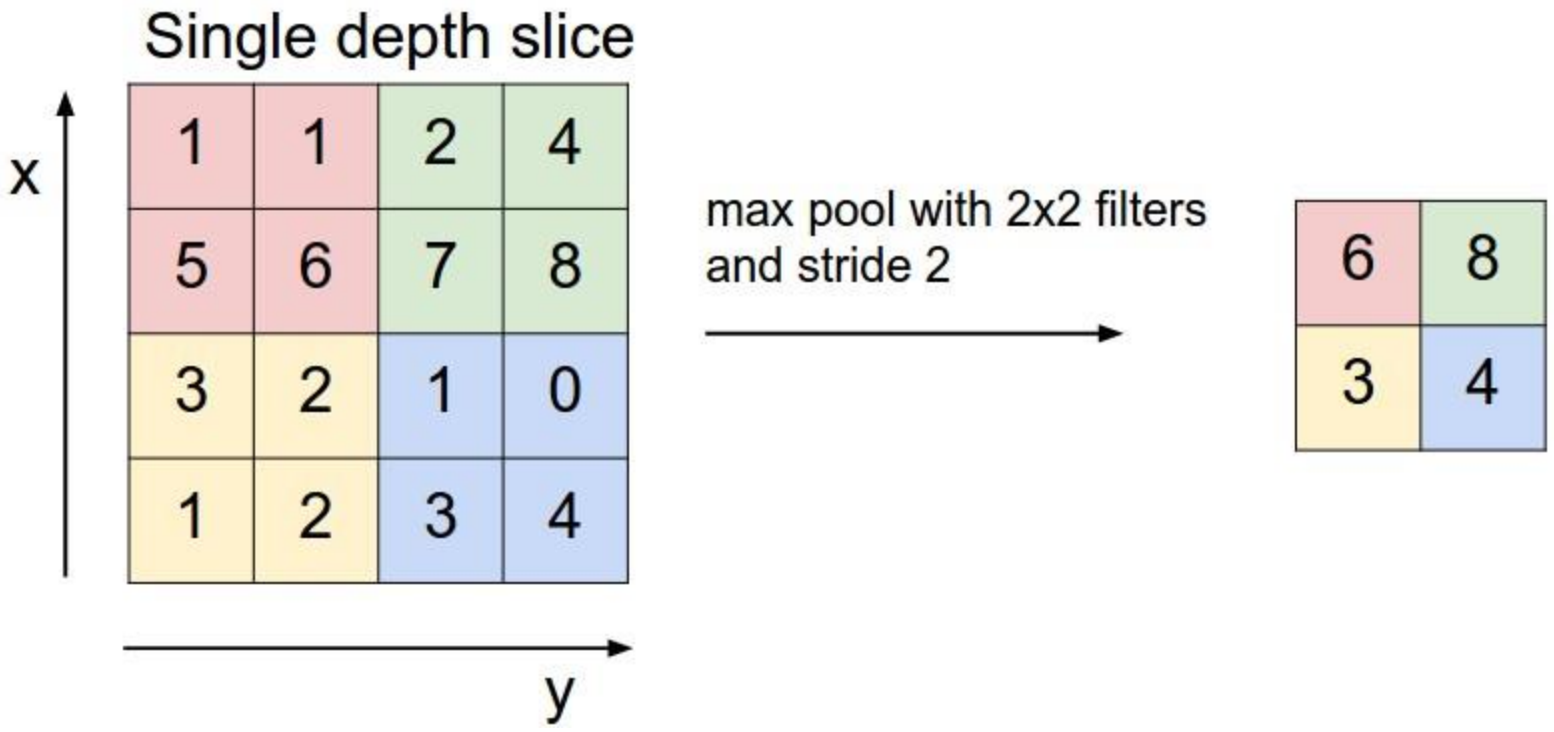
Pooling Layer

- makes the representations smaller and more manageable
- operates over each activation map independently:



Source: cs231n, Stanford University

Max Pooling



Source: cs231n, Stanford University

Pooling Layer

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires two hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

Source: cs231n, Stanford University

Fully Connected Layer

- Connect every neuron in one layer to every neuron in another layer

- Same as the traditional multi-layer perceptron neural network

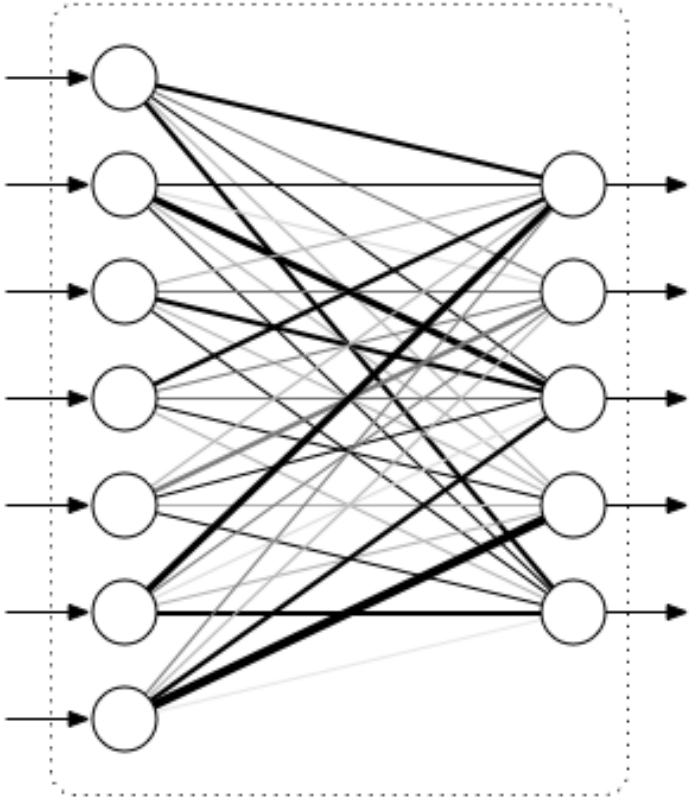


Image Source: machinethink.net

Fully Connected Layer

- Connect every neuron in one layer to every neuron in another layer
- Same as the traditional multi-layer perceptron neural network

No. of Neurons (Last FC)
= No. of classes

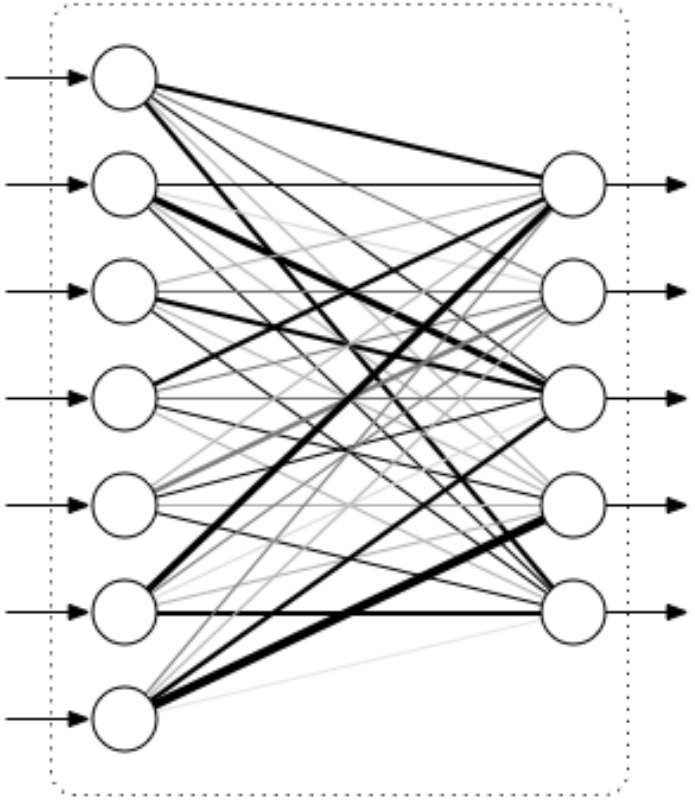


Image Source: machinethink.net

Loss/Classification Layer

- SVM Classifier (SVM Loss/Hinge Loss/Max-margin Loss)

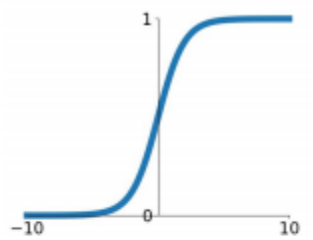
- Softmax Classifier (Softmax Loss/Cross-entropy Loss)

Non-linearity Layer

Activation Functions

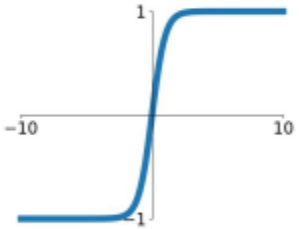
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



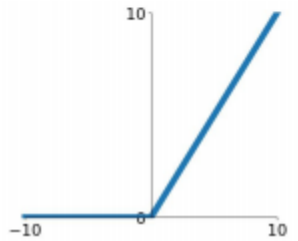
tanh

$$\tanh(x)$$



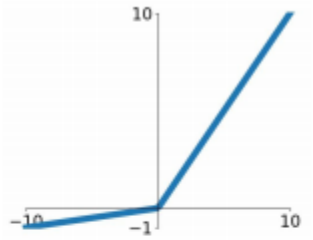
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

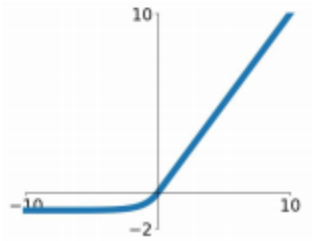


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Source: cs231n, Stanford University

A typical CNN structure

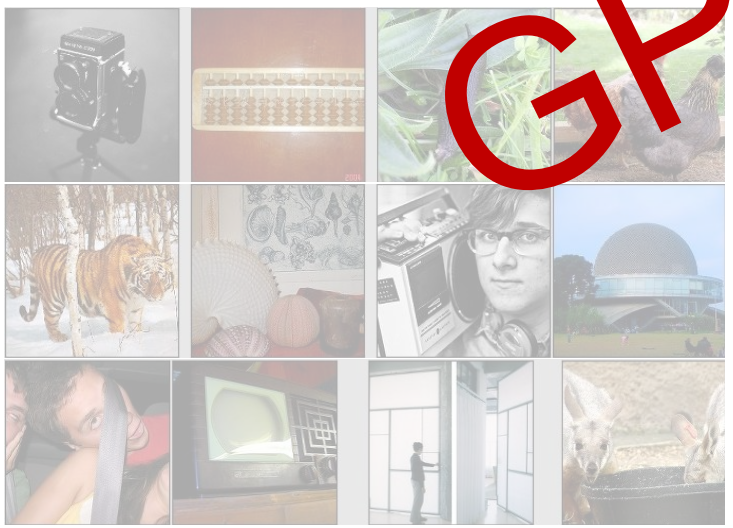
Image Source: machinethink.net

ImageNet Challenge

- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- Challenge: 1.2 million training images, 1000 classes

www.image-net.org/challenges/LSVRC/

ImageNet Challenge

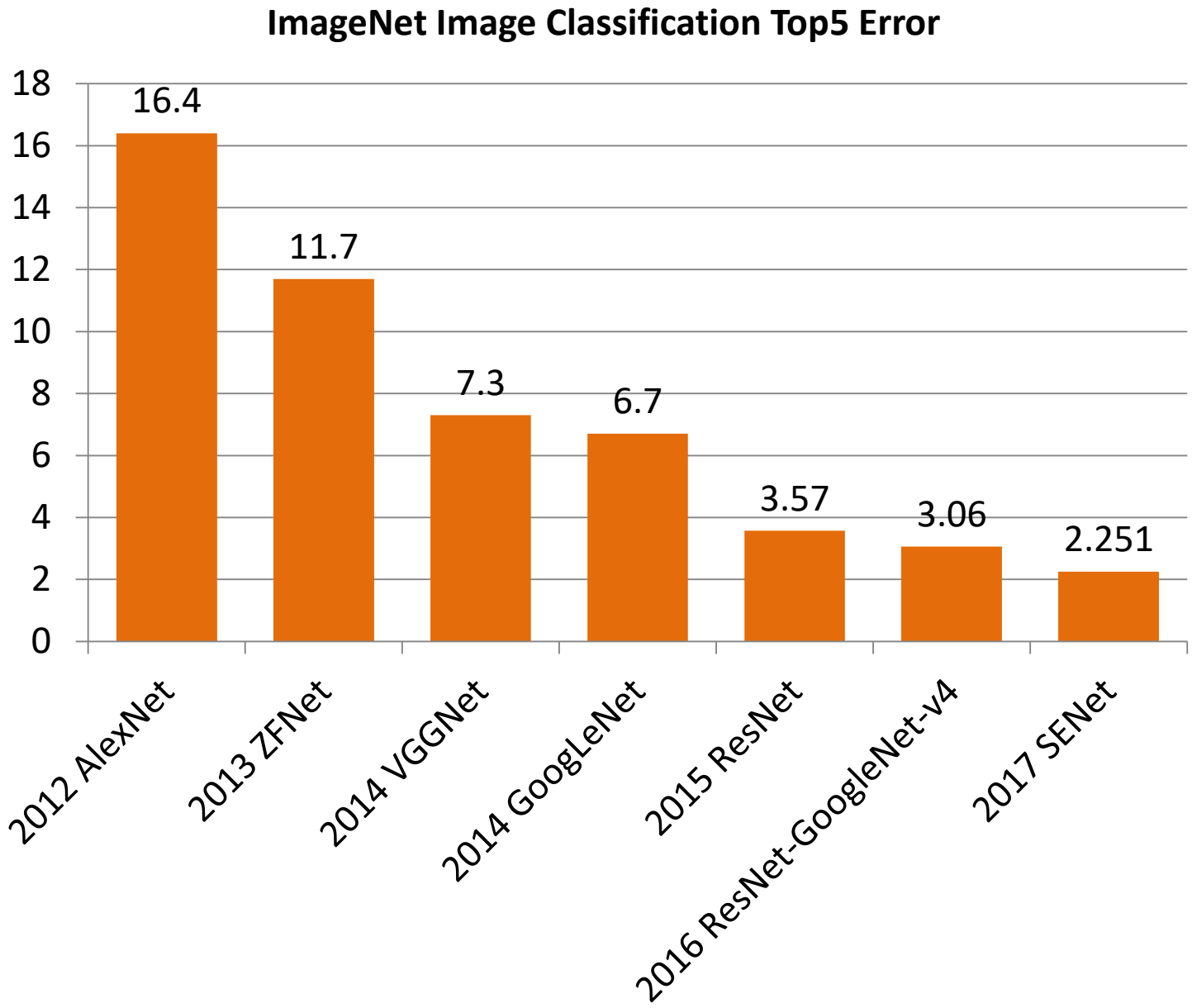


- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- Challenge: 1.2 million training images, 1000 classes

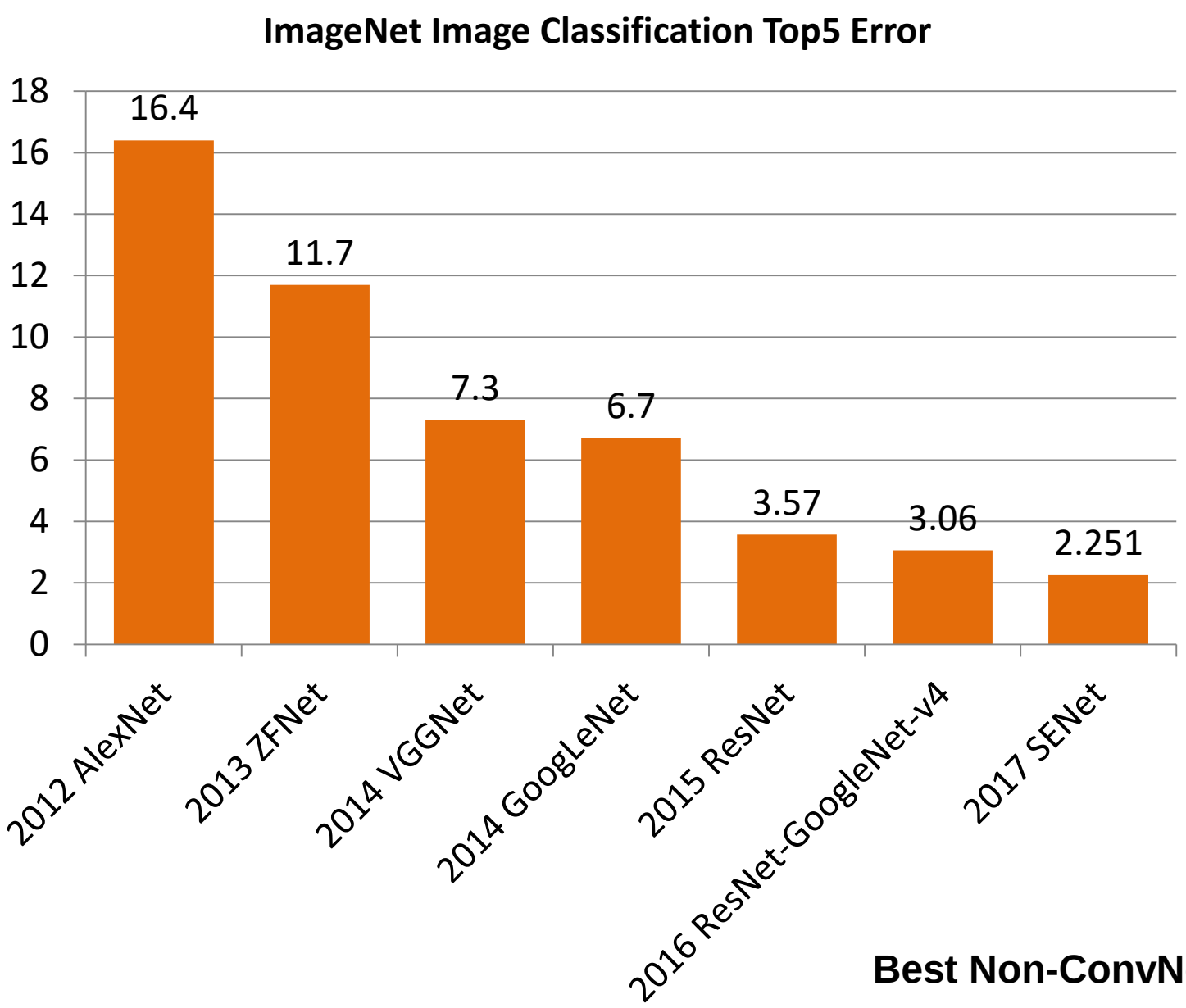
GPUs + Data

www.image-net.org/challenges/LSVRC/

Progress on ImageNet Challenge



Progress on ImageNet Challenge



Best Non-ConvNet in 2012: 26.2%

Things to remember

- Neural network and Image
  - Neuroscience, Perceptron, Problems due to High Dimensionality and Local Relationship
- Convolutional neural network (CNN)
  - Convolution Layer,
  - Nonlinearity Layer,
  - Pooling Layer,
  - Fully Connected Layer,
  - Loss/Classification Layer
- Progress on ImageNet challenge
  - Latest SENet, Winner 2017

Acknowledgements

- Thanks to the following researchers for making their teaching/research material online
  - Forsyth
  - Steve Seitz
  - Noah Snavely
  - J.B. Huang
  - Derek Hoiem
  - D. Lowe
  - A. Bobick
  - S. Lazebnik
  - K. Grauman
  - R. Zaleski
  - Antonio Torralba
  - Rob Fergus
  - Leibe
  - And many more …….

Next Class

Training Aspects of CNN

- Activation Functions
- Dataset Preparation
- Data Preprocessing
- Weight Initialization
- Optimization Methods
- Learning Rate
- Transfer Learning
- Generalization