

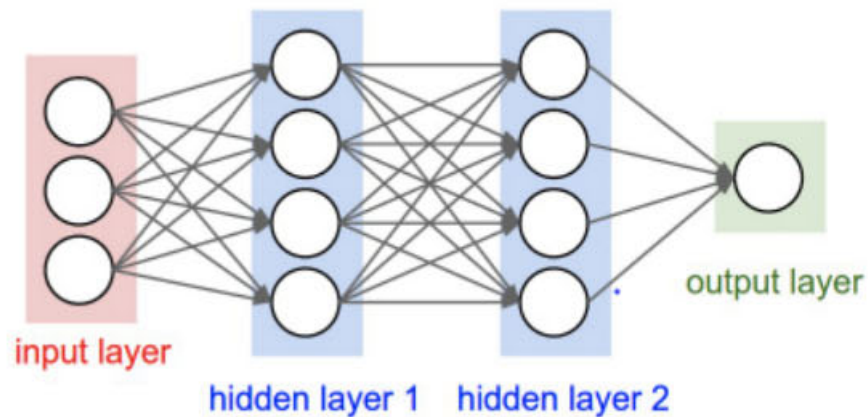
# Machine Learning

## Multilayer Networks

Jian Liu

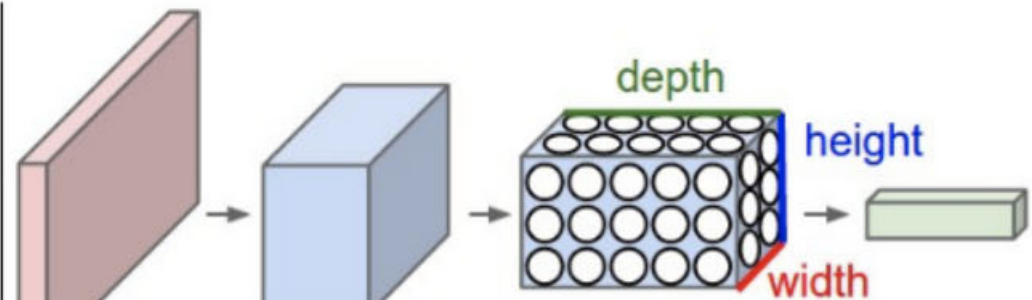
### Part 1: MLP

### Part 2: CNN



MLP

[towardsdatascience](https://towardsdatascience.com/)



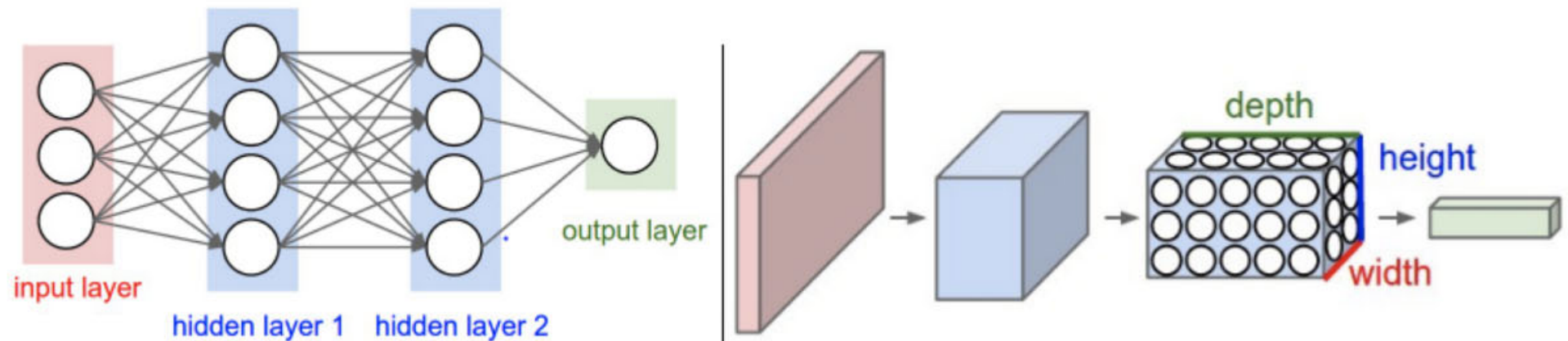
CNN

# Machine Learning

## Multilayer Networks

Jian Liu

### Part 2: CNN



MLP

[towardsdatascience](https://towardsdatascience.com/)

CNN

# Why Convnets?

## HOW A DEEP NEURAL NETWORK SEES

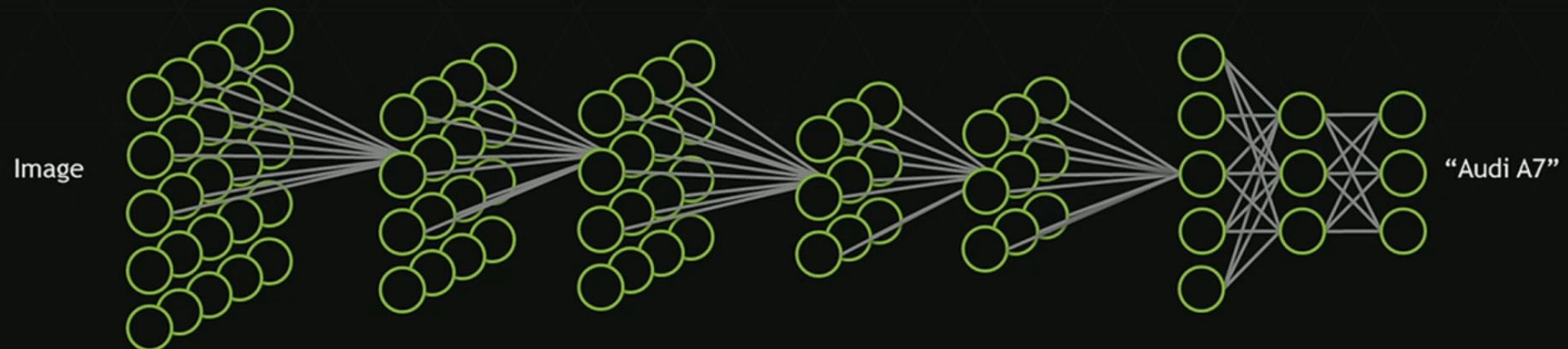
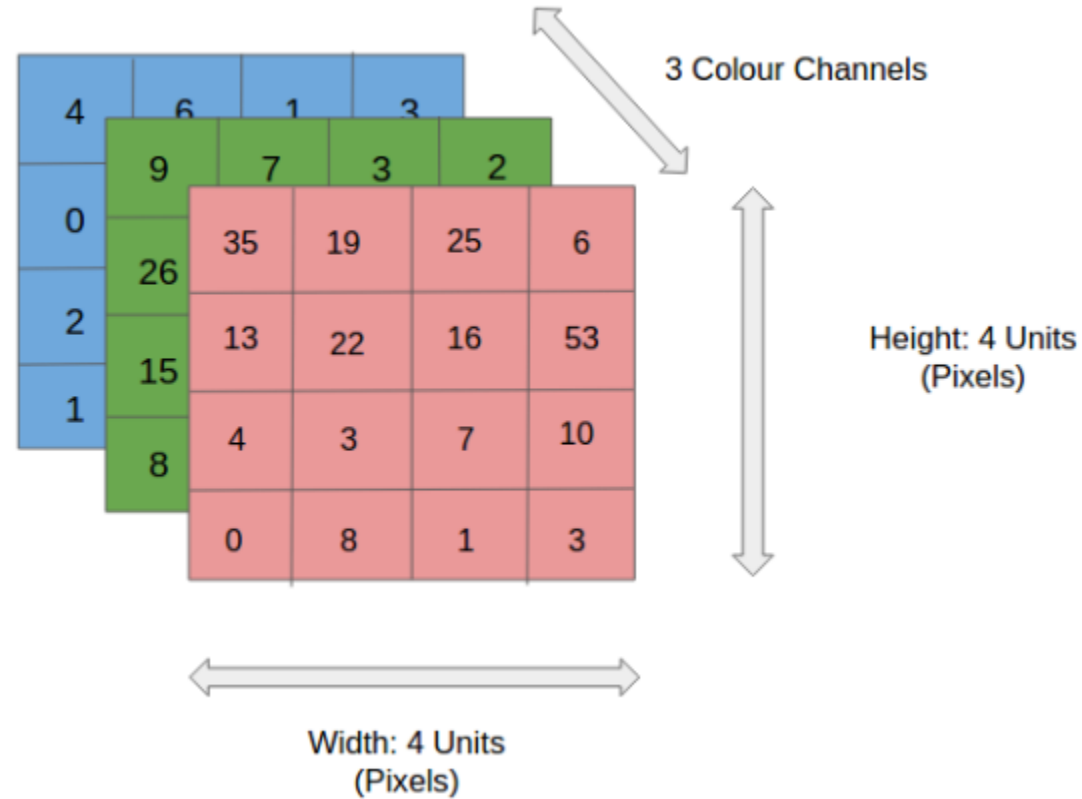


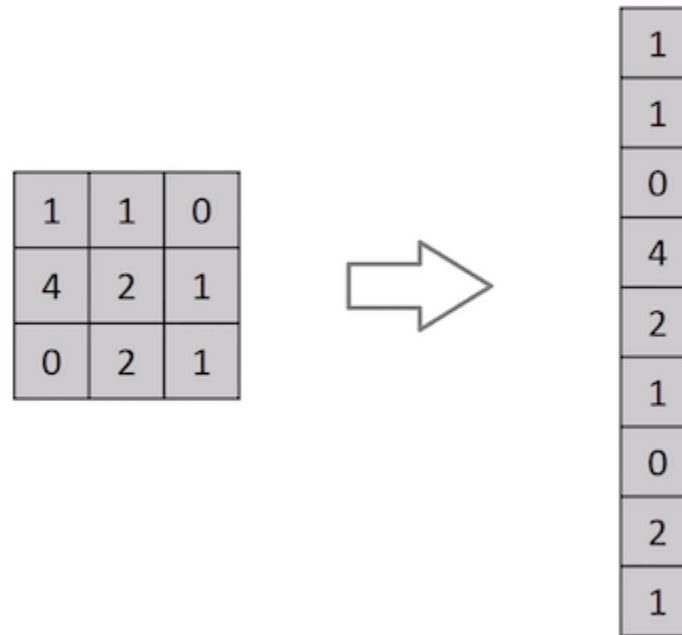
Image source: "Unsupervised Learning of Hierarchical Representations with Convolutional Deep Belief Networks" ICML 2009 & Comm. ACM 2011.  
Honglak Lee, Roger Grosse, Rajesh Ranganath, and Andrew Ng.

# Why Convnets?



4x4x3 RGB Image

# Why Convnets?

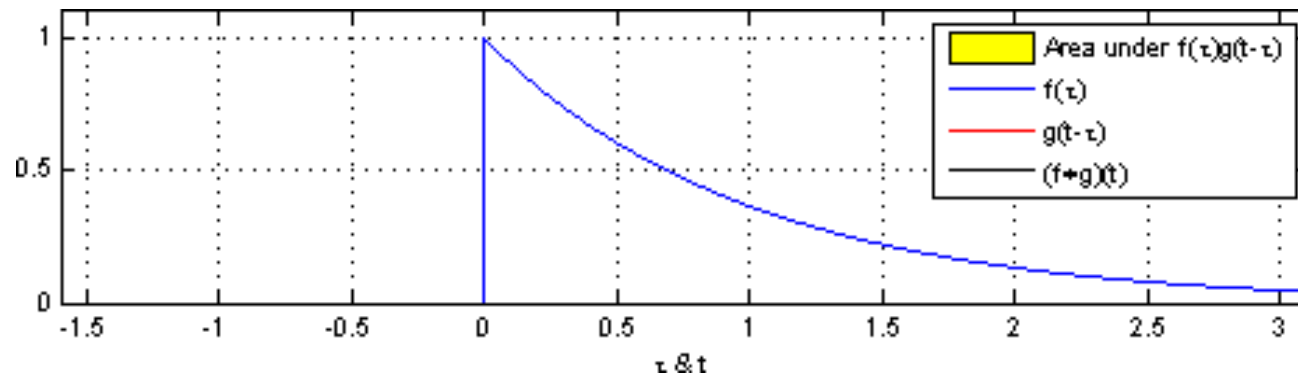


Flattening of a 3x3 image matrix into a 9x1 vector

A ConvNet is able to successfully capture the **Spatial and Temporal dependencies** in an image through the application of relevant **filters**.

# What is the convolution?

$$f(x) * g(x) = \int_{-\infty}^{\infty} f(\tau) g(x - \tau) d\tau$$



[From Wikipedia]

# Filter application

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

1	1	1
0	0	1
0	0	1

1				

# Filter application

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

1	1			

1	1	1
0	0	1
0	0	1



# Filter application

$\mathbf{x} =$

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

$\mathbf{w} =$

1	1	1
0	0	1
0	0	1

$+ w_0$

1	1	1	1	0
1	1	1	2	0
3	4	4	5	2
2	2	1	2	1
2	3	3	3	2

$$= \mathbf{w}^T \mathbf{x} + w_0$$

The filter can be implemented with a neuron!

However, the input is not “static” because the filter is slid across the image

# Padding

**x=**

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

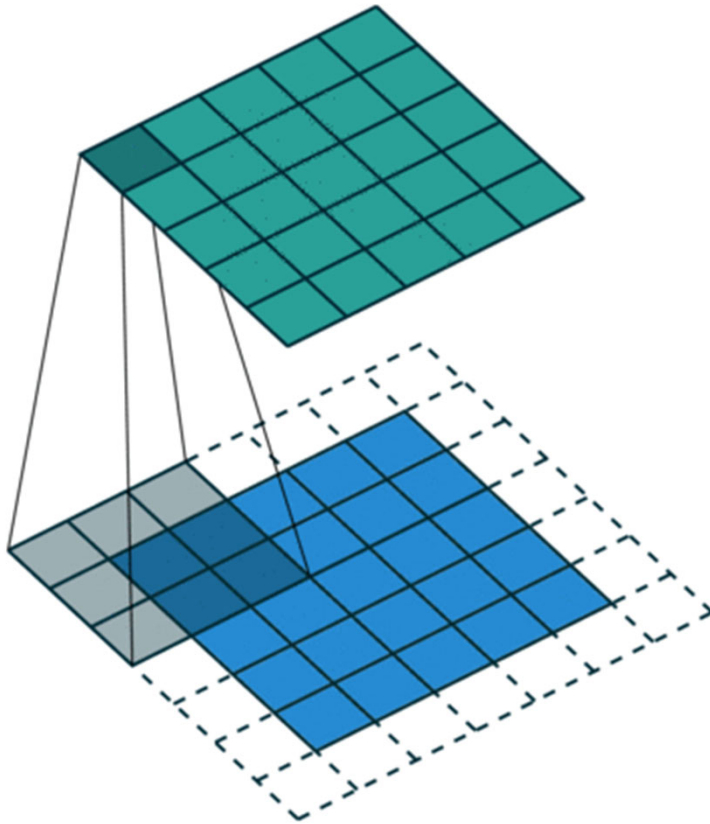
**w=**

1	1	1
0	0	1
0	0	1

0	0	0	0	0	0	0
1	1	1	1	1	0	
...	1	1	1	2	0	
	3	4	4	5	2	
	2	2	1	2	1	
	2	3	3	3	2	

The application of the filter would reduce the size of the image. This can be prevented by padding the image, typically with zeros.

# Padding



SAME padding: 5x5x1 image is padded with 0s to create a 6x6x1 image

## **Same Padding.**

augment the 5x5x1 image into a 6x6x1 image and then apply the 3x3x1 kernel over it, we find that the convolved matrix turns out to be of dimensions 5x5x1.

# Stride

$x=$

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

1	1	0
3	4	2
2	3	2

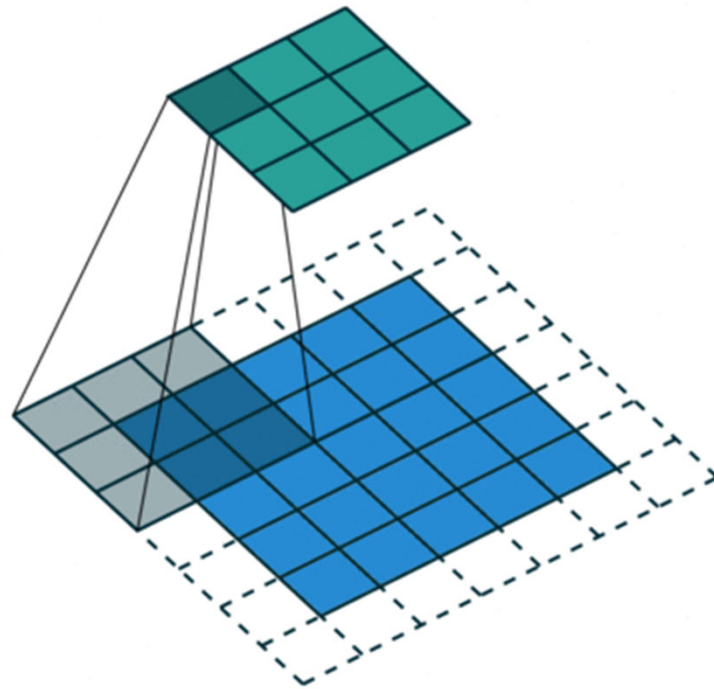
The stride can be more than 1, which downsamples the image.

$w=$

1	1	1
0	0	1
0	0	1

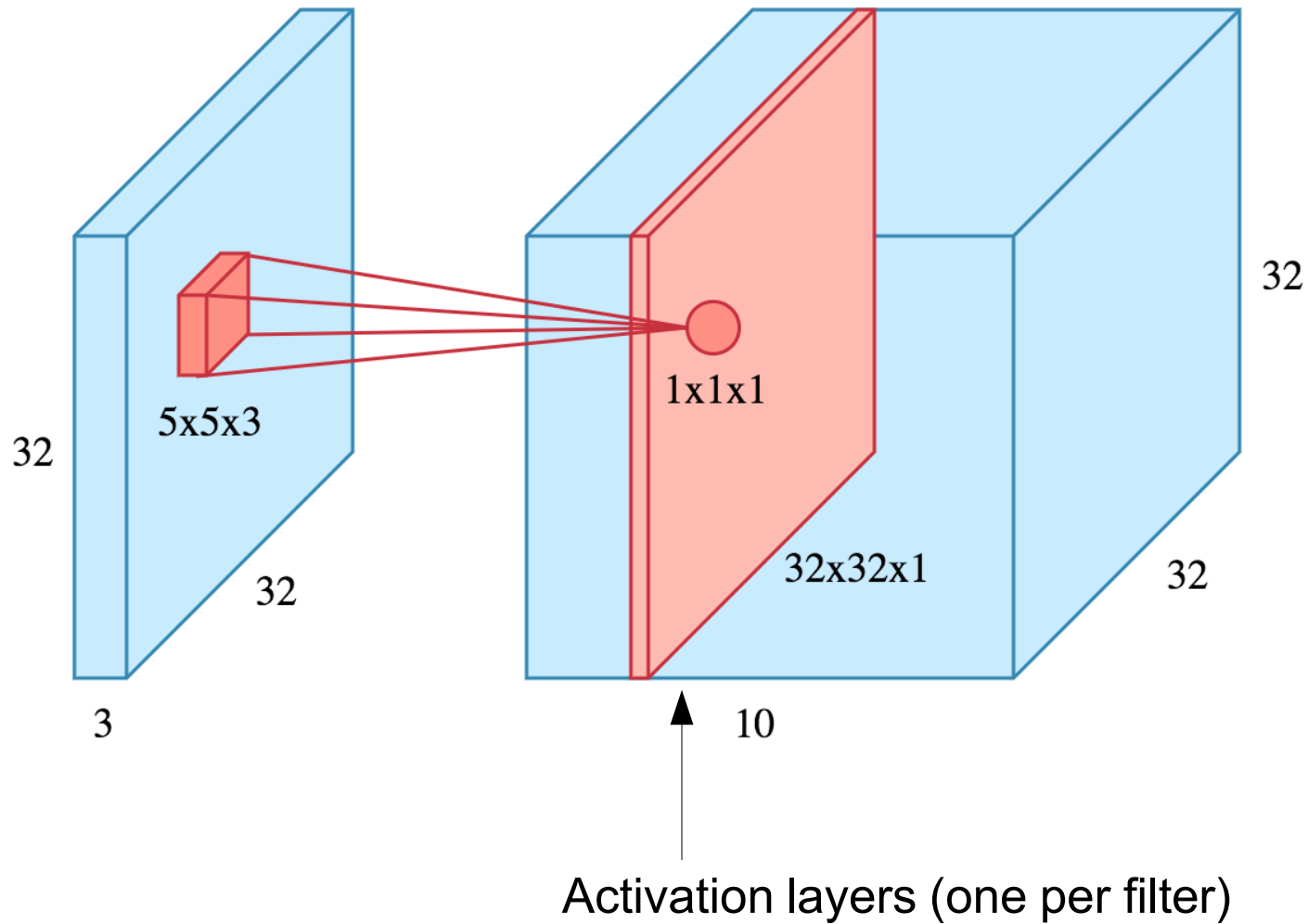
Clearly not all strides are possible. For instance in this image 2 is ok, but 3 would not work.

# Stride



Convolution Operation with Stride Length = 2

# Images and filters



# Filter/Kernel

1 <sub>x1</sub>	1 <sub>x0</sub>	1 <sub>x1</sub>	0	0
0 <sub>x0</sub>	1 <sub>x1</sub>	1 <sub>x0</sub>	1	0
0 <sub>x1</sub>	0 <sub>x0</sub>	1 <sub>x1</sub>	1	1
0	0	1	1	0
0	1	1	0	0

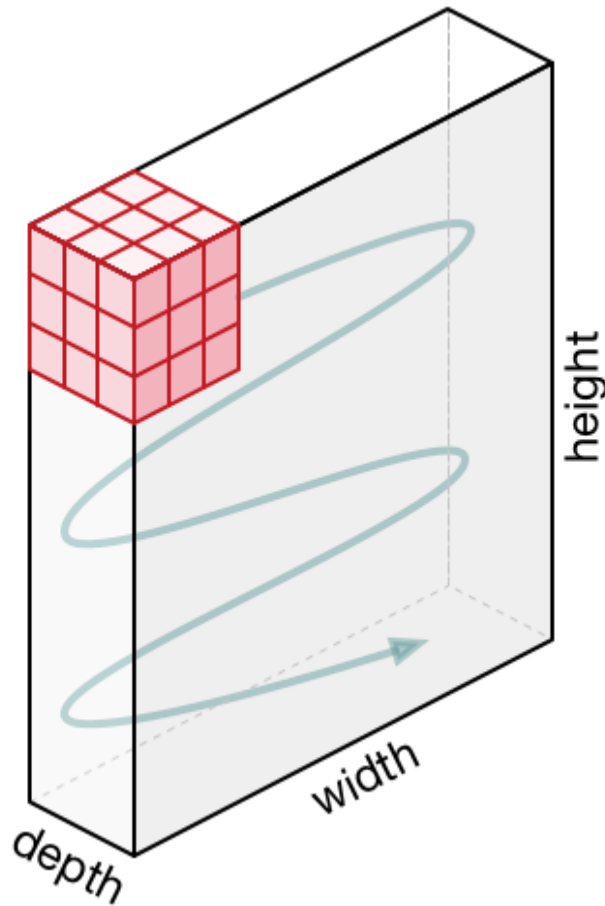
Image

4		

Convolved  
Feature

Convoluting a 5x5x1 image with a 3x3x1 kernel to get a 3x3x1 convolved feature

# Filter/Kernel



Movement of the Kernel

The Kernel shifts 9 times  
because of **Stride Length = 1**  
**(Non-Strided)**

Every time performing a **matrix multiplication operation** between **K** and the **portion P** of the **image** over which the kernel is hovering



# Convolution operation on a MxNx3 image matrix with a 3x3x3 Kernel

0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	143	148	158	...
...	...	...	...	...	...	...

Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...	...	...	...	...	...	...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...	...	...	...	...	...	...

Input Channel #3 (Blue)

-1	-1	1
0	1	-1
0	1	1

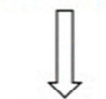
Kernel Channel #1

1	0	0
1	-1	-1
1	0	-1

Kernel Channel #2

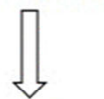
0	1	1
0	1	0
1	-1	1

Kernel Channel #3



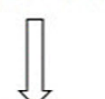
308

+



-498

+



164

+ 1 = -25

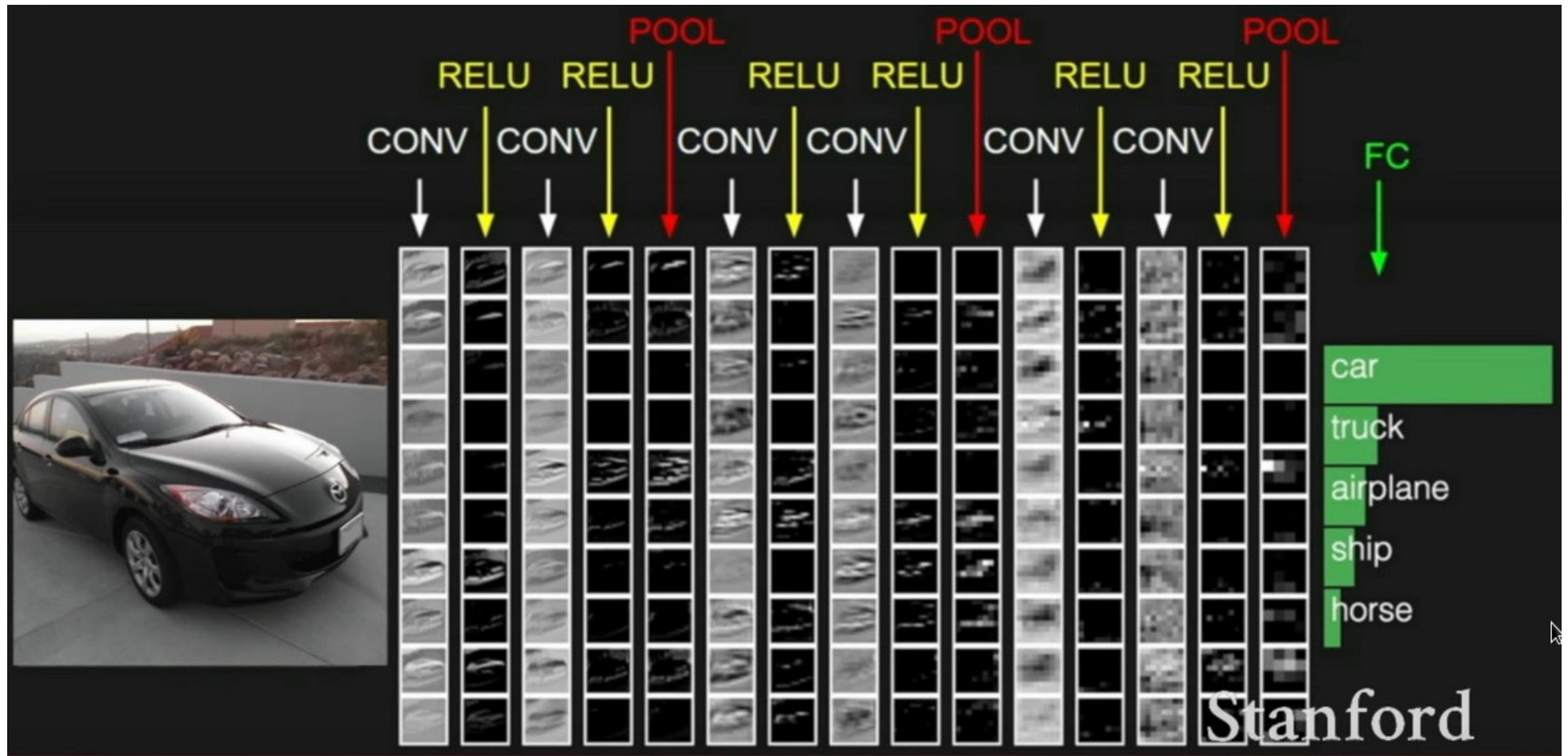


Bias = 1

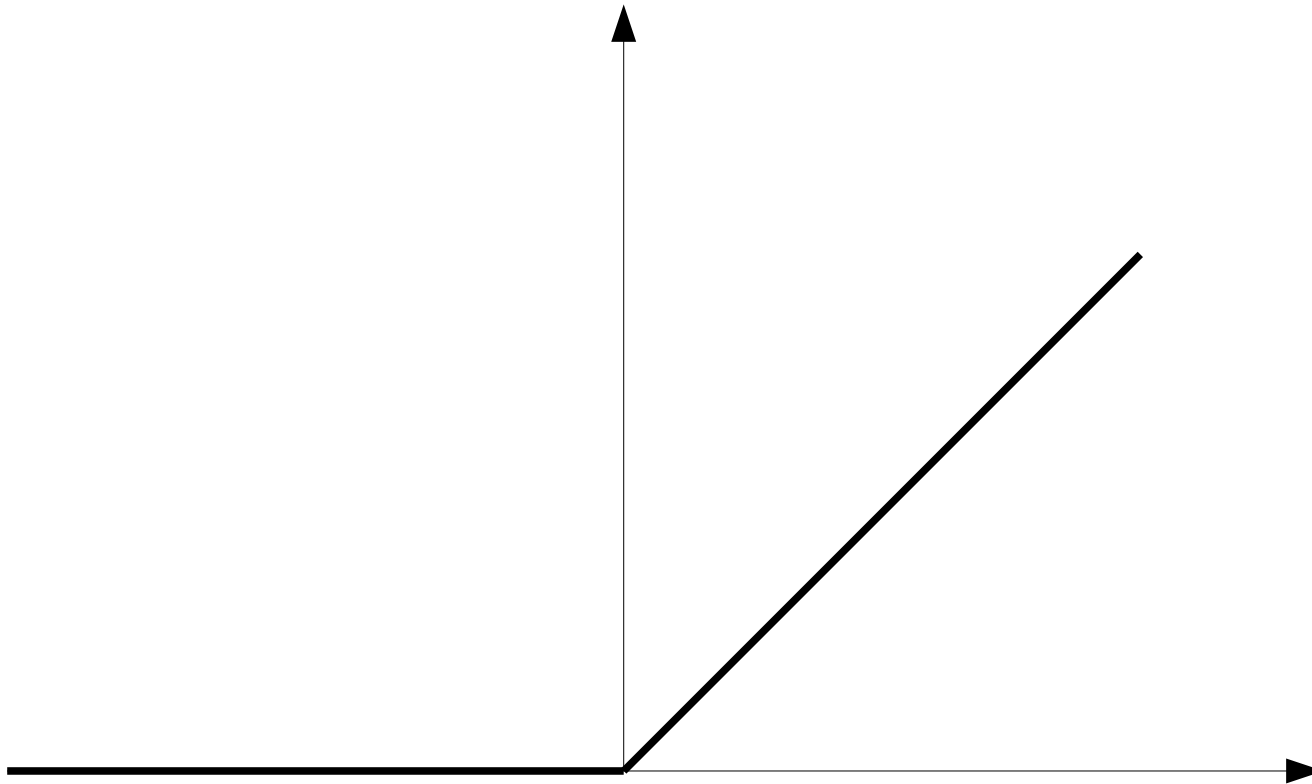
Output

-25				...
				...
				...
				...
...	...	...	...	...

# Architecture

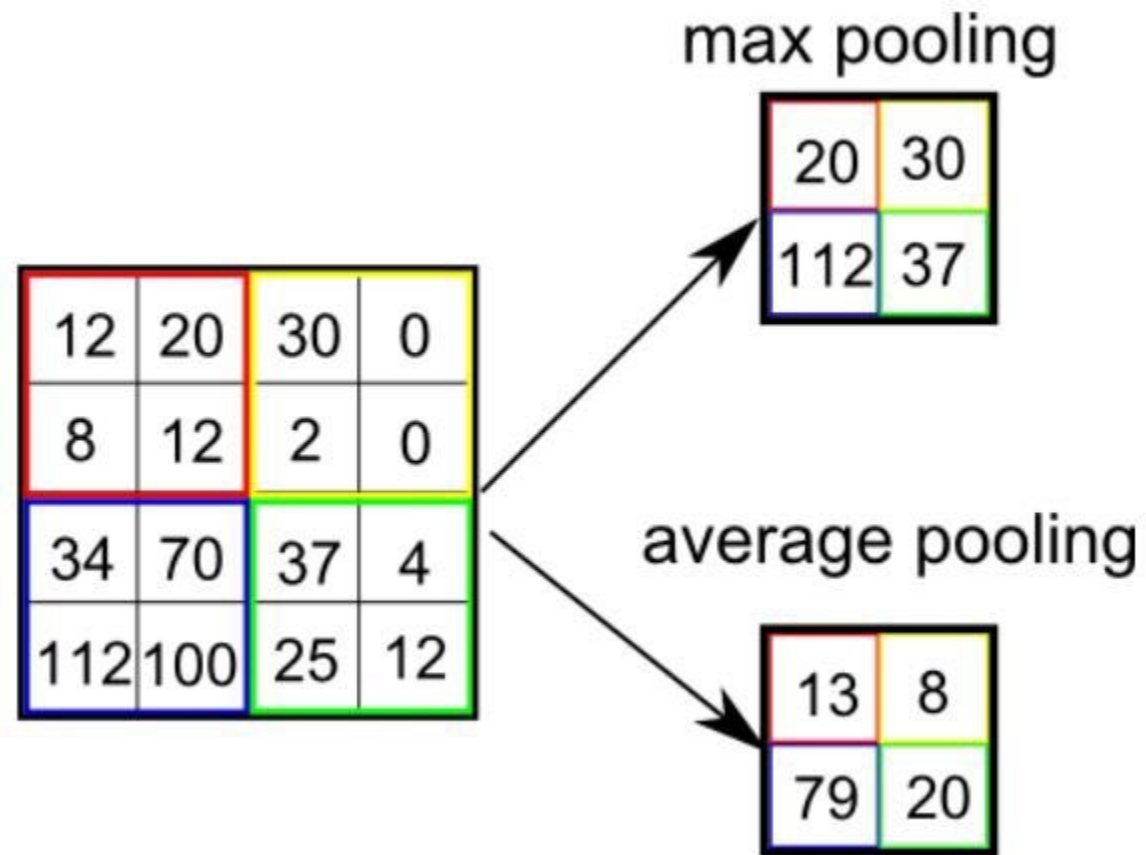


# Rectified Linear Units (ReLUs)



$$o(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$$

# Pooling



# (Max) Pooling

1	1	1	1
1	1	1	2
3	4	4	5
2	2	1	2

1	2
4	5

Max pooling is the most common way to downsample the image, in order to focus on higher-level patterns.

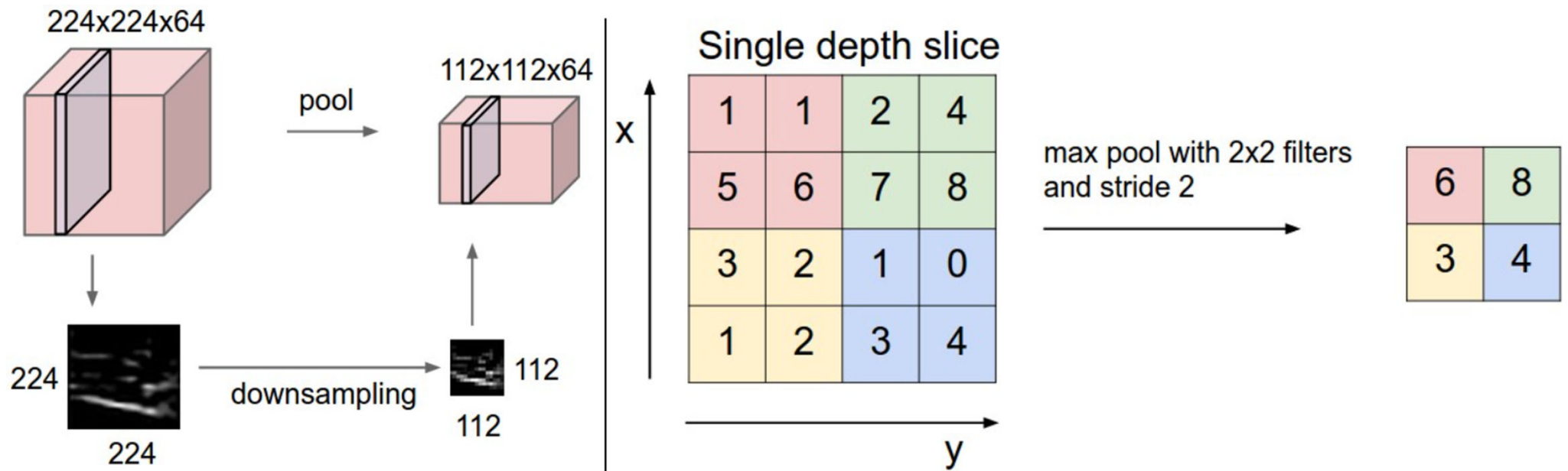
# (Max) Pooling

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

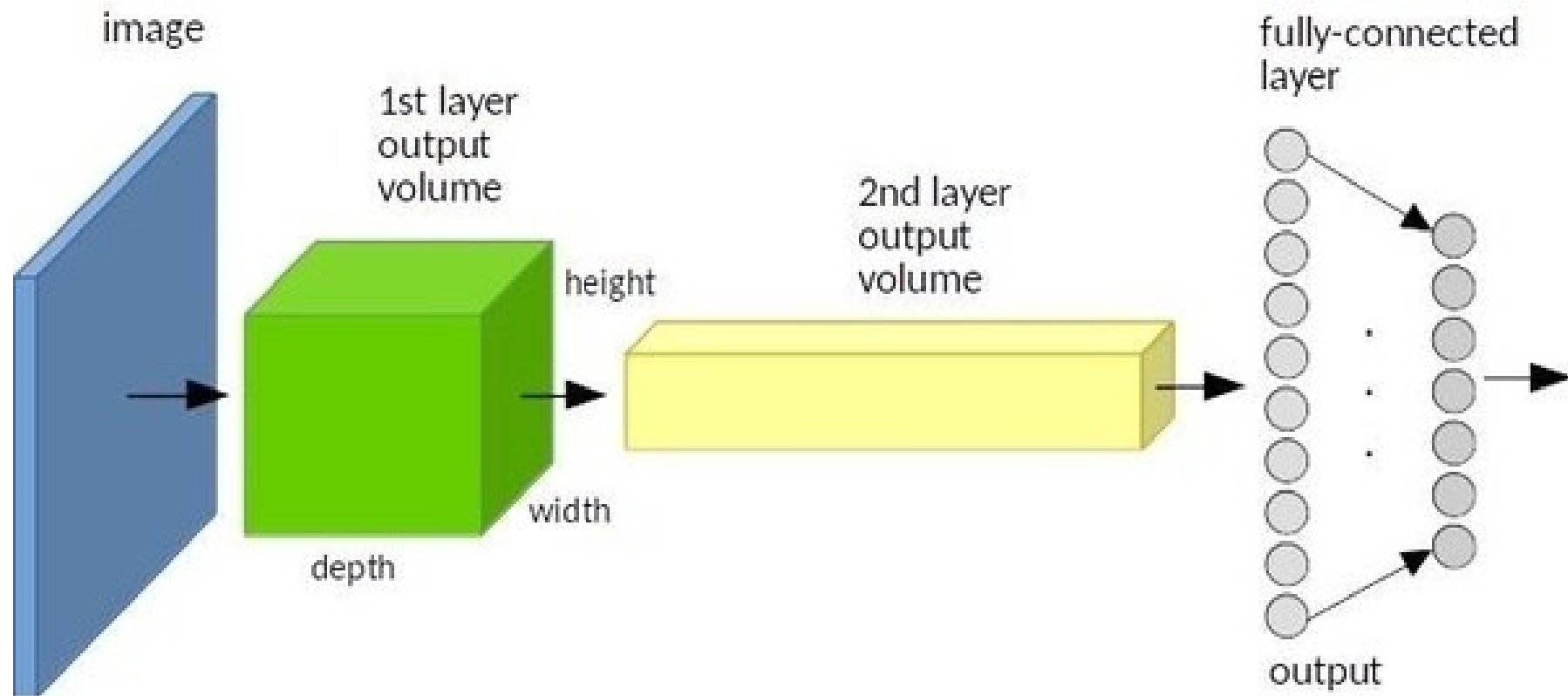
3x3 pooling over 5x5 convolved feature

# Pooling



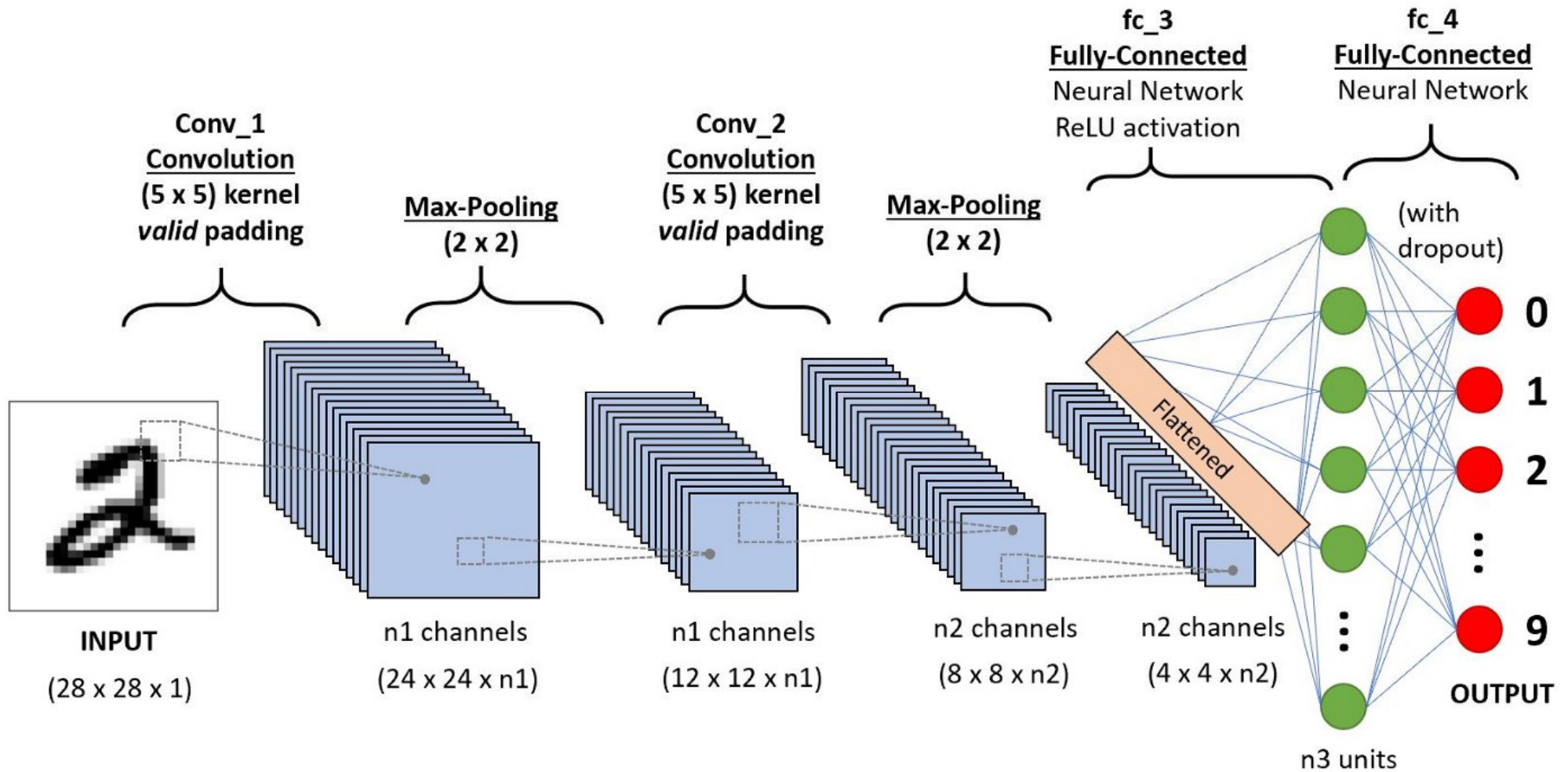
Tssprk\$e}ivhs{ rweq tpw xli\$spq i\$wtexrep)\$  
 mhitirhirx)\$r\$iegl\$hitx\$wpgi\$j\$li\$rtyx\$spq i2

# From convolutional to MLP

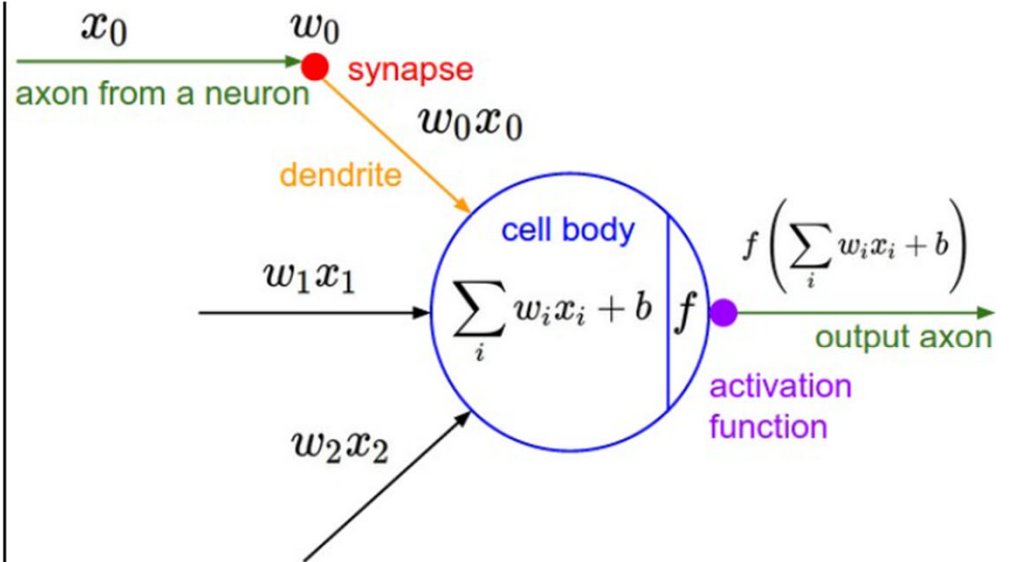
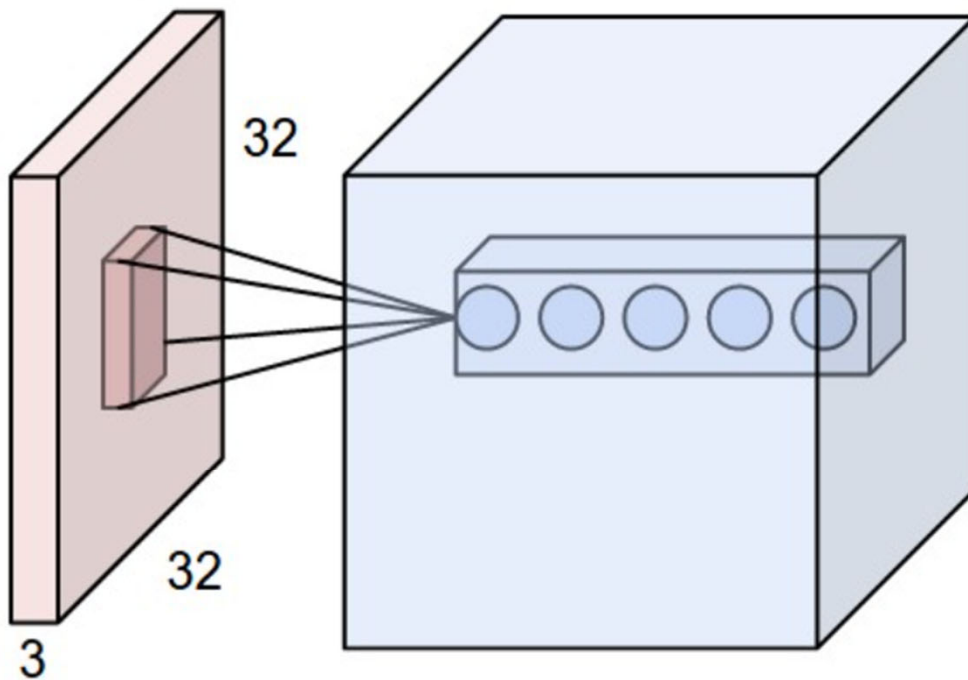




# Classification — Fully Connected Layer (FC Layer)

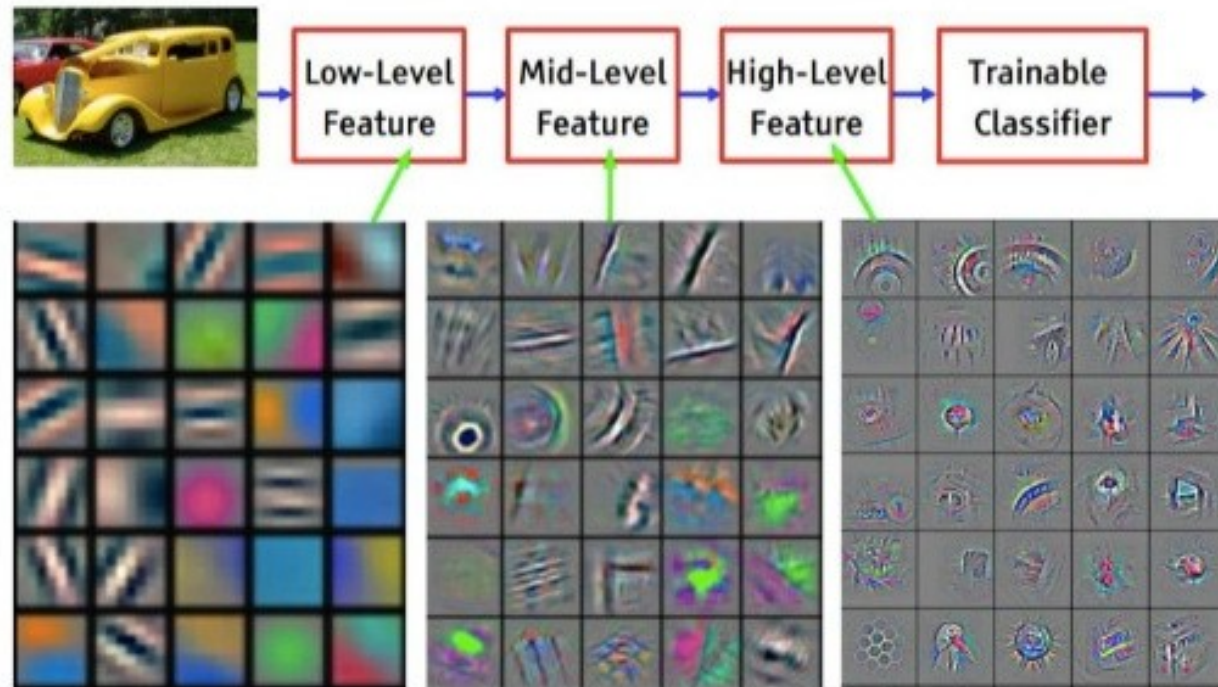


# Convvnets



# Features

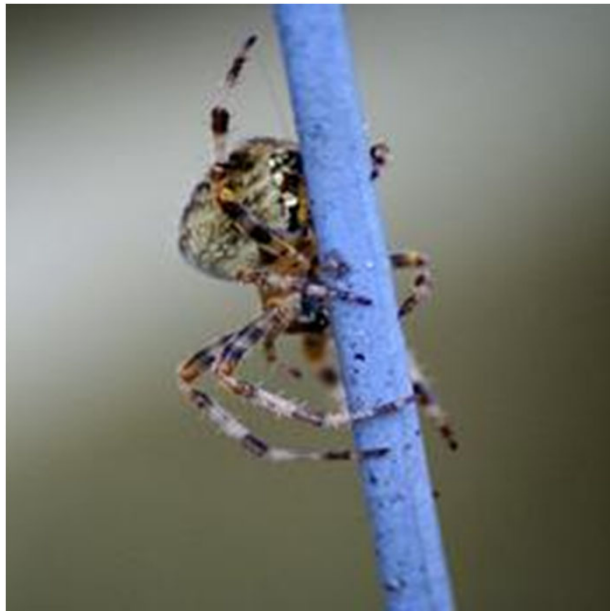
## Convolutional Neural Network



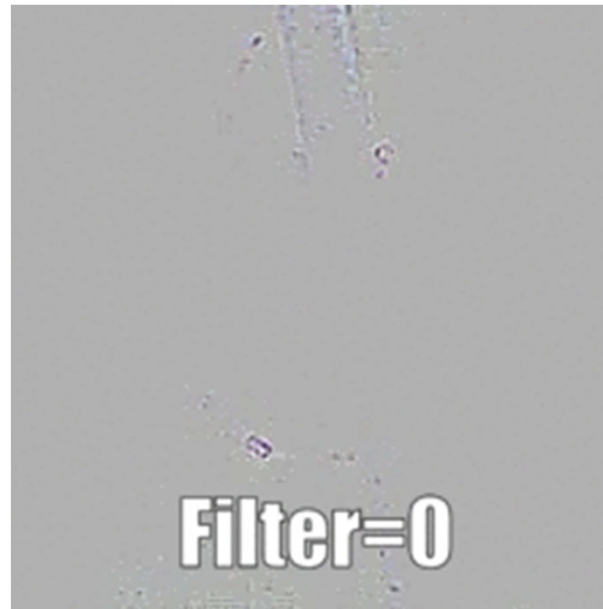
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

# CNN Visualizations

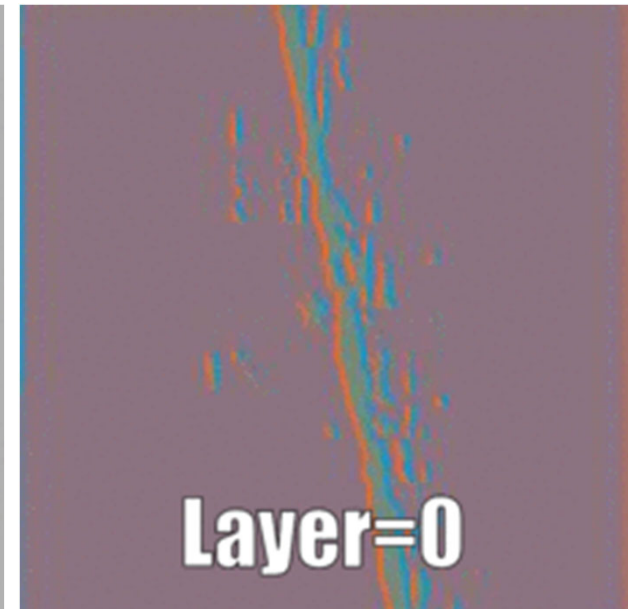
**Input Image**



**Layer Vis. (Filter=0)**



**Filter Vis. (Layer=29)**



# Architectures

## LeNet LeCun et al. in 1998

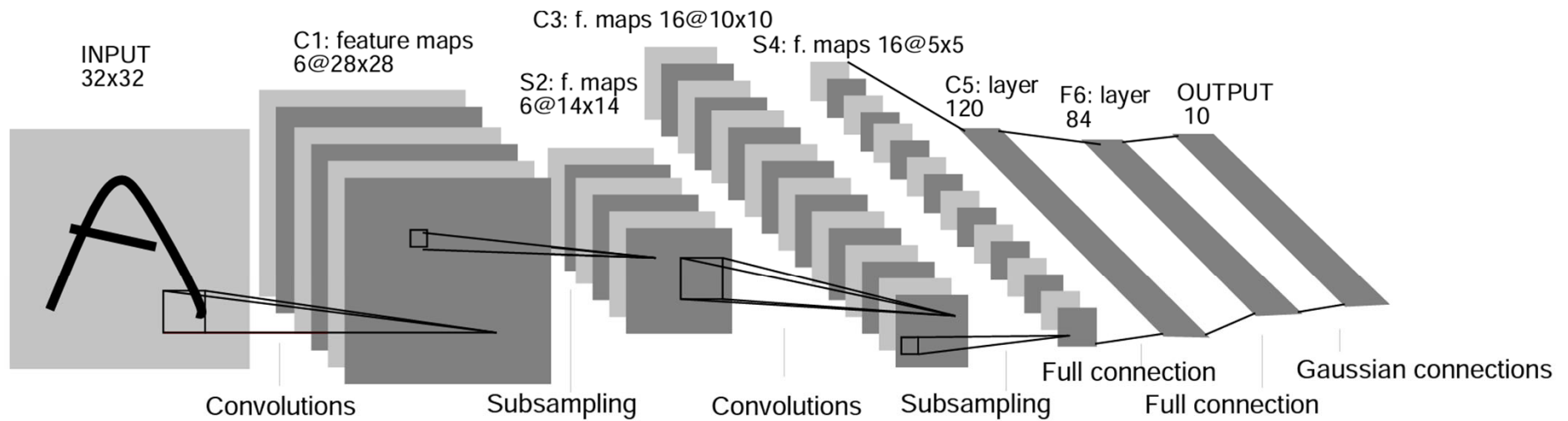
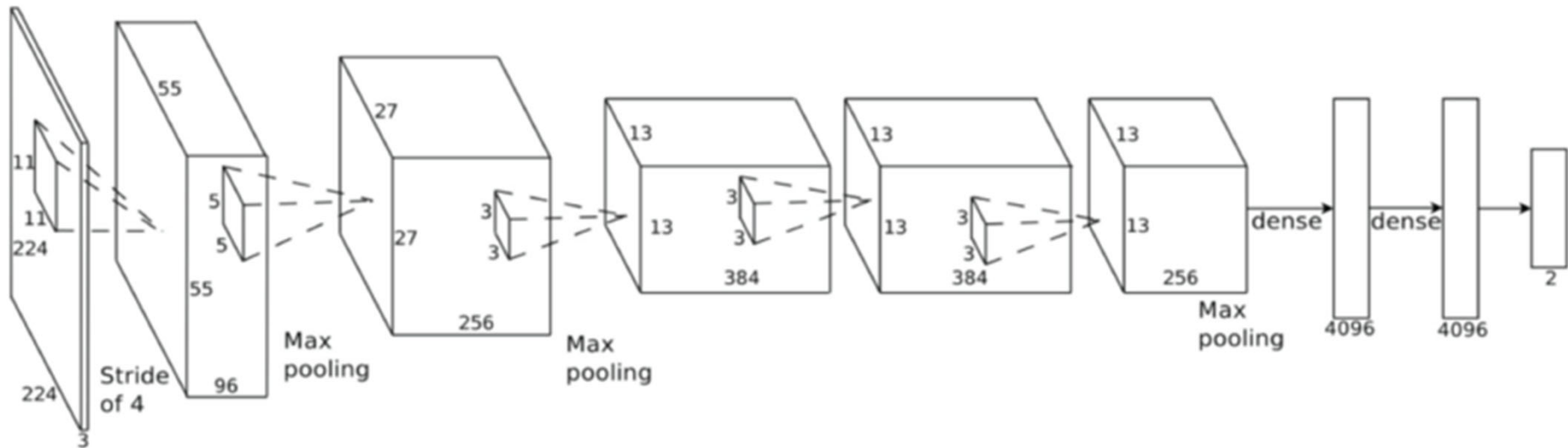


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

# Architectures

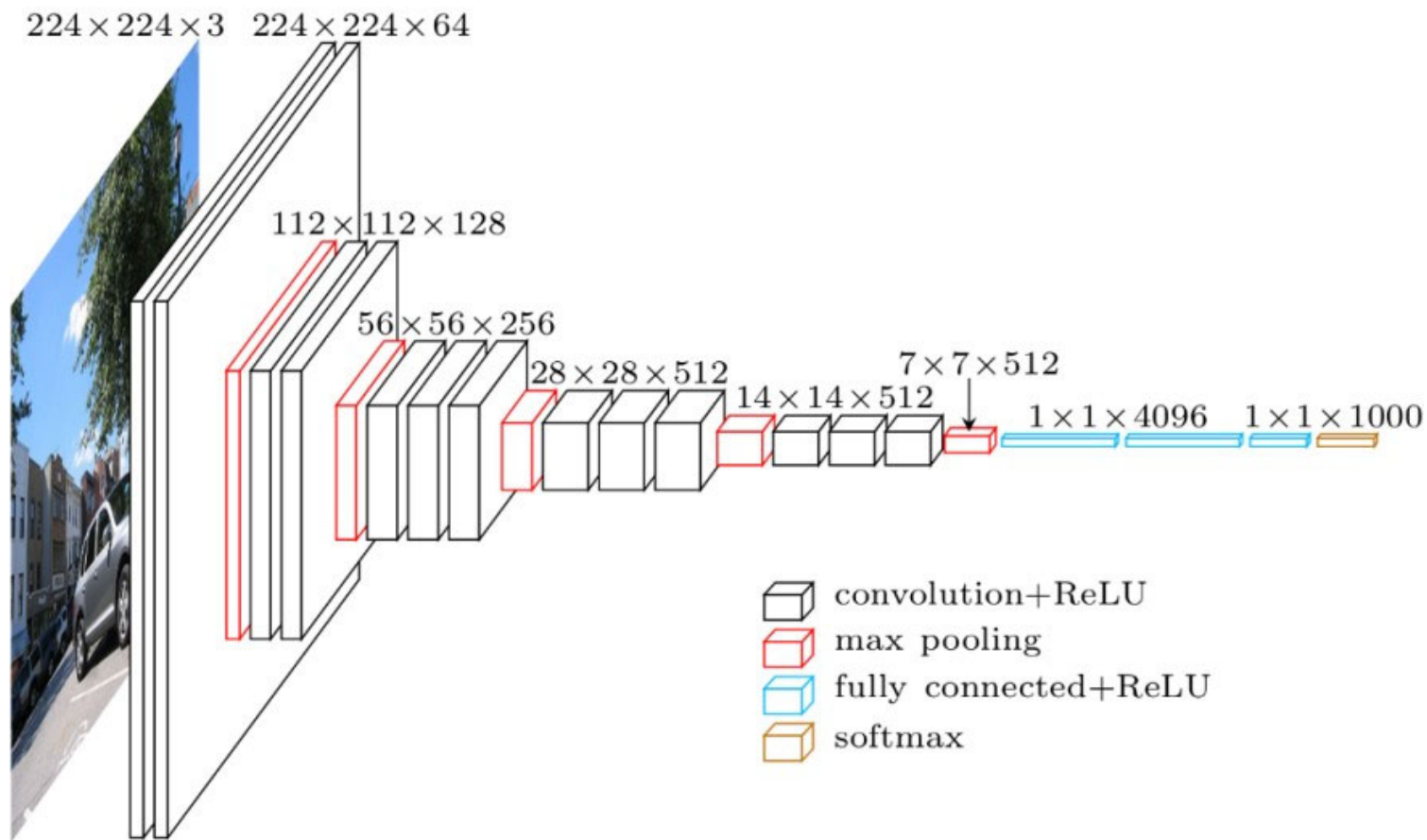
## AlexNet Krizhevsky et al. in 2012





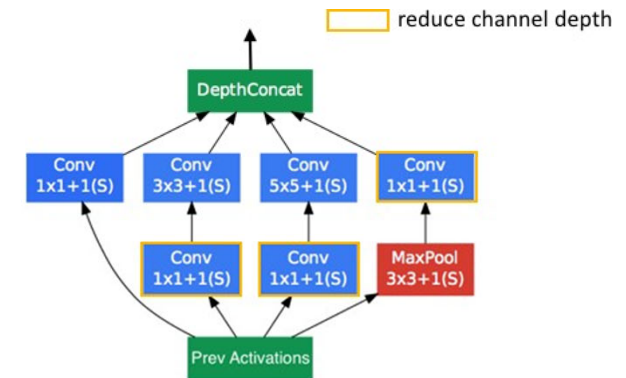
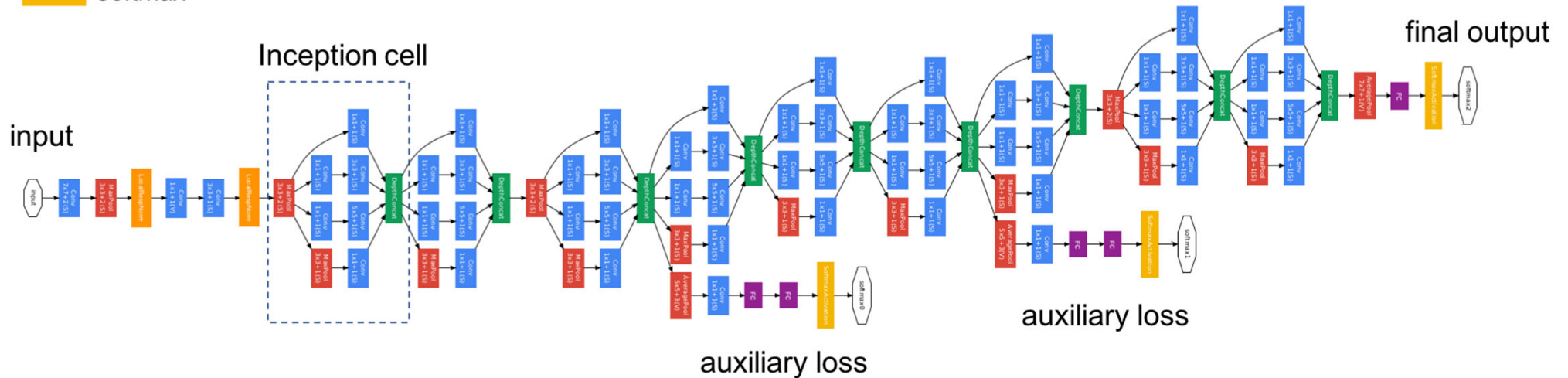
# Architectures

## VGG16 Simonyan and Zisserman 2014



# Architectures

## Inception (Google) Szegedy, et al 2015





# Architectures

## ResNet

He, et al 2015

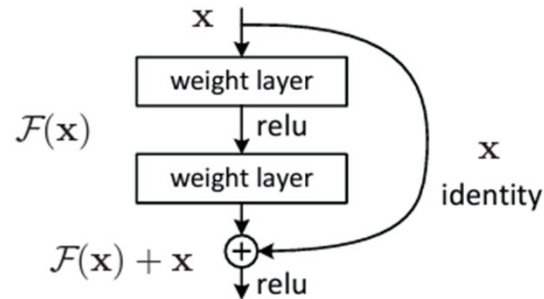
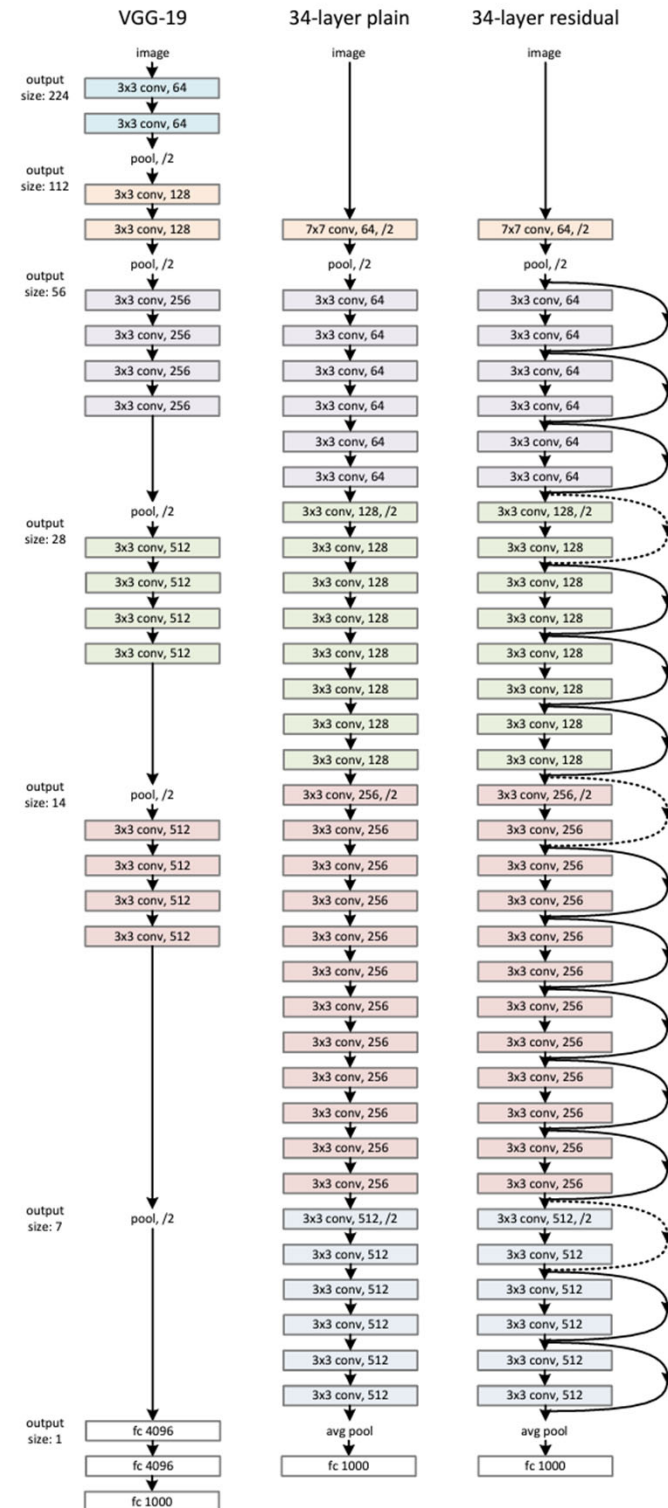
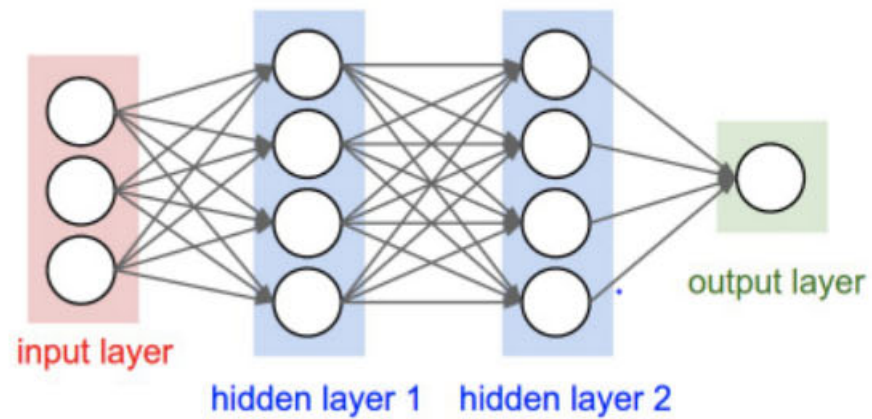


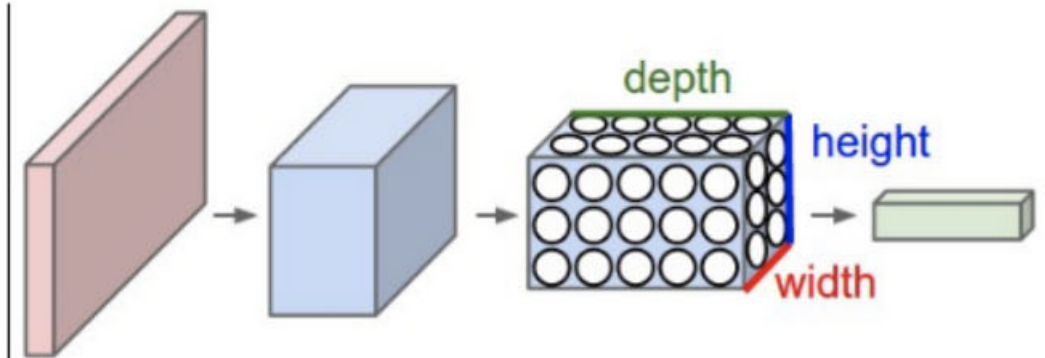
Figure 2. Residual learning: a building block.



# Deep learning



MLP



CNN