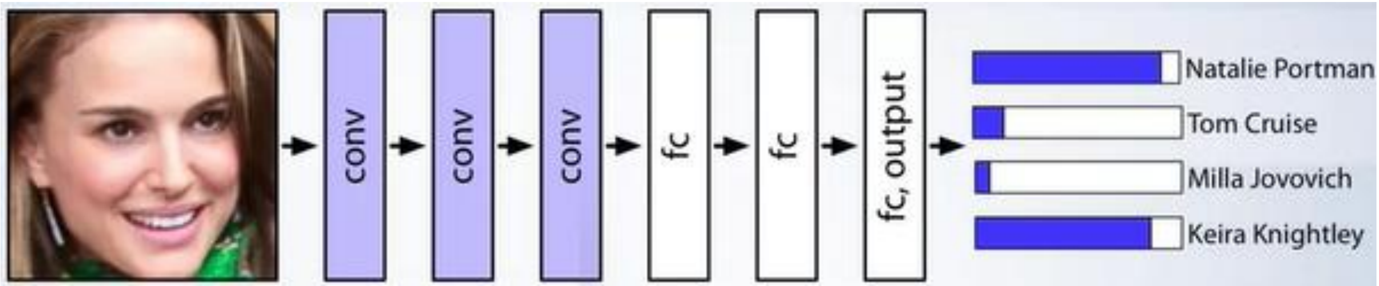
LX CNNs and RNNs

Z. Gu 2021



Acknowledgement: some contents taken from UC Berkeley CS231n cs231n.github.io/

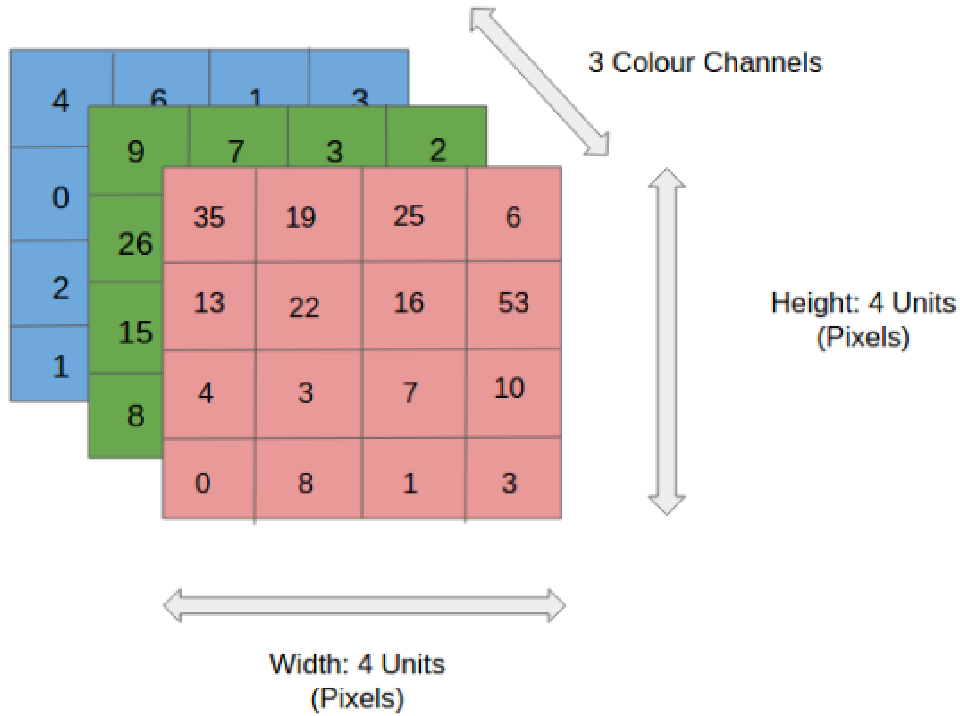
Classic Computer Vision

- Most “classic” (non-ML) CV algorithms are implemented in the OpenCV library, including
  - Core Operations:
    - basic operations on image like pixel editing, geometric transformations, code optimization, some mathematical tools etc.
  - Image Processing
    - Thresholding, smoothing, edge detection, Hough Line Transform…
  - Feature Detection and Description
    - HOG, SIFT, SURF, BRIEF, ORB…
  - Video analysis
    - Object tracking w. optical flow
  - Camera Calibration and 3D Reconstruction
- They are simple, fast and reliable (e.g., for lane detection), and are often used in conjunction w. complex ML/DL algorithms, which may be sometimes unreliable and unpredictable.

OpenCV

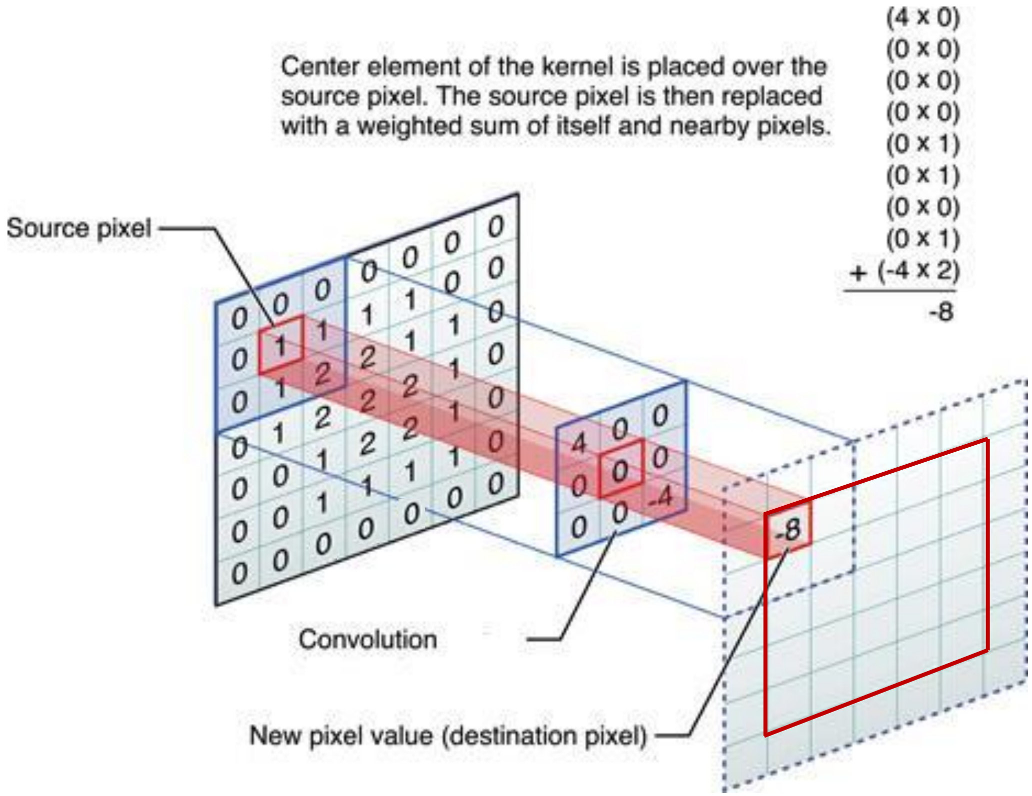
Input Image Encoding

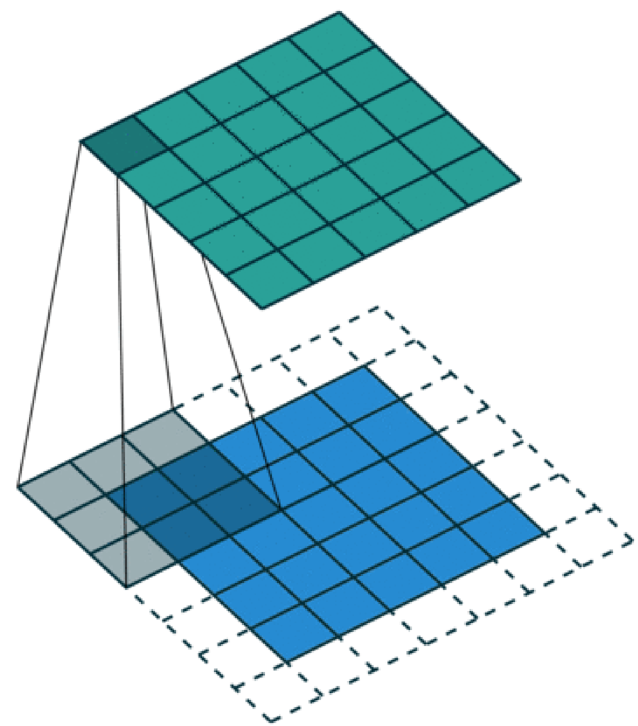
- A size $N \times N$ color image has volume $N \times N \times 3$, w. $N \times N$ pixels and 3 color components (Red, Green, and Blue, RGB) for each pixel
  - There are a number of color space encodings, incl. RGB, HSV, CMYK, etc.
- A size $N \times N$ greyscale image has volume $N \times N \times 1$
- Color depth, or bit depth, is number of bits used for each color component of a single pixel
  - Typical value is 8, so pixel value has range $[0, 255]$
  - Larger depth is possible, i.e., true color (24-bit) is used in computer and phone display for human eyes, but 8-bit is typically enough for CV tasks



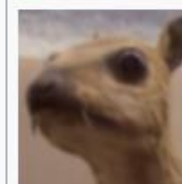
Filters/Kernels in Computer Vision

- Convolution operation: we slide (convolve) each filter across the width and height of the input volume and compute dot products between the entries of the filter (kernel) and the input at any position. As we slide the filter over the width and height of the input volume we will produce a 2-dimensional activation map that gives the responses of that filter at every spatial position.
  - dot product operation: elementwise multiplication of a filter w. corresponding input values, then summing them to generate one output value
  - Used to extract features for downstream tasks (classification or regression)



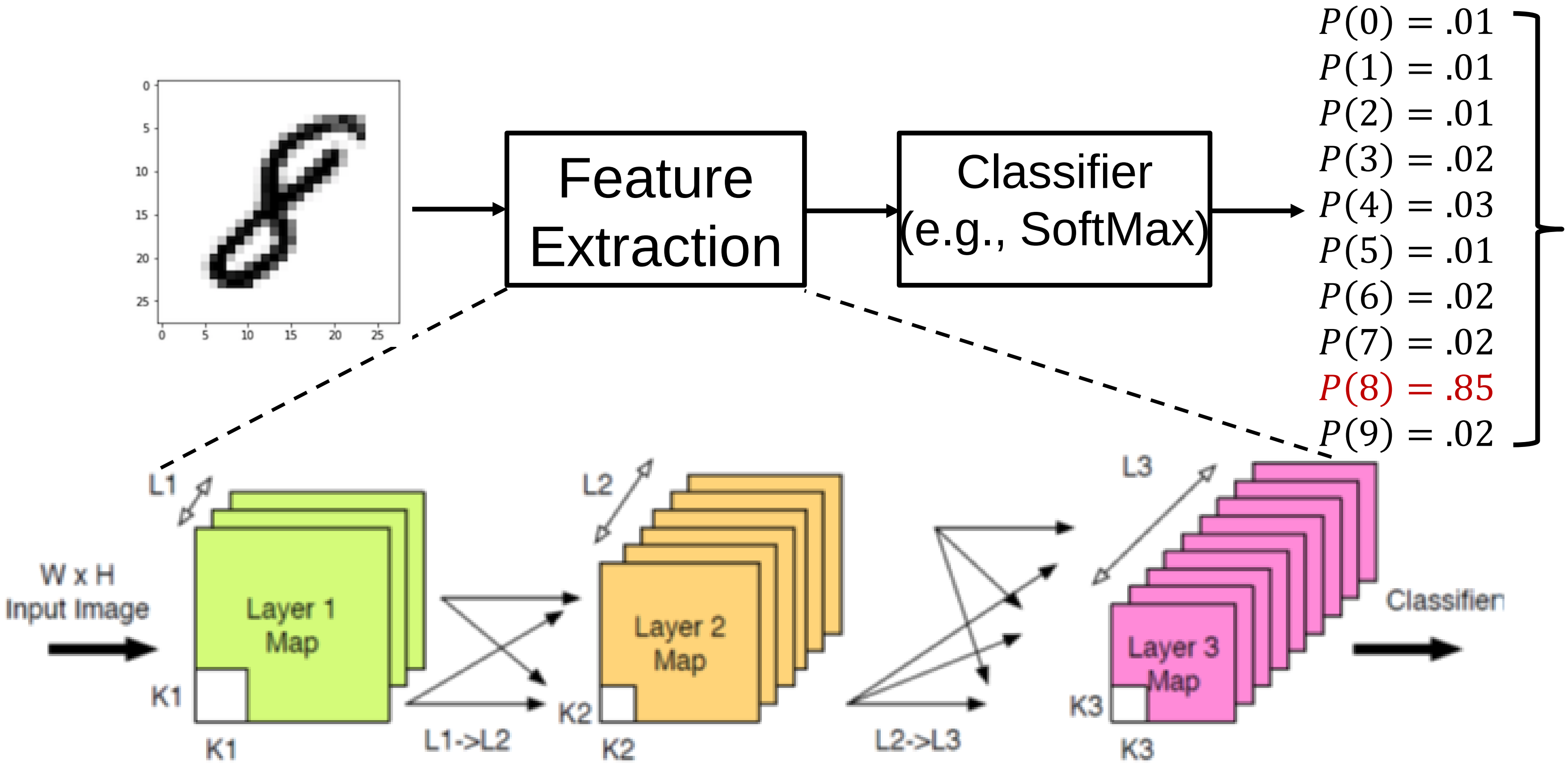


Effects of Convolution w. Common Filters

Operation	Kernel ω	Image result g(x,y)
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur 3 × 3 (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	
Gaussian blur 5 × 5 (approximation)	$\frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	
Unsharp masking 5 × 5 Based on Gaussian blur with amount as 1 and threshold as 0 (with no image mask)	$\frac{-1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	

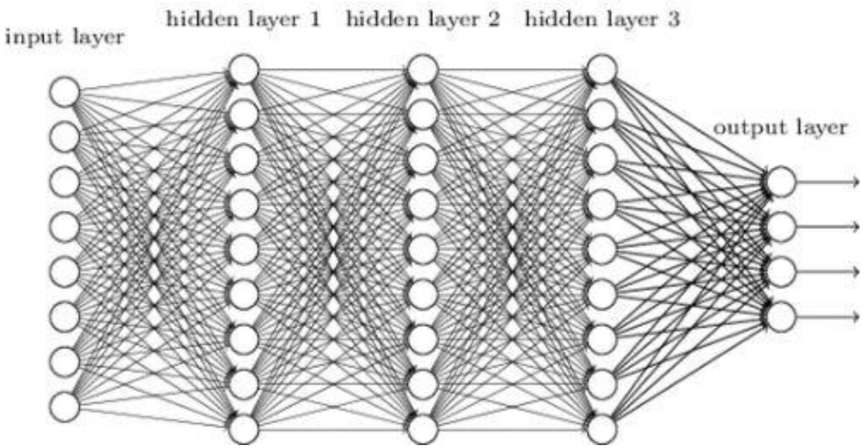
- These filters were designed, or "hand-crafted", by CV researchers. They extract features used by downstream tasks such as classification, image segmentation, etc.

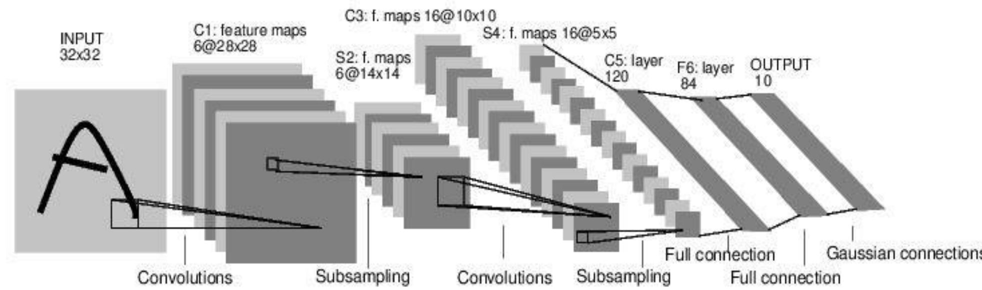
Convolutional Neural Networks (CNN)



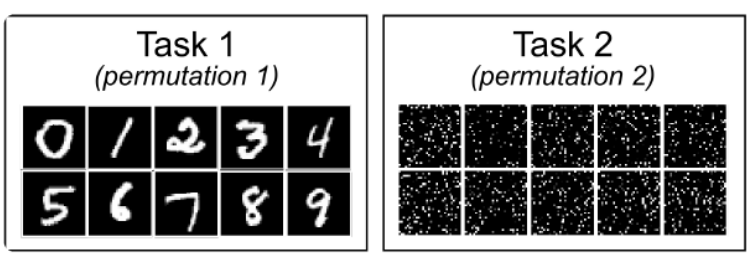
- A CNN (also called ConvNet) is a sequence of Convolutional (CONV) Layers, Pooling (POOL) Layers and non-linear activation functions for feature extraction, followed by one or more Fully-Connected (FC) Layers for classification based on the extracted features
- Difference from classic CV: learn custom filters in CONV layers from data by supervised learning, instead of using hand-crafted filters

Multi-Layer Perceptron vs. CNN





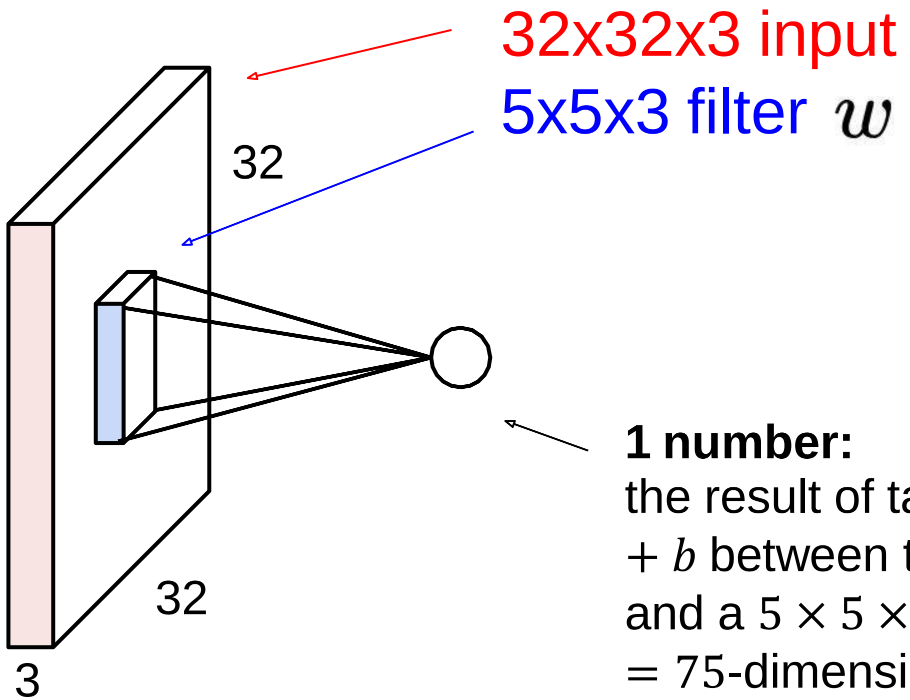
- In an MLP, all layers are fully connected
- Cannot alter input image size
- Permutation invariance
  - Cannot recognize geometry/locality of input
  - Below two images, with same set of pixels but different permutations, will generate the exact same output in an MLP
  - Not useful for image recognition



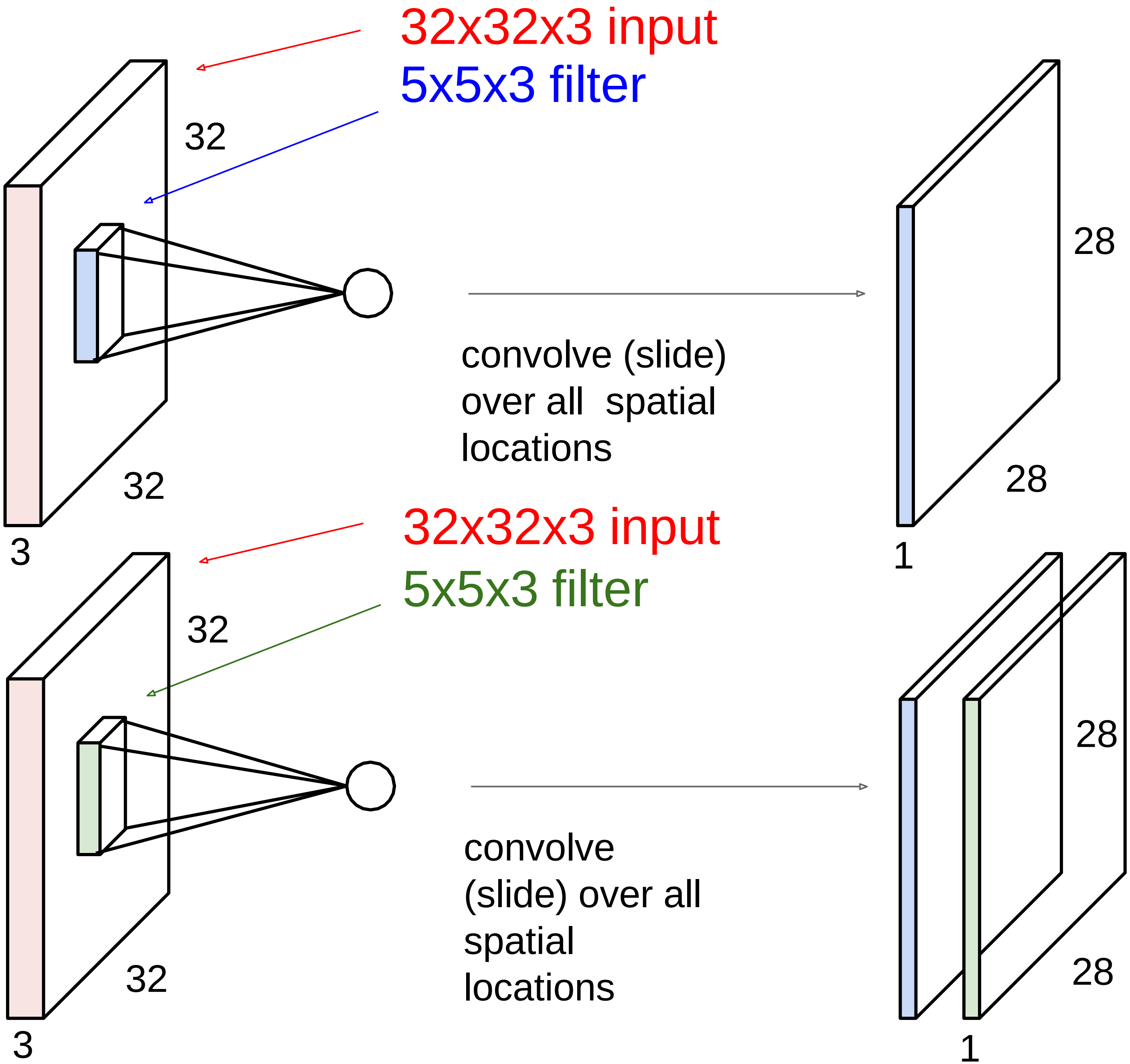
- In a CNN, only the last few (typically <=3) MLP layers(s) are fully connected
- CONV layers can handle images of arbitrary size (but not the last MLP layer(s))
- Not permutation invariance
  - Can recognize geometry/locality of input
- Translation invariance
- Fewer params than MLP (less prune to overfitting)

Convolution Operation

- Filters always have the same depth as the input volume
  - The input may be a color image w. 3 channels (e.g., RGB), hence depth is 3, or intermediate activation maps generated by hidden layers of a CNN. We use the terms "input volume" and "output volume" to emphasize they may be 3D matrices
- Convolution: slide the filter over the image spatially, computing dot products $w^T x + b$ to generate an activation map as output



1 number:
the result of taking a dot product $w^T x$ $+ b$ between the filter w. weights w, bias b, and a $5 \times 5 \times 3$ image patch x, w. $5 * 5 * 3$ $= 75$-dimensional dot product + bias

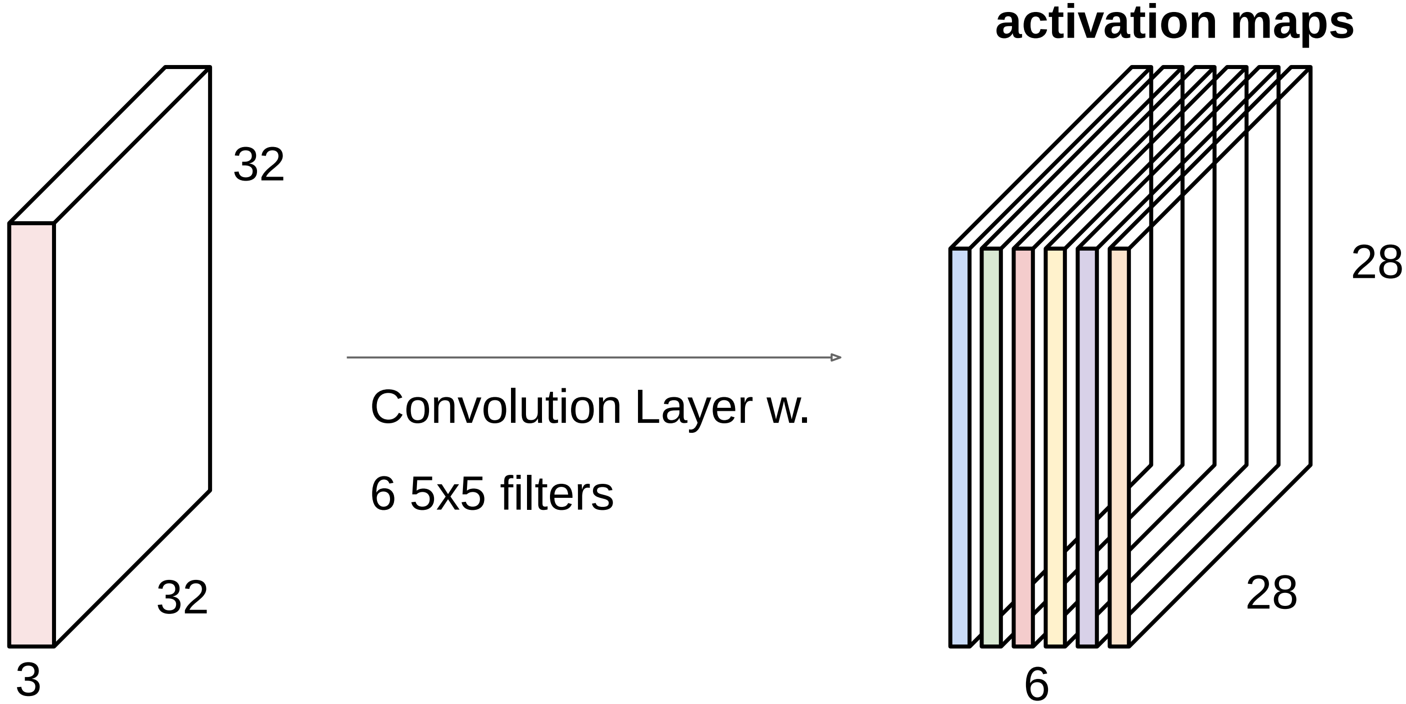


One (blue) filter generates one 2D activation map as output

Multiple (blue and green) filters generate multiple (blue and green) 2D activation maps, stacked along the depth dimension to produce the 3D output volume

Stacked Activation Maps

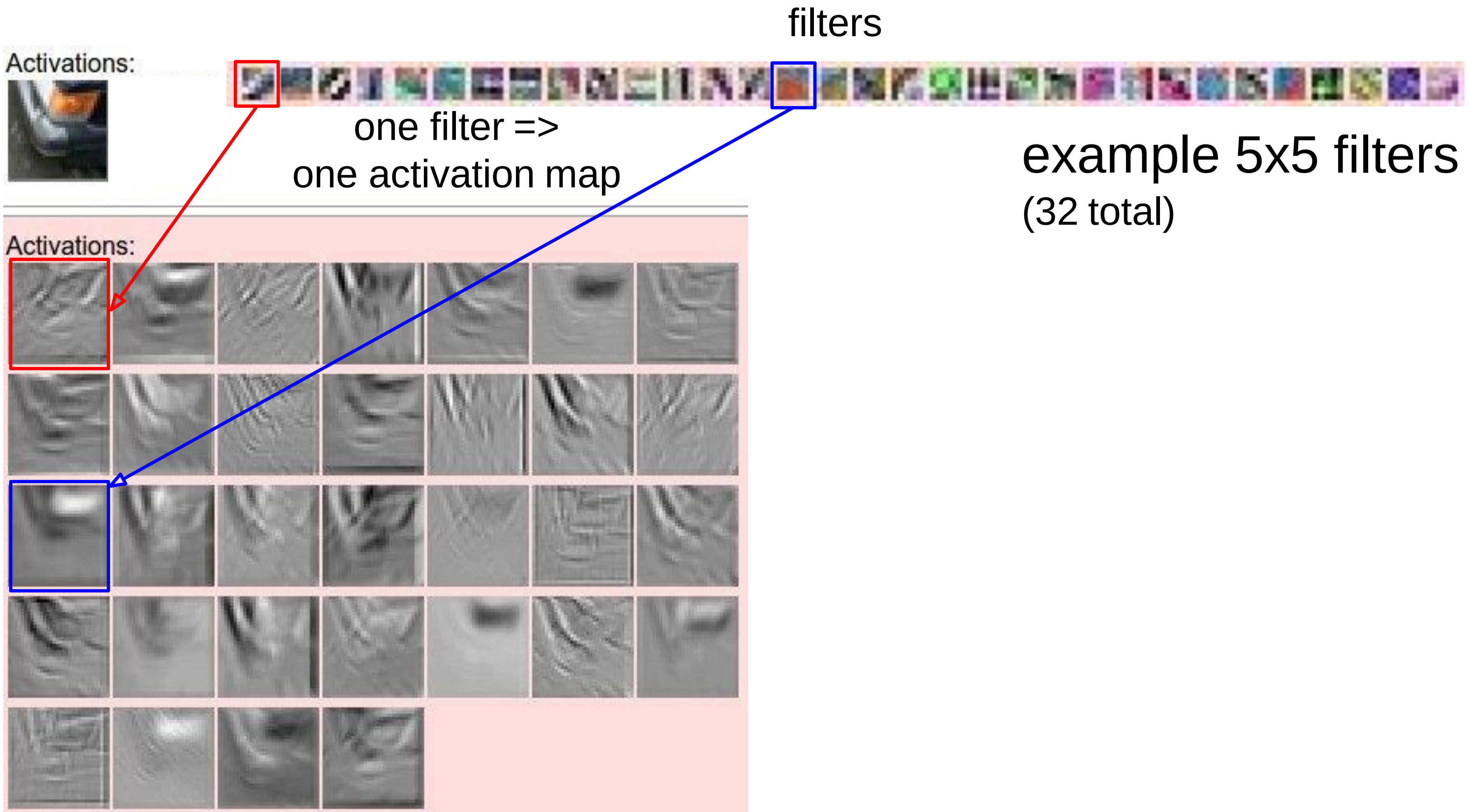
- If we have 6 5×5 filters, we'll get 6 separate activation maps (also called feature maps).
- We stack these up to get an output volume (a new "image") of size $28 \times 28 \times 6$, an intermediate representation to be passed to subsequent layers



Receptive Field and Weight Sharing

- Each neuron in a CONV layer has local connectivity to a small patch of the input volume w. size of the filter, called its Receptive Field
  - Each neuron covers a limited, narrow “field of view”
  - In contrast, each neuron in a FC layer has RF that covers the entire input volume
- Weight sharing: all neurons in the same CONV layer share the same filter params w, b
  - It helps to reduce the number of params significantly compared to fully-connected networks

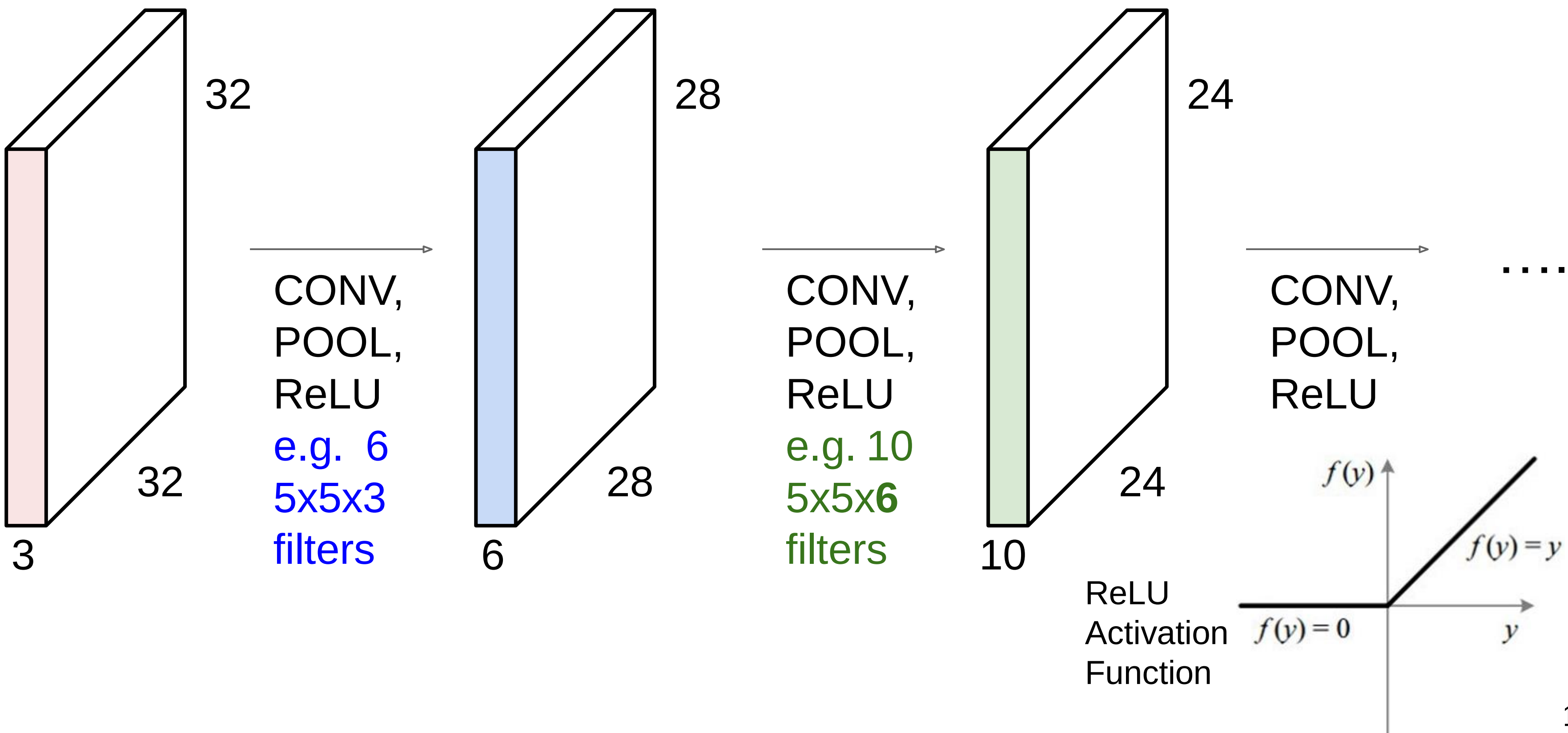
Filters and Activation Maps Example



example 5x5 filters
(32 total)

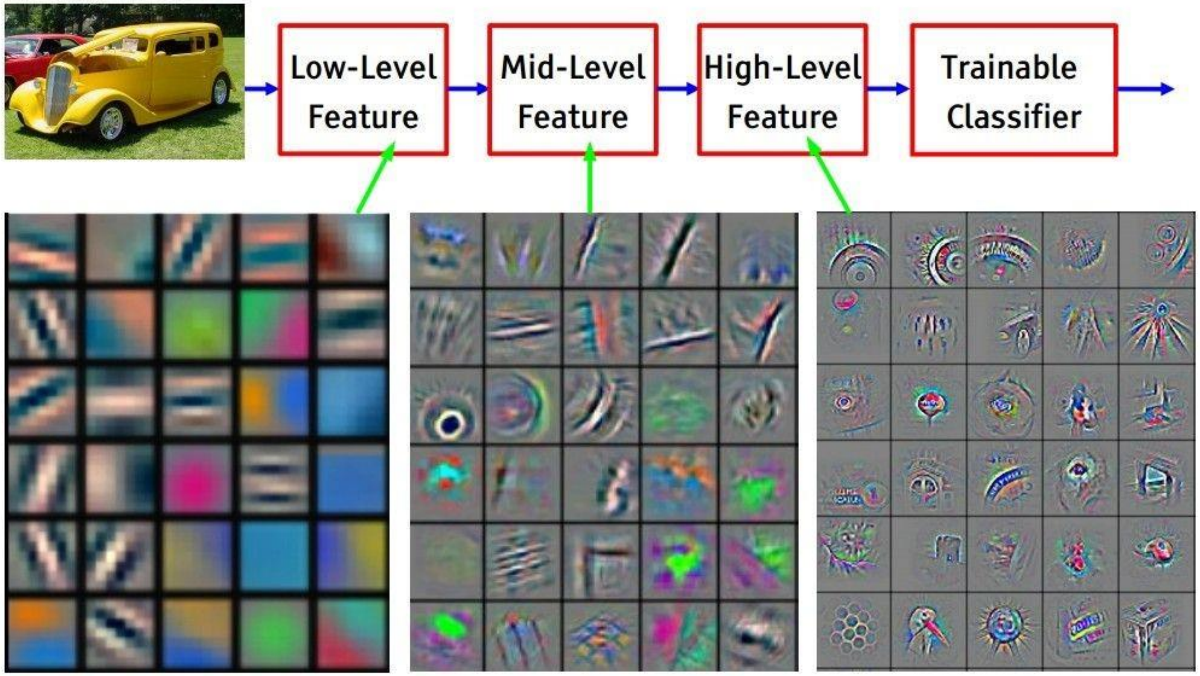
Typical CNN Architecture

- Multiple layers, each consisting of CONV, POOL and non-linear activation functions (e.g., ReLU), are stacked into a deep network
  - Many variants possible, e.g., multiple CONV layers can be stacked without POOL and activation functions in-between



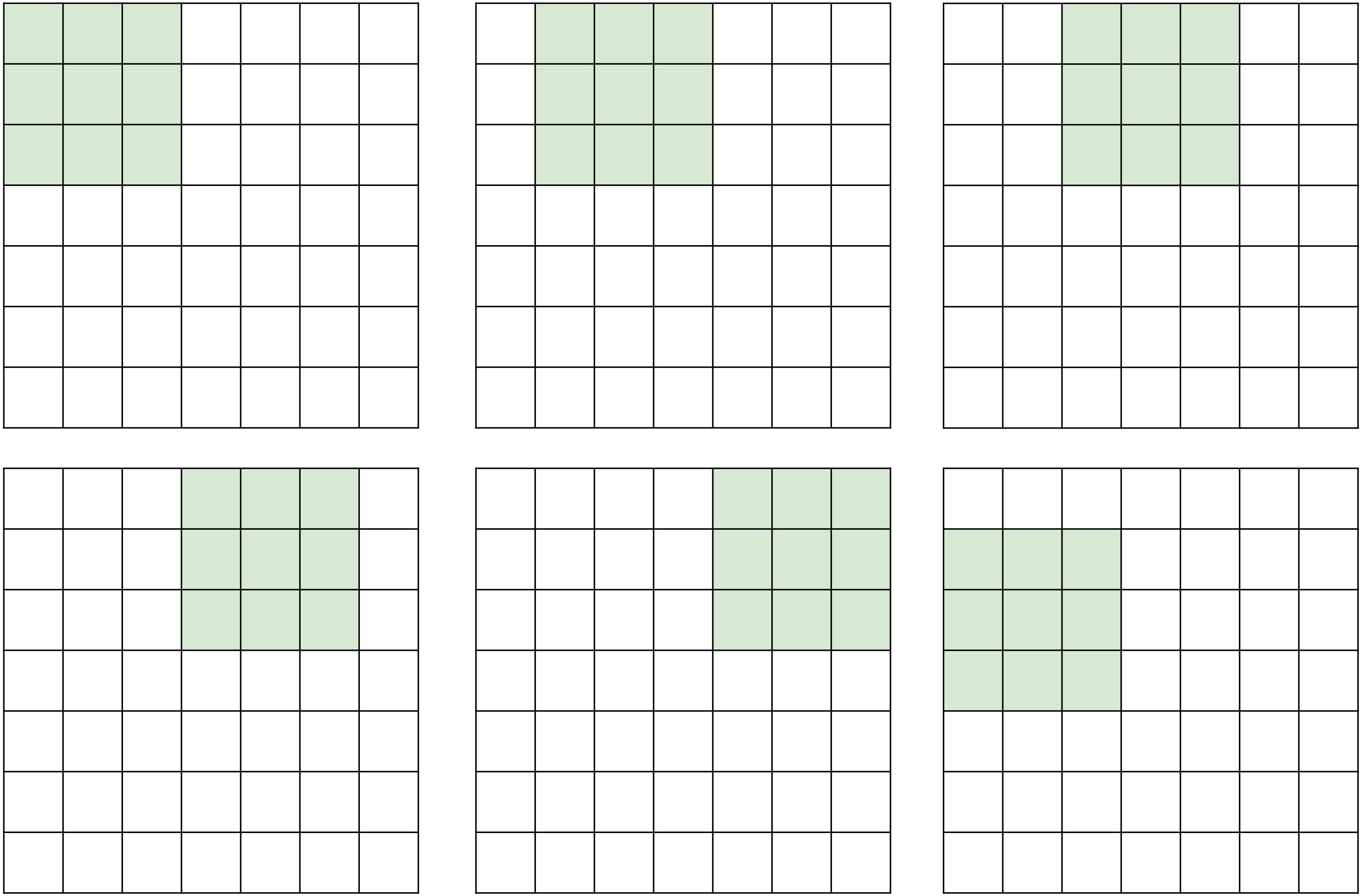
Feature Hierarchy

- Multiple hidden layers can to extract a hierarchy of increasingly-abstract features layer-by-layer, until the last layer produces a classification result

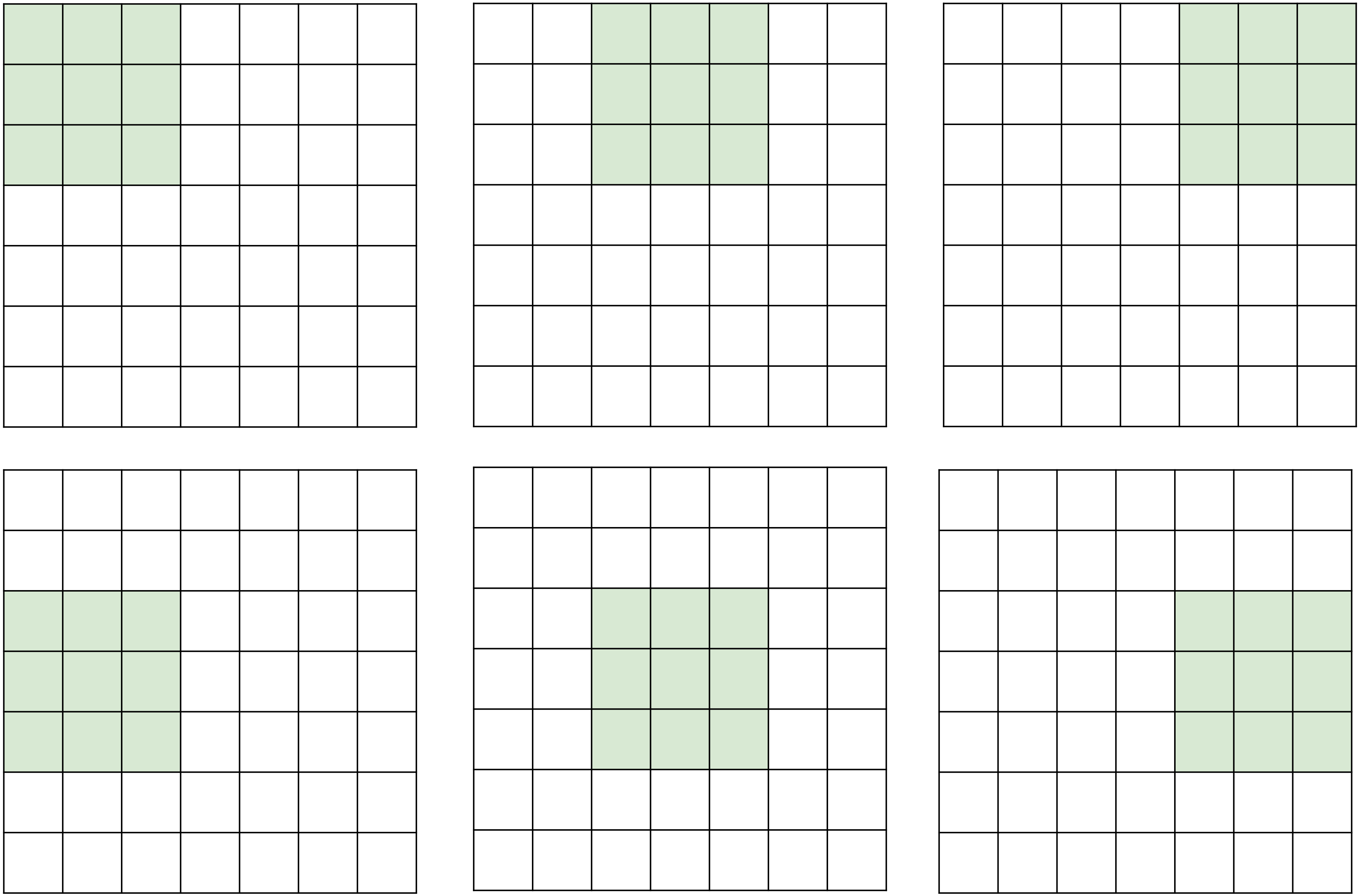


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

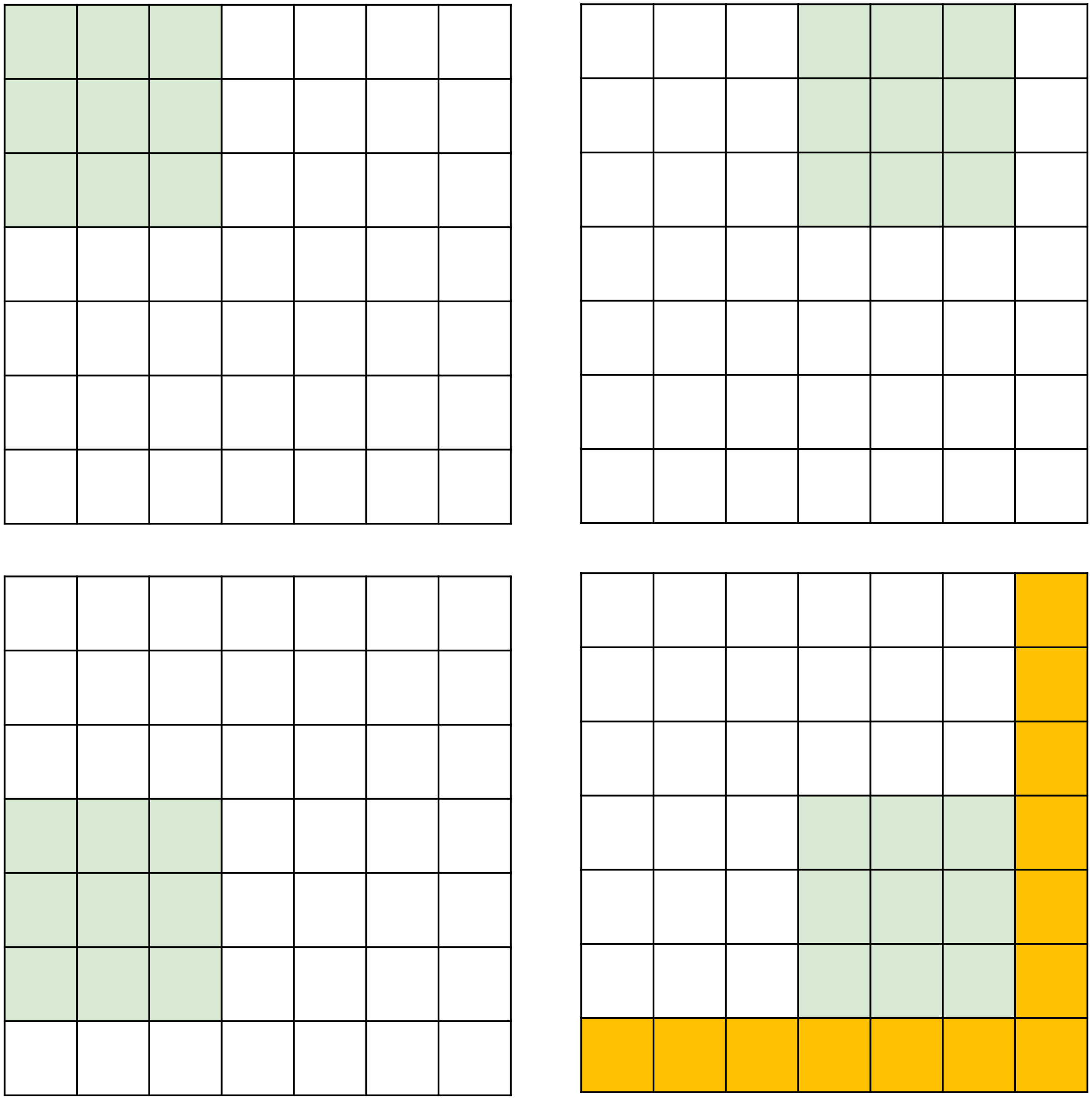
7x7 input, 3x3 filter, stride=1 ⇒ output: 5x5 filter



7x7 input, 3x3 filter, stride=2 ⇒ output: 3x3 filter



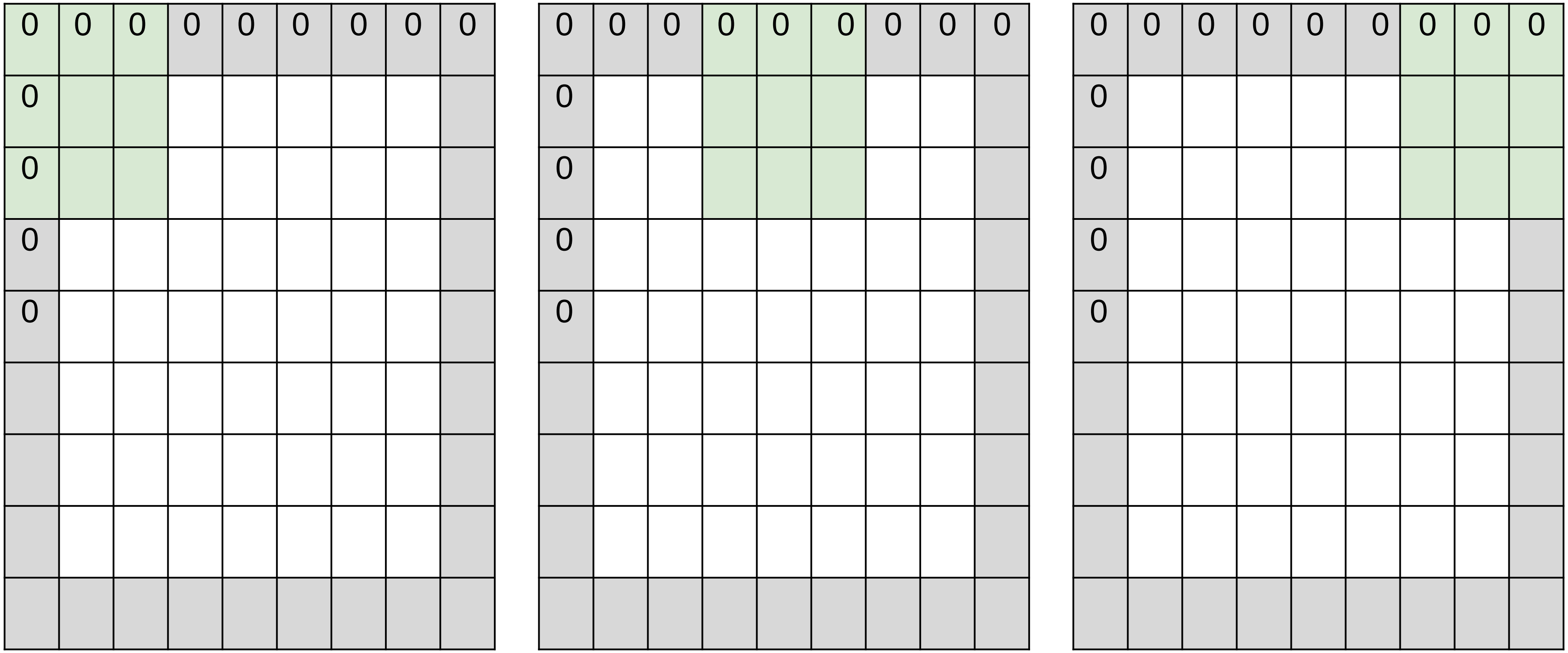
7x7 input, 3x3 filter, stride=3 ⇒ output: ???



The rightmost and bottom columns are not processed!

Solution: Add Padding

- 7x7 input, 3x3 filter, stride=3, zero padding w. 1 ⇒ output: 3x3 filter



Computation of CONV Layer Sizes

Summary. To summarize, the Conv Layer:

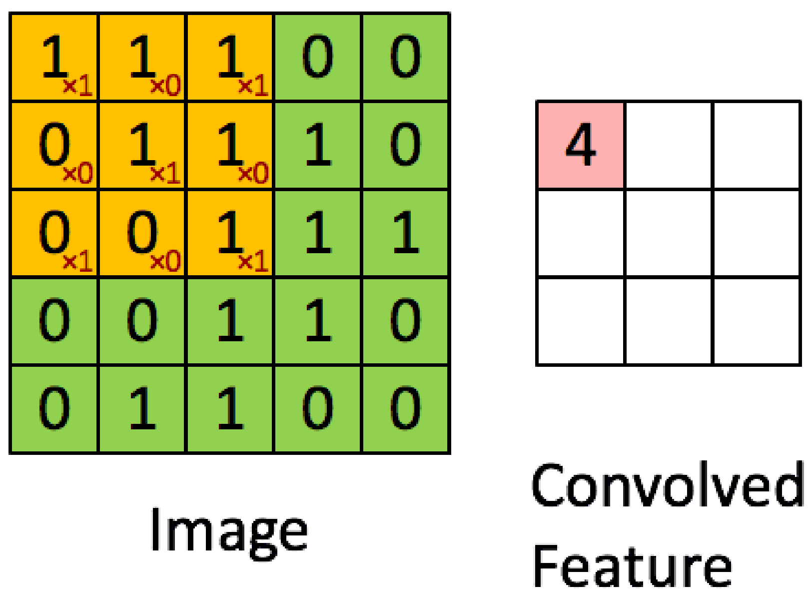
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (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.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Common settings:
K = (powers of 2, e.g. 32, 64, 128, 512)
- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 1, S = 1, P = 0

- It is common to have square input shape, i.e., $W_1 = H_1 = N_1$, but general rectangle shape size is possible
- A filter always has square shape, and always has the same depth D_1 as the input volume
- In practice, it is common to have stride $S = 1$, filter size $F \times F$, and zero-pad $P = \frac{1}{2}(F - 1)$. Then output activation map has same spatial size as input. This is called "same padding"
  - $W_2 = \frac{1}{S}(W_1 + 2P - F) + 1 = \frac{1}{1}(W_1 + F - 1 - F) + 1 = W_1$; similarly, $H_2 = H_1$
  - e.g., $F < 3 \Rightarrow P = 0$; $F = 3 \Rightarrow P = 1$; $F = 5 \Rightarrow P = 2$

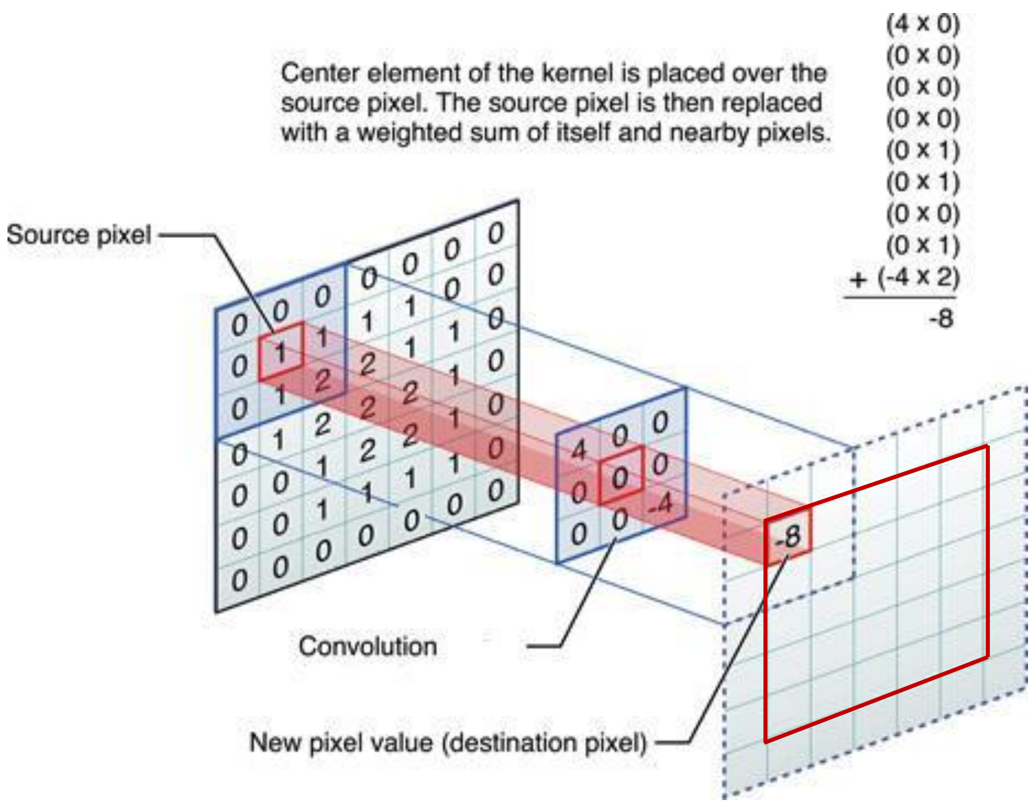
CONV Example 1: No Pad

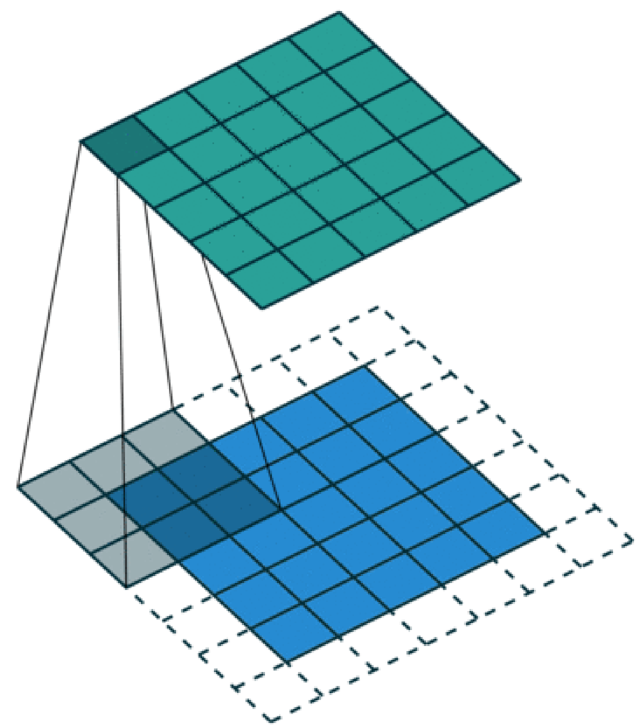
- Input volume: $5 \times 5 \times 1$ ($W_1 = H_1 = N_1 = 32, D_1 = 3$)(e.g., a greyscale image)
- A $3 \times 3 \times 1$ filter $\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$ ($K = 1, F = 3$) w. stride $S = 1$, no pad
- Output activation map:
  - Spatial size: $\mathrm{W}_2 = \mathrm{H}_2 = \mathrm{N}_2 = \frac{1}{S}(N_1 + 2P - F) + 1 = \frac{1}{1}(5 - 3) + 1 = 3$
  - Depth: $D_2 = K = 1$
- Output volume: $3 \times 3 \times 1$
- Even though the fig shows sequential computation, convolution operations are inherently parallel, hence suitable for efficient implementation on parallel hardware, e.g., GPU, FPGA…



CONV Example 2: Same Padding

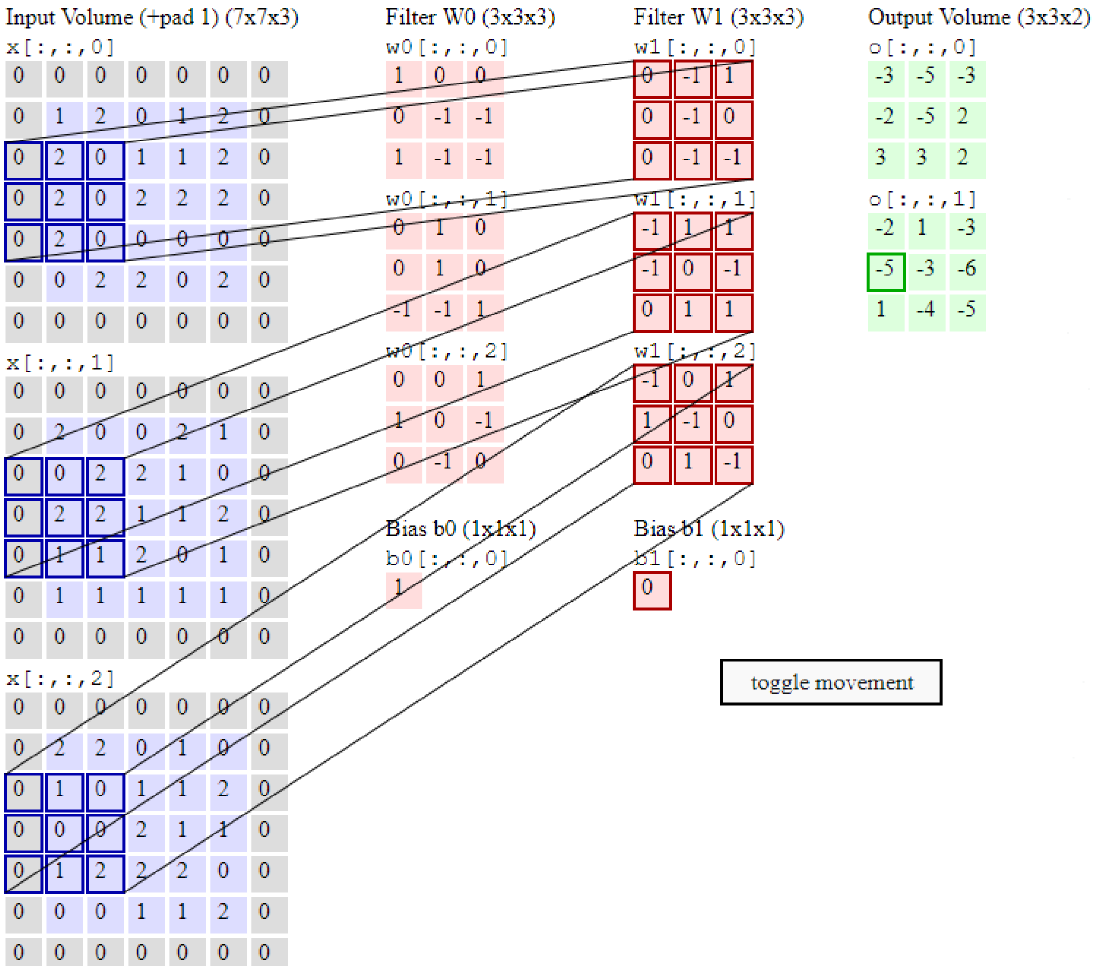
- Input volume: $5 \times 5 \times 1$
- A $3 \times 3 \times 1$ filter ($K = 1, F = 3$) w. stride $S = 1$, pad $P = 1$
- Output volume: $5 \times 5 \times 1$ (since $\frac{1}{1}(5 + 2 - 3) + 1 = 5$)
- Output activation map has the same spatial dimension as input (5×5)

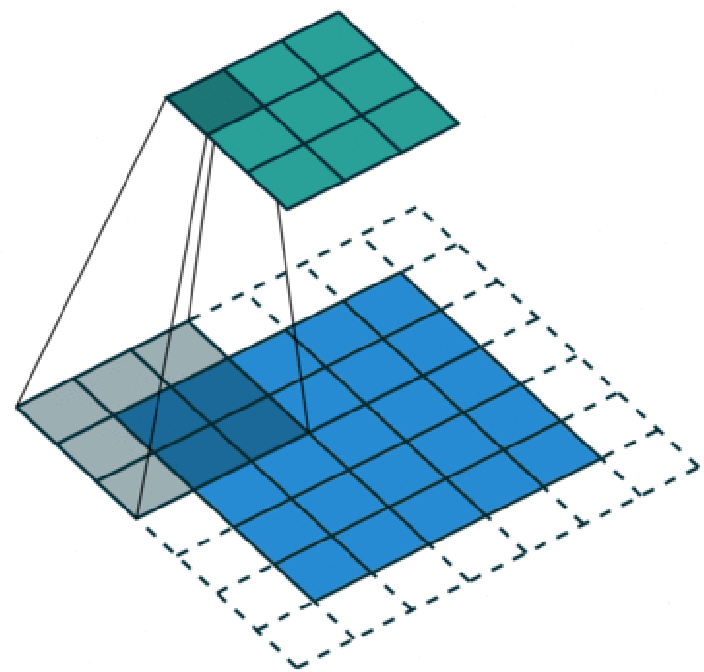




CONV Example 3: Stride $S = 2$

- Input volume: $5 \times 5 \times 3$
- $2\ 3 \times 3 \times 3$ filters ($K = 2, F = 3$) w. stride $S = 2$, pad $P = 1$
- Output volumes: $2\ 3 \times 3 \times 1$ (since $\frac{1}{2}(5 + 2 * 1 - 3) + 1 = 3$)
  - Animation: https://cs231n.github.io/convolutional-networks/





CONV Example 4: Input Depth $D_1 = 3$

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	...
...	...	...	...	...	...	...

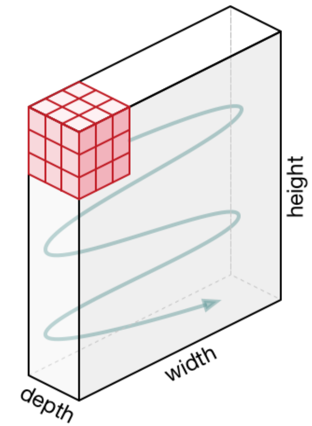
Input Channel #1 (Red)

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)



Movement of the filter

-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

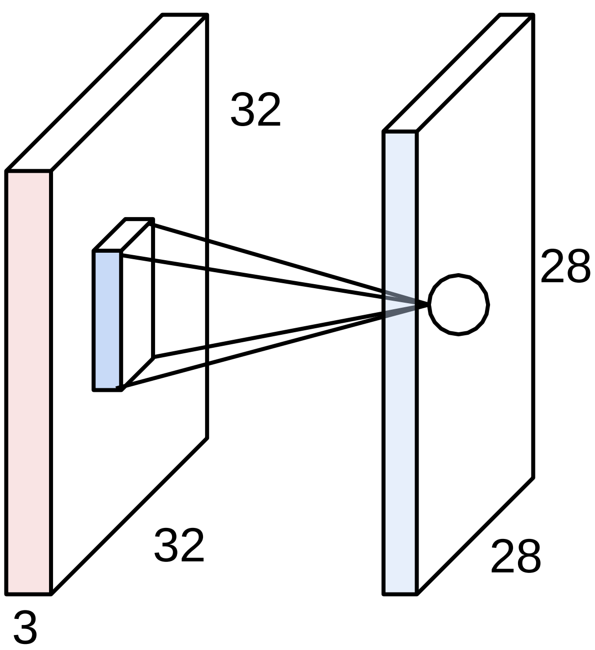
-25				...
				...
				...
				...
...	...	...	...	...

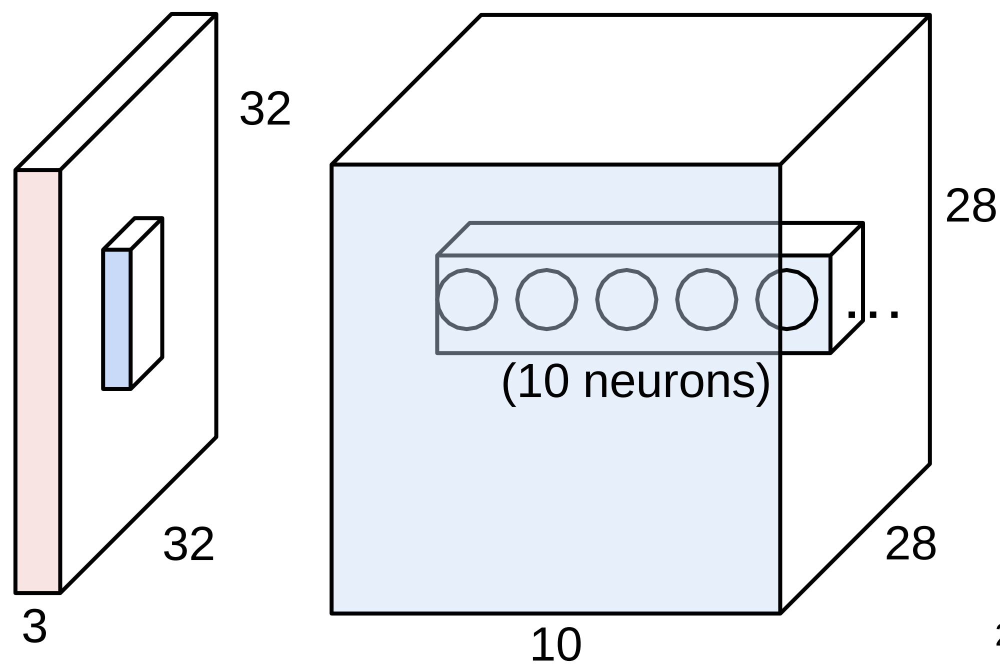
- Input volume: $M \times N \times 3$
- A $3 \times 3 \times 3$ filter ($K = 1, F = 3$) w. stride $S = 1$, pad $P = 1$
- Output volume: $M \times N \times 3$ (since $\frac{1}{1}(M + 2 * 1 - 3) + 1 = M$, $\frac{1}{1}(N + 2 * 1 - 3) + 1 = N$)

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

CONV Example 5: Multiple Filters $K = 10$

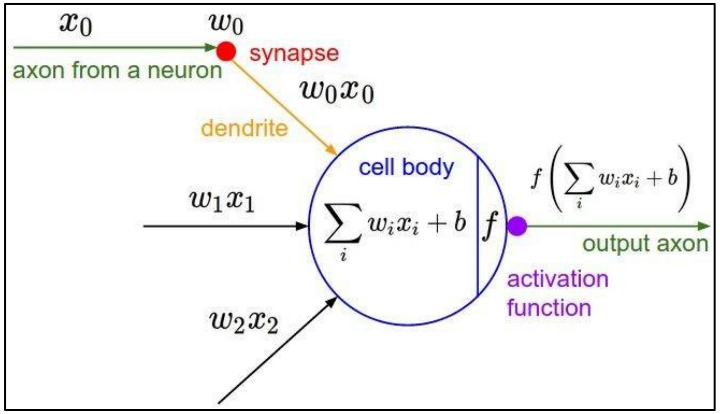
- Input volume: $32 \times 32 \times 3$ $(W_1 = H_1 = N_1 = 32, D_1 = 3)$
- 10 $5 \times 5 \times 3$ filters ($K = 10, F = 5$) w. stride $S = 1,$ no pad ($P = 0$)
- Each output activation map:
  - Spatial size: $\mathrm{W}_2 = \mathrm{H}_2 = \mathrm{N}_2 = \frac{1}{S}(N_1 + 2P - F) + 1 = \frac{1}{1}(32 - 5) + 1 = 28$
  - Depth: $D_2 = K = 10$
- Output volume: $28 \times 28 \times 10$
- No. params (weights and biases) in this layer: each filter has $5 * 5 * 3 + 1 = 76$ params, so 10 filters add up to $76 * 10 = 760$ params

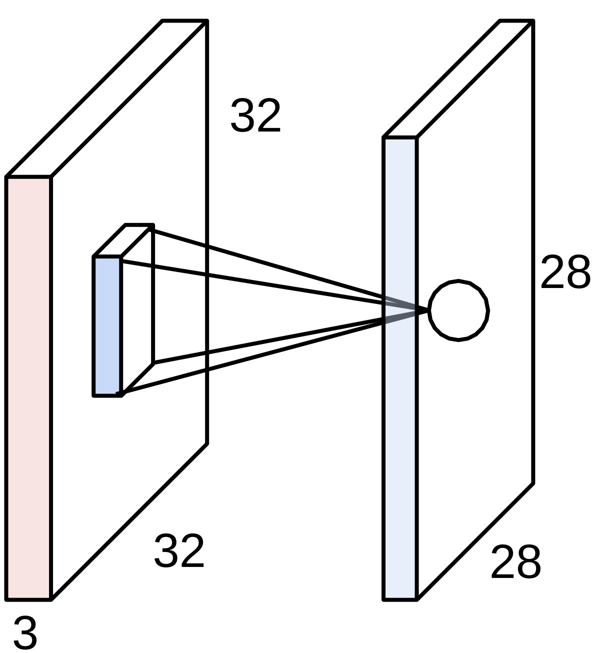


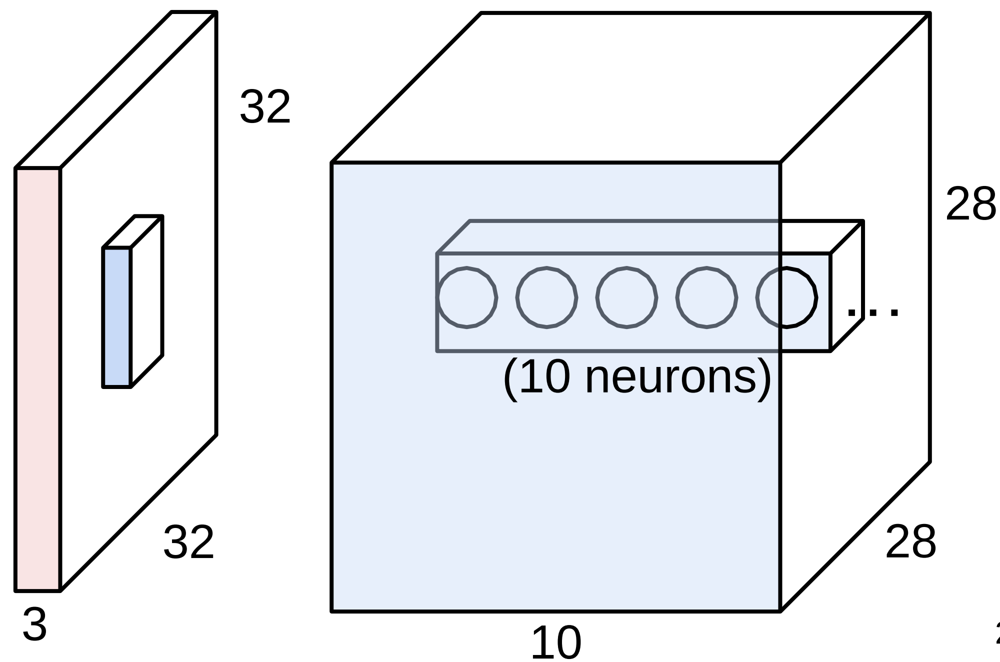


CONV Example 5: Neuron View

- One activation map is a 28×28 sheet of neuron outputs.
- With 10 filters, the CONV layer consists of neurons arranged in a 3D grid ($28 \times 28 \times 10$).
  - For each 5×5 patch of the input, there are 10 different neurons all looking at it, each extracting different features





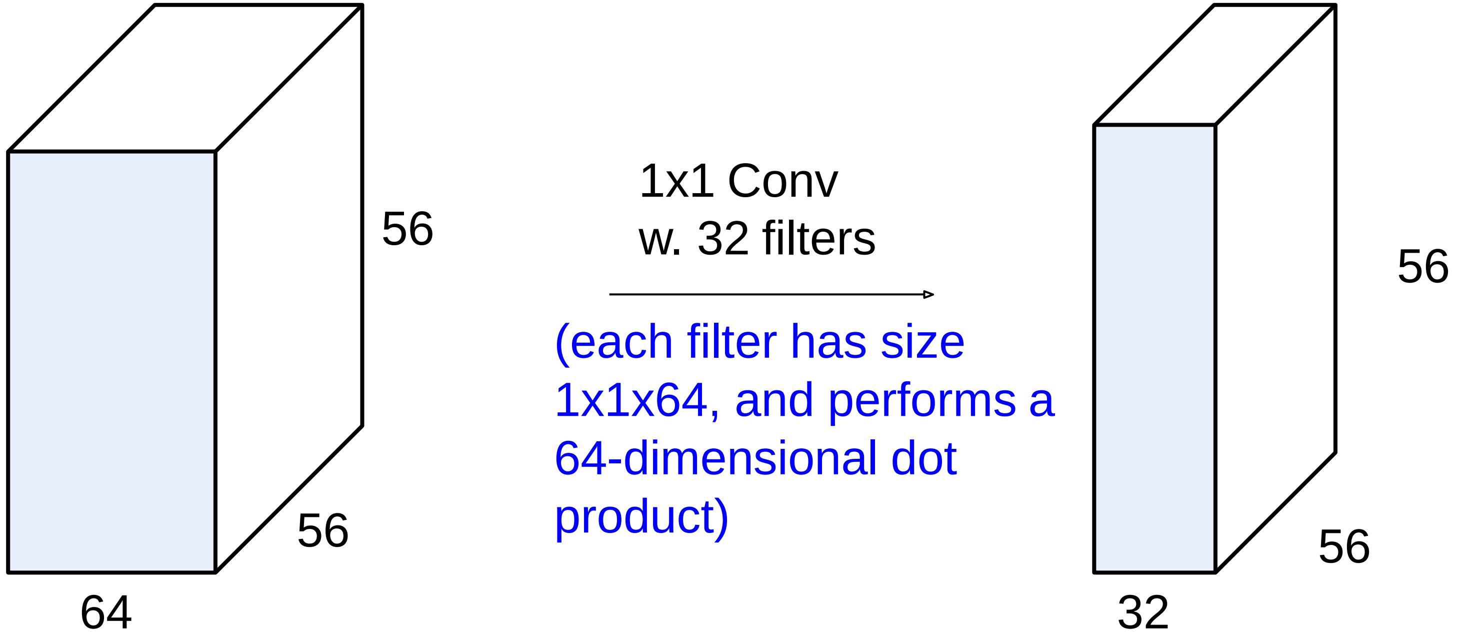


CONV Example 6: Pad $P = 2$

- Input volume: $32 \times 32 \times 3$ $(W_1 = H_1 = N_1 = 32, D_1 = 3)$
- 10 $5 \times 5 \times 3$ filters ($K = 10, F = 5$) w. stride $S = 1$, pad $P = 2$
- Each activation map:
  - Spatial size: $\mathrm{W}_2 = \mathrm{H}_2 = \mathrm{N}_2 = \frac{1}{S}(N_1 + 2P - F) + 1 = \frac{1}{1}(32 + 2 * 2 - 5) + 1 = 32$
  - Depth: $D_2 = K = 10$
- Output volume:$32 \times 32 \times 10$
- No. params: each filter has $5 * 5 * 3 + 1 = 76$ params, so 10 filters add up to $76 * 10 = 760$ params

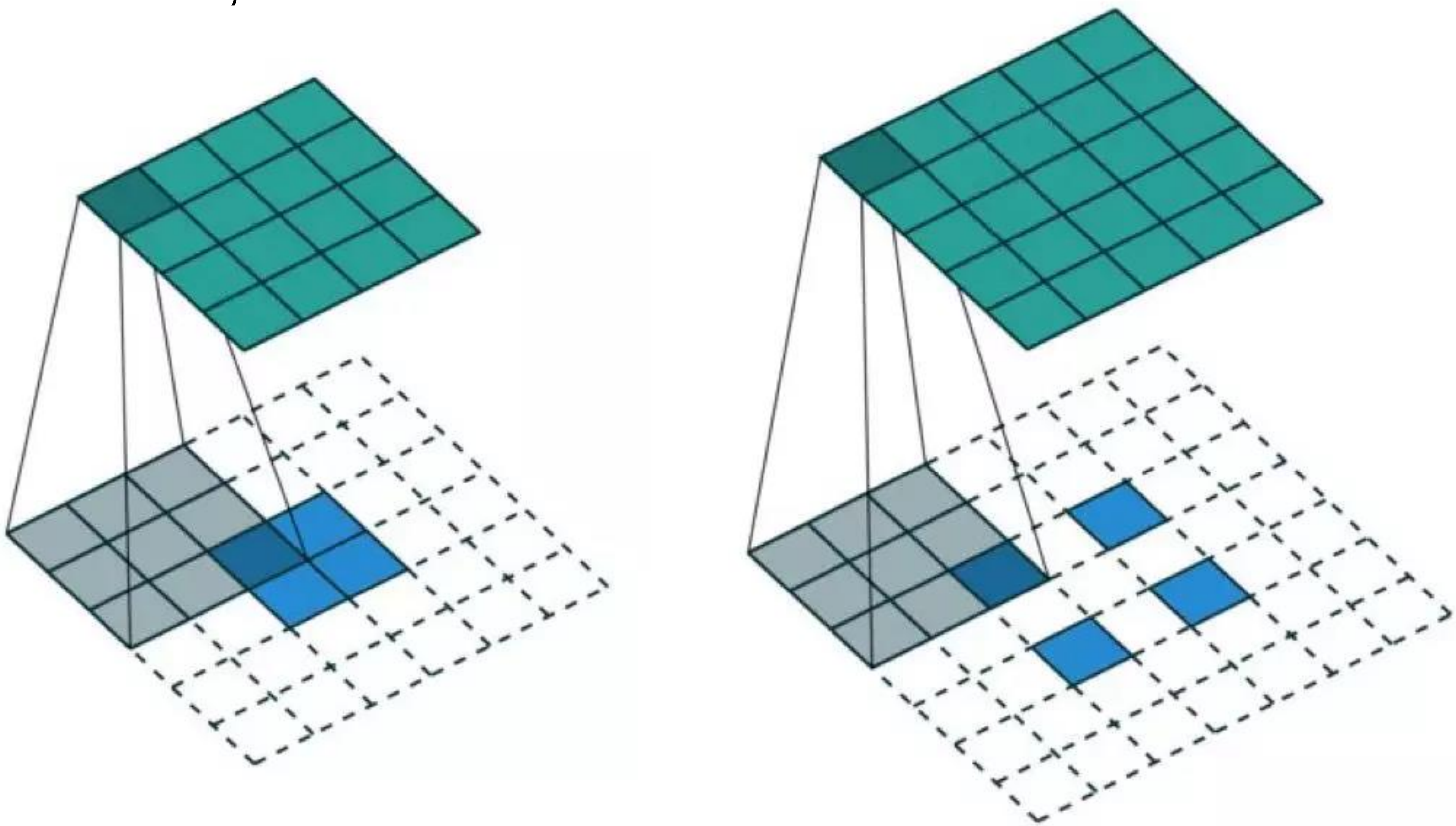
CONV Example 7: 1×1 Filter

- Input volume: $56 \times 56 \times 64$ $(W_1 = H_1 = N_1 = 56, D_1 = 64)$
- 32 $1 \times 1 \times 64$ filters $(K = 32, F = 1)$ w. stride $S = 1,$ no pad
- Each activation map:
  - Spatial size: $\mathrm{W_2 = H_2 = N_2} = \frac{1}{S}(N_1 + 2P - F) + 1 = \frac{1}{1}(56 - 1) + 1 = 56$
  - Depth: $D_2 = K = 32$
- Output volume:$56 \times 56 \times 32$
- No. params: each filter has $1 * 1 * 64 + 1 = 65$ params, so 32 filters add up to $65 * 32 = 2080$ params
- A 1×1 filter performs "mixing" of the 64 input channels, then applies a non-linear activation function



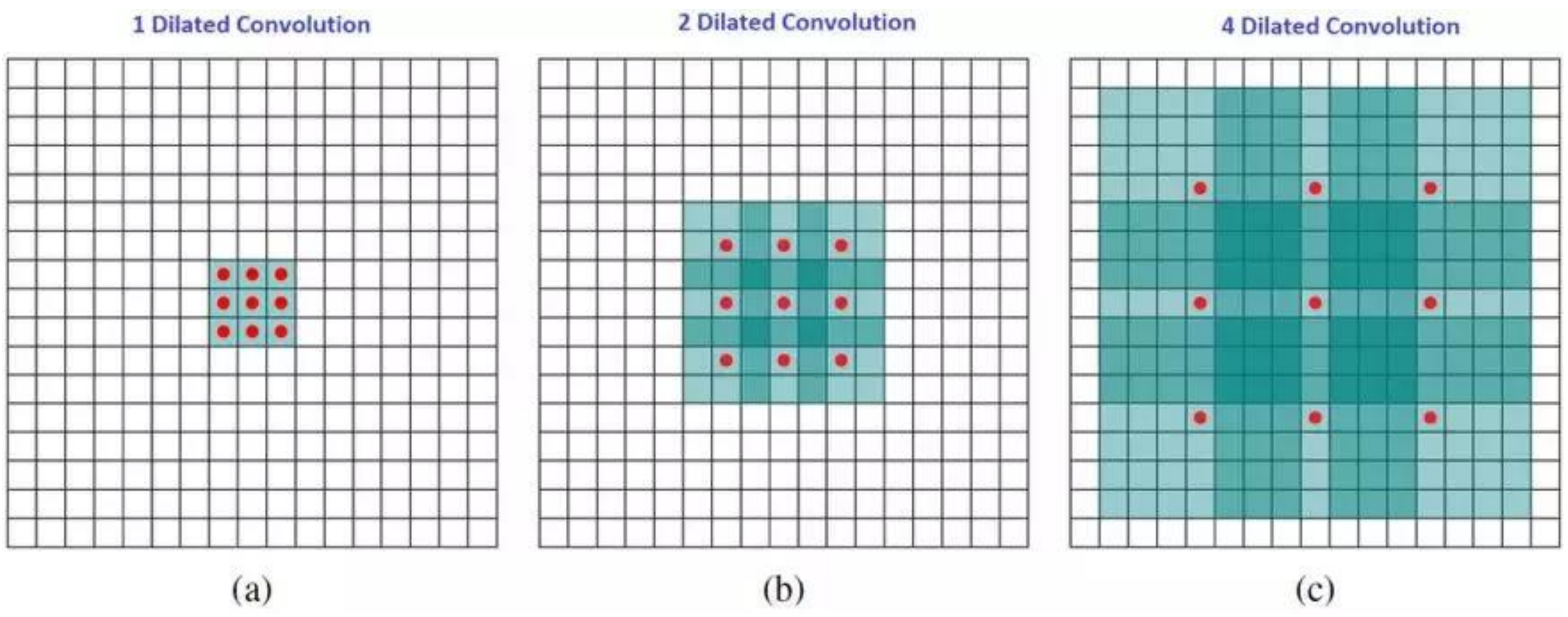
Transposed Convolution

- The output of Transposed Convolution has larger spatial size than the input (up-sampling)
  - Right fig shows fractionally-strided convolution, where zeros are inserted between input elements, which makes the kernel move at a slower pace than with unit strides
- Applications include image super-resolution, segmentation, auto-encoders, etc.



Dilated Convolution

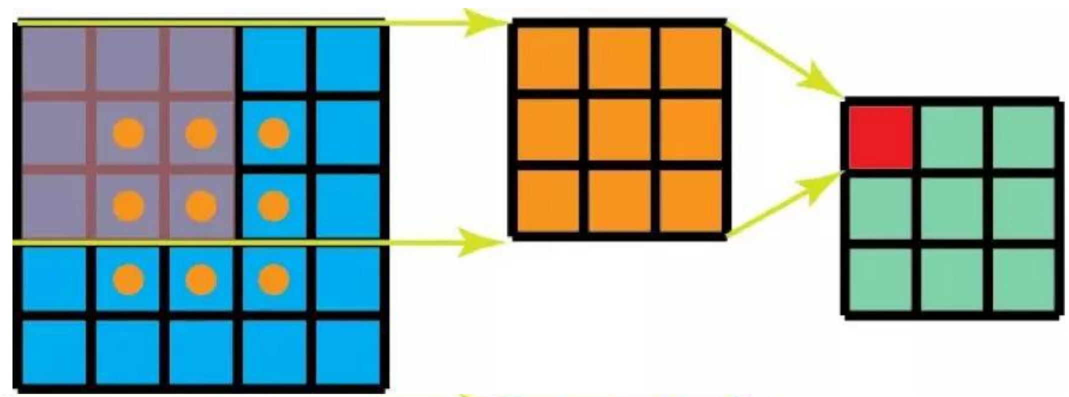
- Zeros are inserted between filter elements to increase receptive field size without increasing # params.

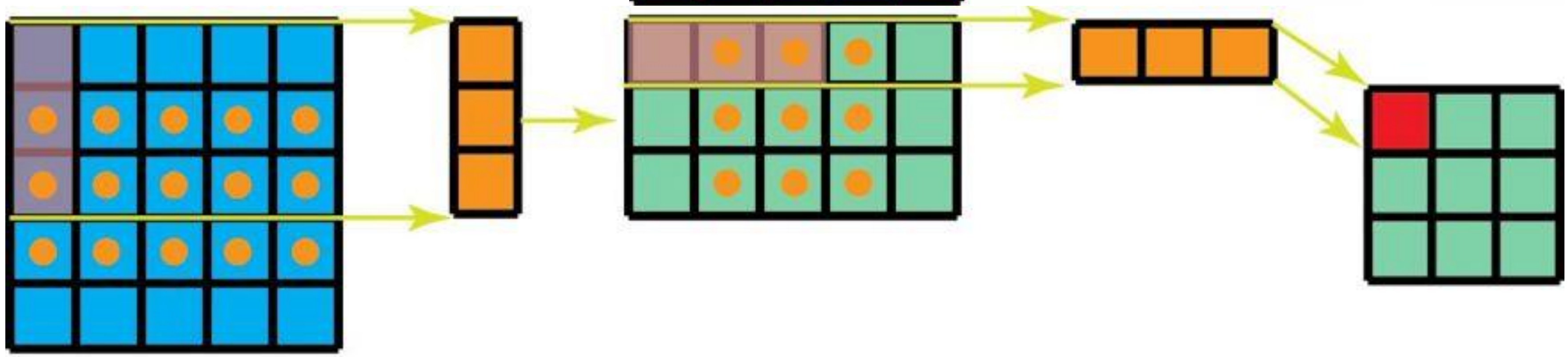


Spatial Separable Convolution

- Helps reduce # params and # arithmetic operations, e.g., total # arithmetic operations:
- Upper right: the Sobel kernel for detecting edges can be spatially separated (Not all kernels can be spatially separated)
- Middle right: Regular convolution of a 3×3 filter with 5×5 input: $3 * 3 * 3 * 3 = 81$ ($3 * 3$ operations for each of $3 * 3$ positions)
- Bottom: Spatial Separable Convolution of a 3×1 filter and 1×3 filter with 5×5 input: $3 * 1 * 5 * 3 + 3 * 1 * 3 * 3 = 72$ ($3 * 1$ operations for each of $5 * 3$ positions for 1st convolution, plus $3 * 1$ operations for each of $3 * 3$ positions for 2nd convolution)

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$$

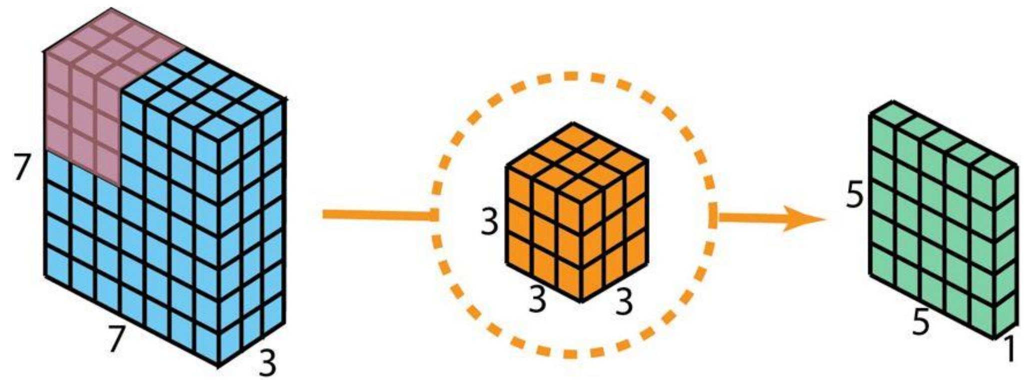


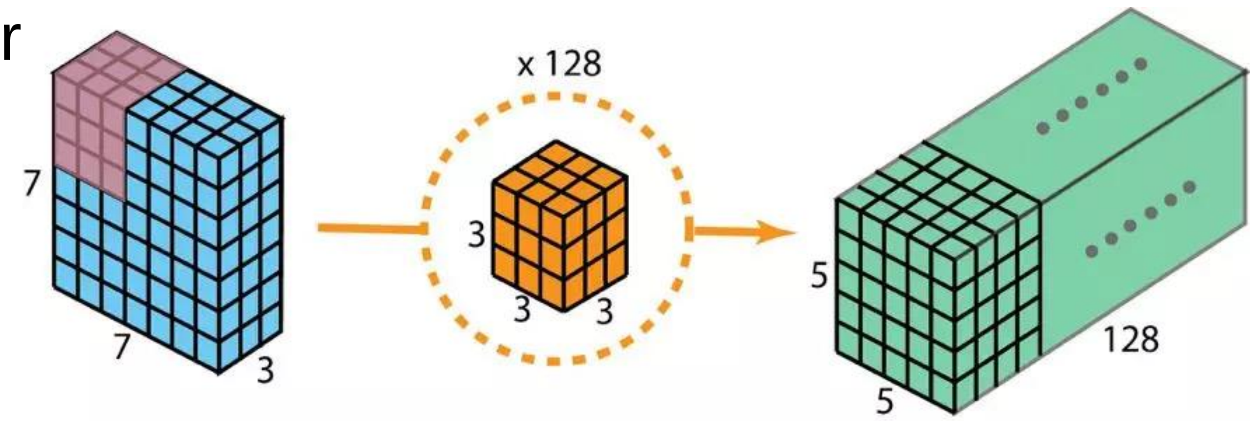


https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

Depthwise Separable Convolution: Review of Regular Convolution

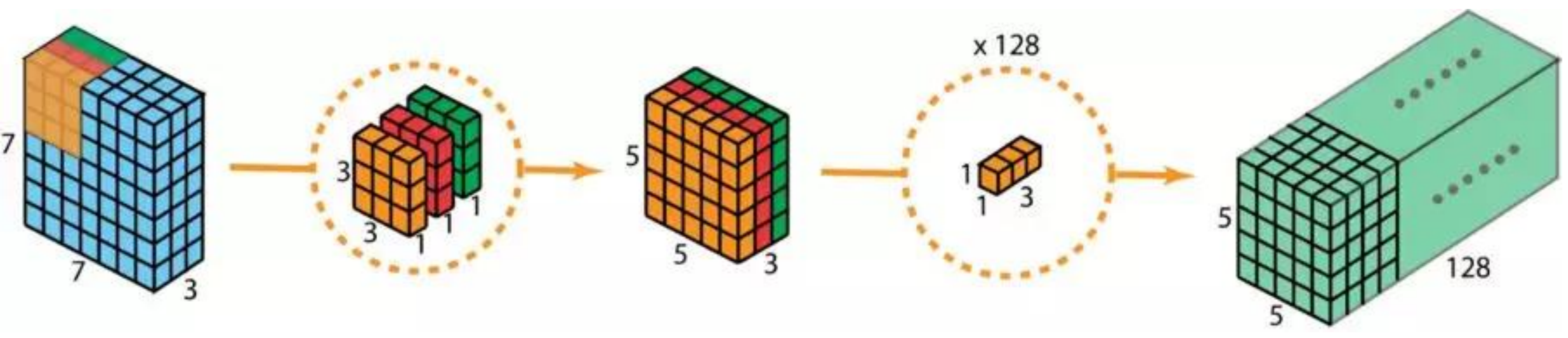
- Upper right: Regular convolution of a $3 \times 3 \times 3$ filter with $7 \times 7 \times 3$ input: $3 * 3 * 3 * 5 * 5 = 675$ ($3 * 3 * 3$ operations for each of $5 * 5$ positions)
- Lower right: Regular convolution of 128 $3 \times 3 \times 3$ filters with $7 \times 7 \times 3$ input: $128 * 675 = 86400$ operations (675 operations for each of 128 filters)





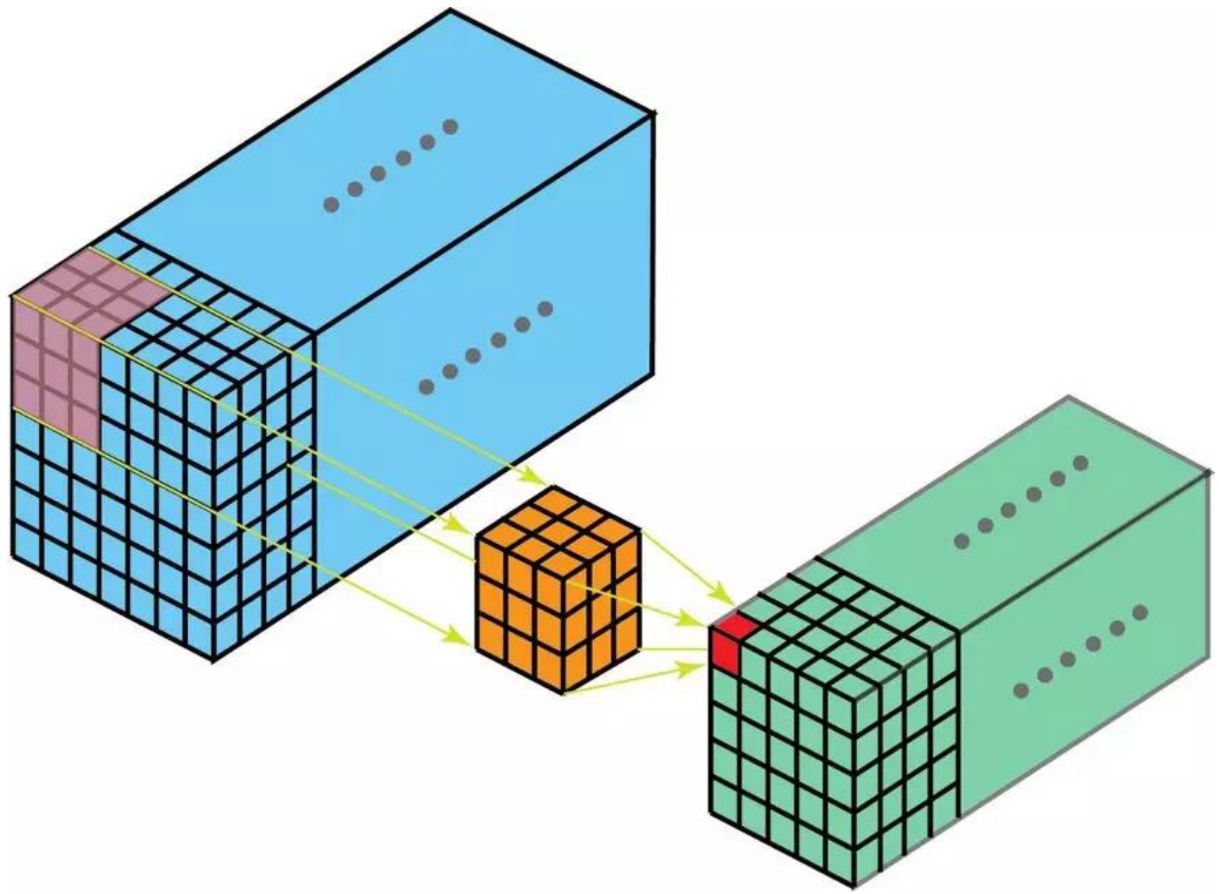
Depthwise Separable Convolution

- First, we use 3 $3 \times 3 \times 1$ filters, convolve each with 1 channel of the input to generate a $5 \times 5 \times 1$ output, then stack them together to get $5 \times 5 \times 3$ output volume
  - # arithmetic operations: $3 * 3 * 3 * 1 * 5 * 5 = 675$ ($3 * 3 * 1$ operations for each of $5 * 5$ positions, for each of 3 filters)
- Then, we use 128 $1 \times 1 \times 3$ filters, convolve each with 3 channels of its input to generate $5 \times 5 \times 128$ output volume
  - # arithmetic operations: $128 * 1 * 1 * 3 * 5 * 5 = 9600$ ($1 * 1 * 3$ operations for each of $5 * 5$ positions, for each of 128 filters)
- Total # arithmetic operations: $675 + 9600 = 10275$
  - Only 12% of 86400 operations for regular convolution



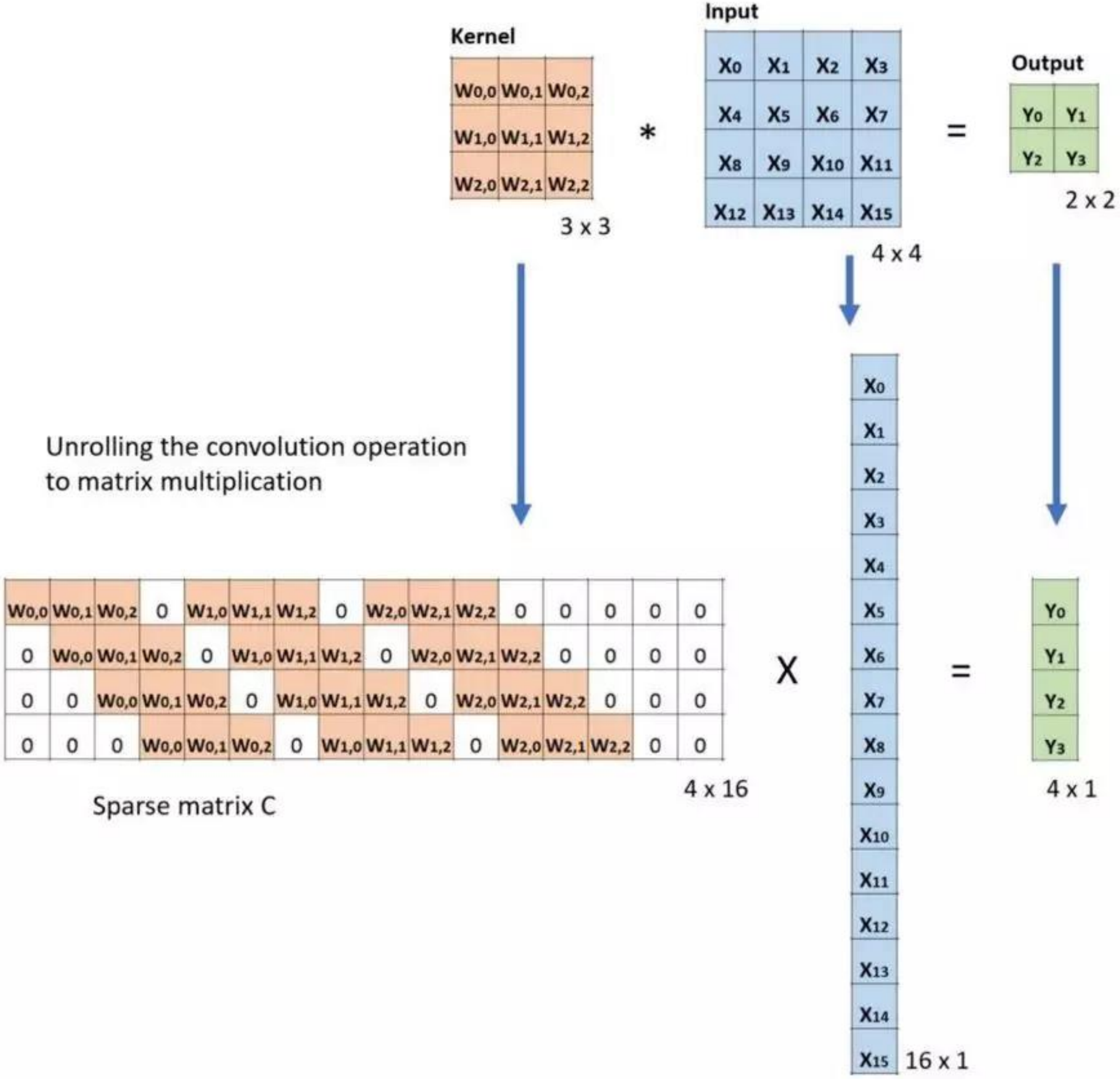
3D Convolution

- 3D filter slides along all 3 axes (width, height, depth). Very computation intensive
- Useful for 3D images such as medical CT/MRI images, or Point Clouds from Lidar



Converting Convolution to Matrix Multiplication

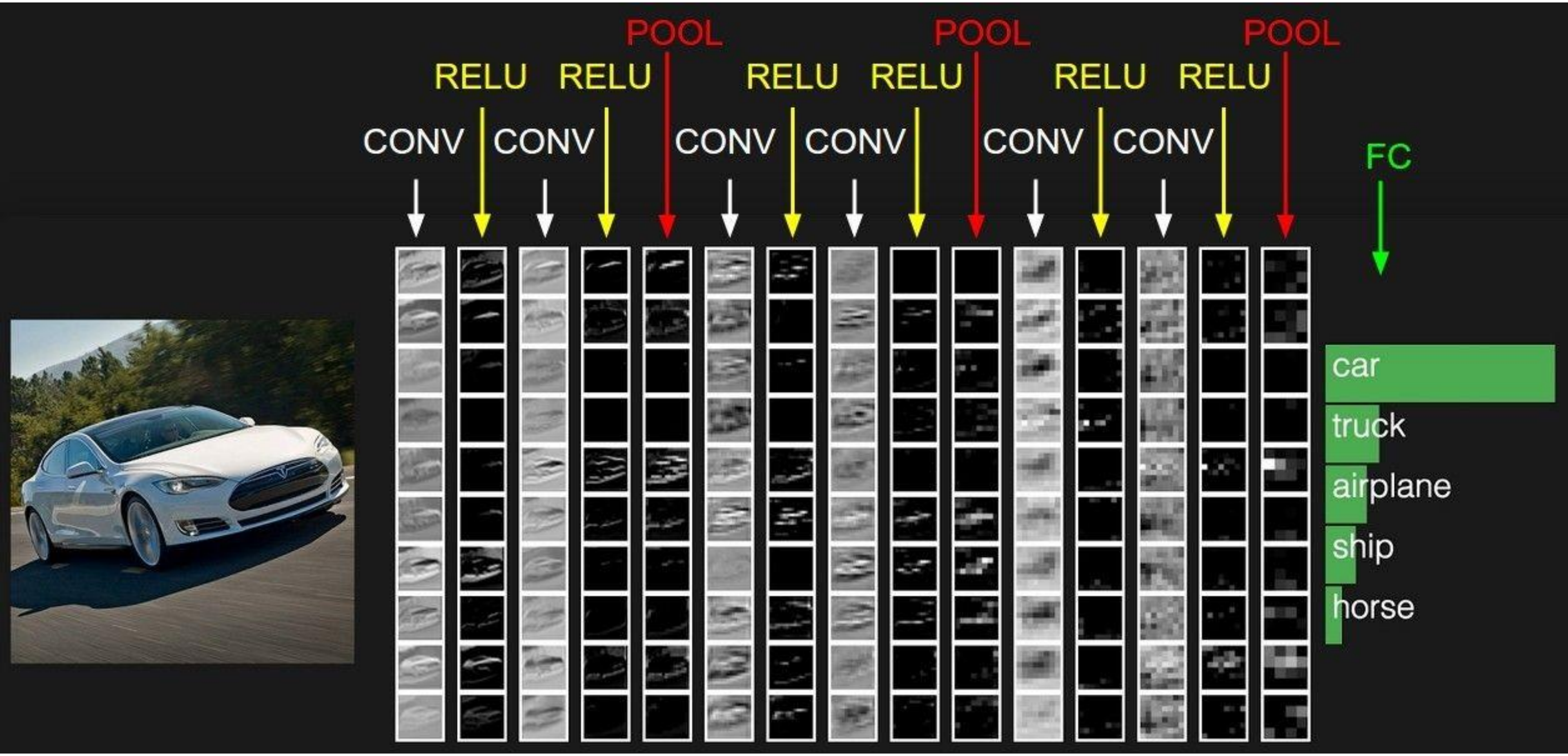
- Facilitates parallel HW implementation, since parallel HW (GPU, FPGA…) can handle matrix multiplication efficiently, at the expense of increased memory size for storing the weights (the biases are not shown in fig)



Quiz 1

- What does a CONV layer w. filter volume $K \times K \times D_1$ equal to its input volume $N \times N \times D_1$, i.e., $K = D$, w. stride $S = 1$ and no pad look like?
- ANS: It consists of a single neuron (since $F = N_1 \Rightarrow \mathrm{N}_2 = \frac{1}{S}(N_1 + 2P - F) + 1 = 1)$

Pooling and Fully-Connected Layers



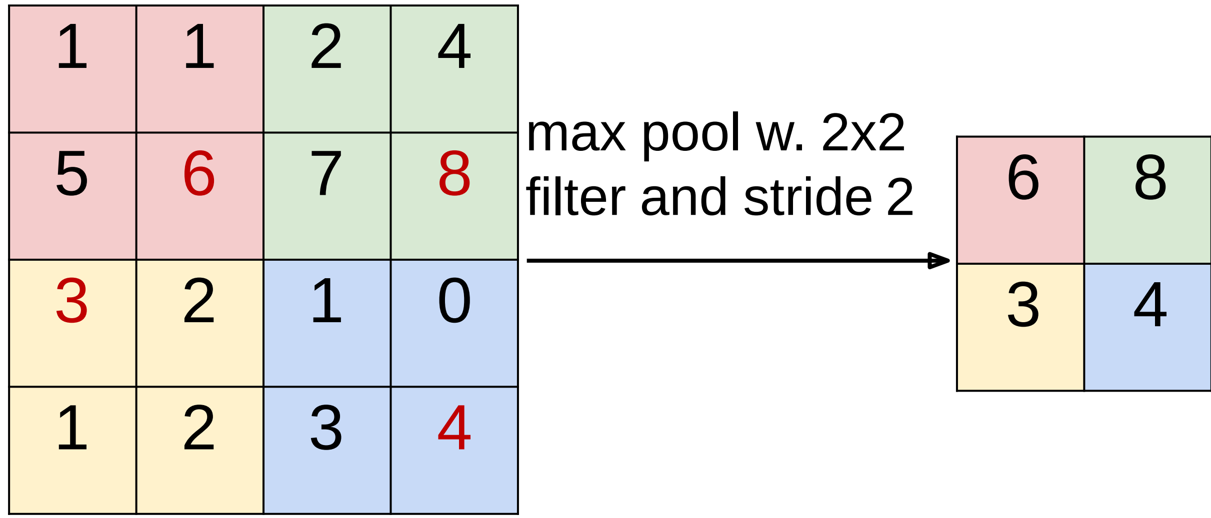
Pooling (Sub-Sampling) Layer

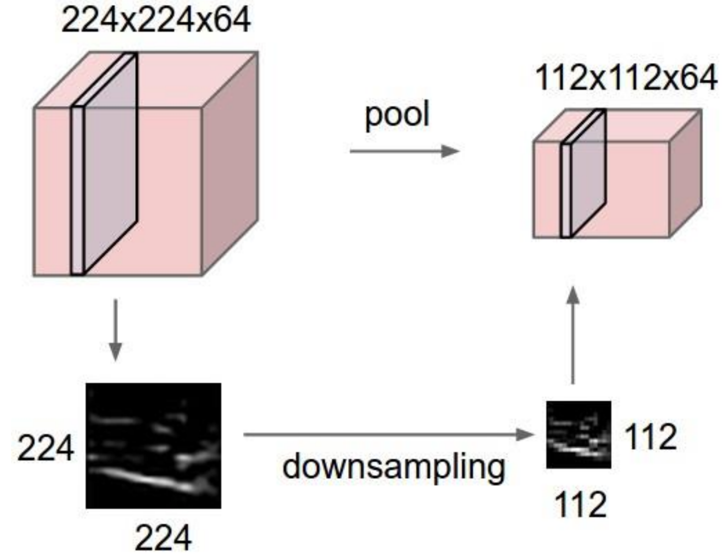
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires two hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters since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

- A pooling filter has depth 1, and operates over each activation map independently, hence the input volume and output volume always have the same depth D_1(unlike a CONV filter, which always has the same depth D_1 as the input volume, and output volume has depth $D_2 = K$, the No. filters)
  - Common settings: $F = 3, S = 2$, or $F = 3, S = 2$
- Example: pooling w. a 2×2 filter w. stride $S = 2$, no pad
- Output volume: $\frac{W_1}{2} \times \frac{H_1}{2} \times \mathrm{D}_1$(since $\frac{1}{2}(W_1 - 2) + 1 = \frac{W_1}{2}, \frac{1}{2}(H_1 - 2) + 1 = \frac{H_1}{2}$)

Max Pooling w. Examples

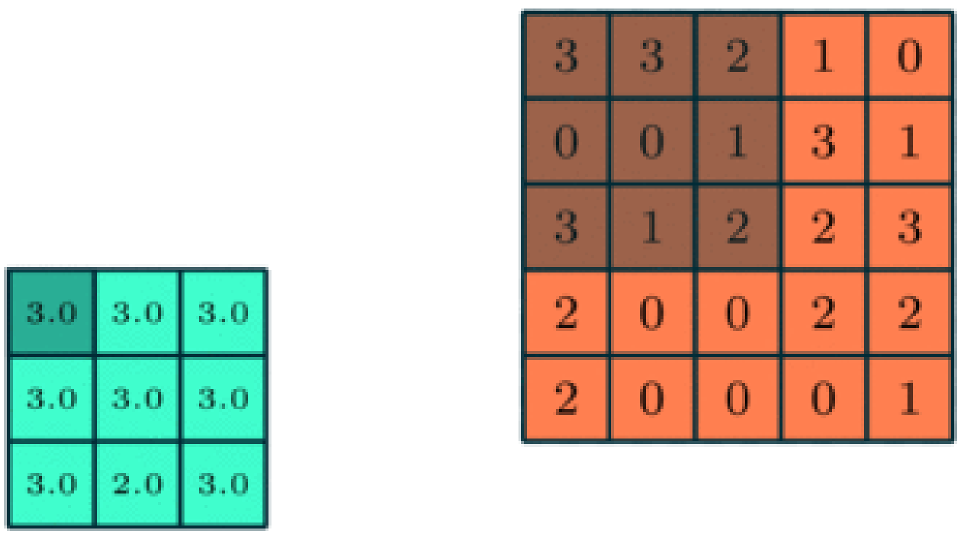
- Max pooling: take the max element among the $F * F$ elements in each $F \times F$ patch of each input activation map to reduce its dimension
- Alternative: average pooling is less commonly used





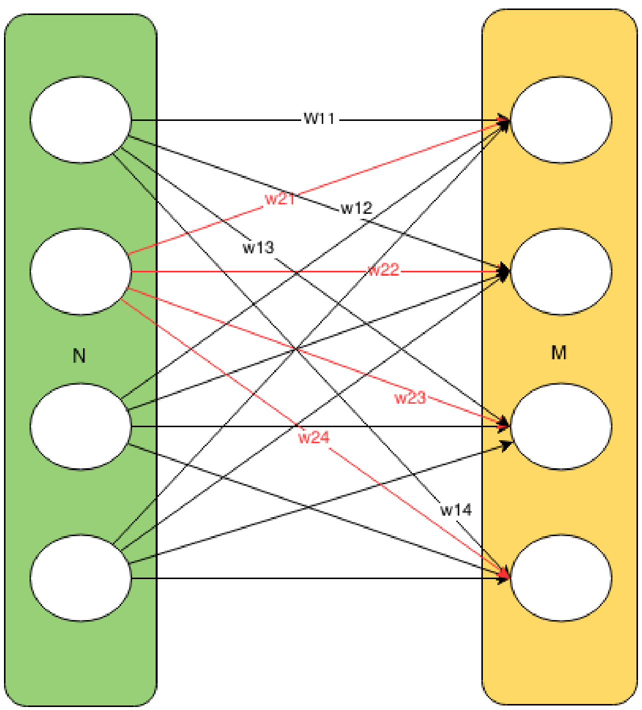
Overlapping Pooling

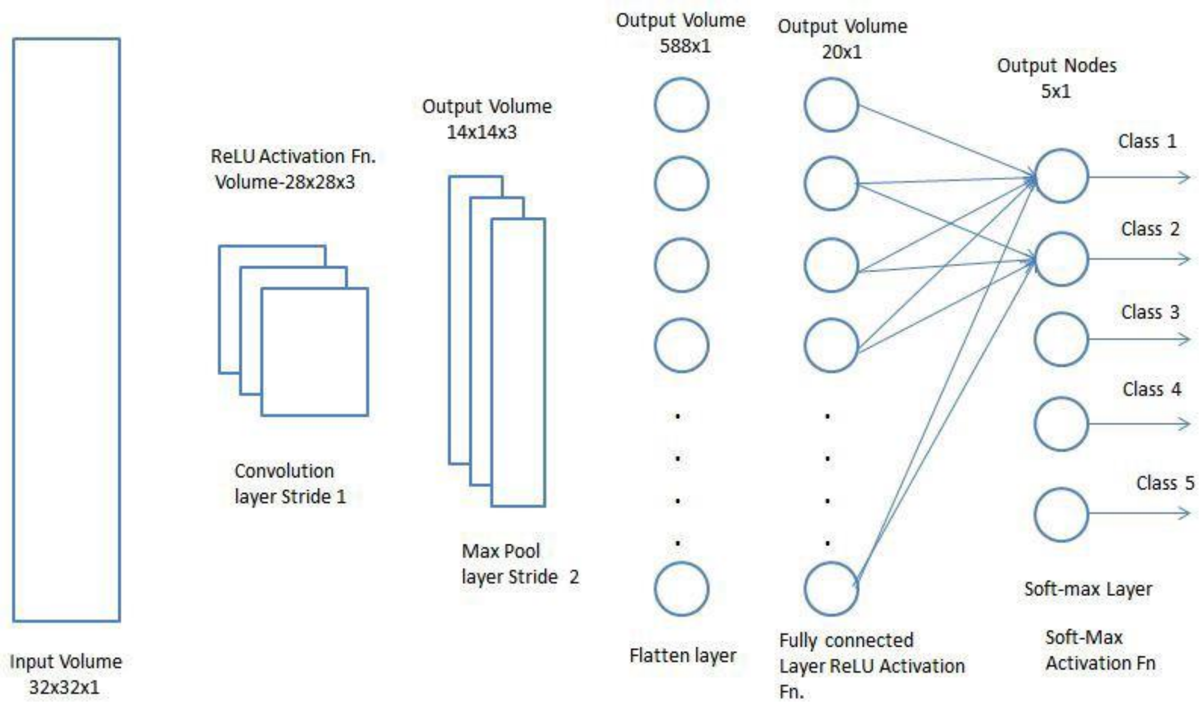
- Input volume: $N \times N \times \mathrm{D}_1$
- A 3×3 filter w. stride $S = 1,$ no pad
- Output volume: $(N-2) \times (N-2) \times \mathrm{D}_1$(since $\frac{1}{1}(N-3) + 1 = N - 2$)
- (This setting is uncommon. It is more common to have $F = 3, S = 2$ for overlapping pooling)



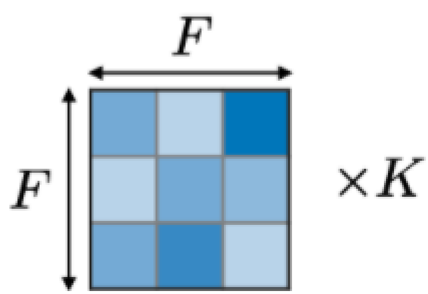
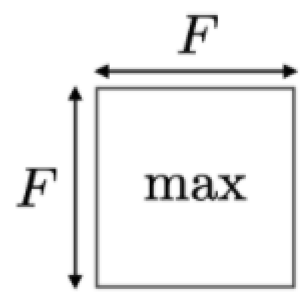
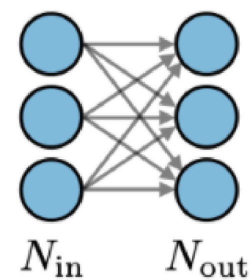
FC Layer

- Contains neurons that connect to the entire input volume w. no weight sharing
  - No. params for FC layer of size N_{out} connected to input layer of size N_{in} is $(N_{in} + 1) * N_{out}$





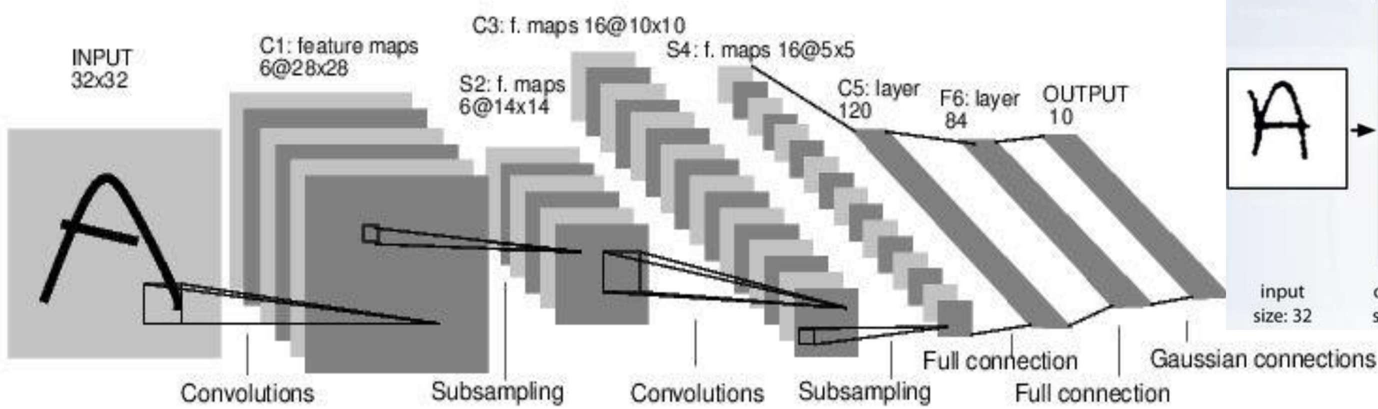
No. Params in Each Layer

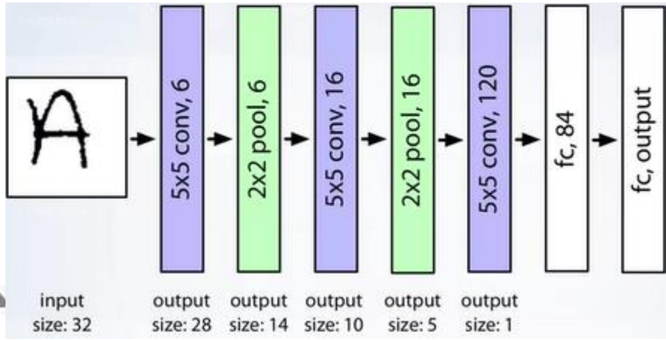
	CONV	POOL	FC
			
Input size	$N_1 \times N_1 \times D_1$	$N_1 \times N_1 \times D_1$	N_{in}
Output Size	$N_2 \times N_2 \times K$	$N_2 \times N_2 \times D_1$	N_{out}
No. params	$(F * F * D_1 + 1) * K$	0	$(N_{in} + 1) * N_{out}$

https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-convolutional-neural-networks

Case Study: LeNet-5 [LeCun et al. 1998]

- Architecture is [CONV-POOL-CONV-POOL-CONV-FC-FC]
- Input image: $32 \times 32 \times 1$ (grey-scale images of hand-written digits w. size 32×32 pixels)
- Conv filters $5 \times 5 \times 1$ w. stride 1; Subsampling (Pooling) layers were 2×2 w. stride 2
- Conv layer C1 maps from input volume $32 \times 32 \times 1$ to 6 feature maps w. volume $28 \times 28 \times 6$ (since $\frac{1}{1}(32-5)+1=28$)
- Subsampling layer S2 maps from input volume $28 \times 28 \times 1$ to 6 feature maps w. volume $14 \times 14 \times 6$ (since $\frac{1}{2}(28-2)+1=14$)
- Conv layer C3 maps from input volume $14 \times 14 \times 6$ to 16 feature maps w. volume $10 \times 10 \times 16$ (since $\frac{1}{1}(14-5)+1=10$)
- Subsampling layer S4 maps from input volume $10 \times 10 \times 16$ to 16 feature maps w. volume $5 \times 5 \times 16$ (since $\frac{1}{2}(10-2)+1=5$)
- Conv layer C5 maps from input volume $5 \times 5 \times 16$ to 120 feature maps w. volume $1 \times 1 \times 120$ (since $\frac{1}{1}(5-5)+1=1$)
  - Fig shows "Full Connection" before C5, but it is actually a Conv layer w. filter size equal to input size, followed by a "flatten" layer to turn it from $1 \times 1 \times 120$ to a linear array of 120 neurons
- Subsequent FC layers F6 and Output have 84 and 10 neurons, respectively





LeNet-5 Summary

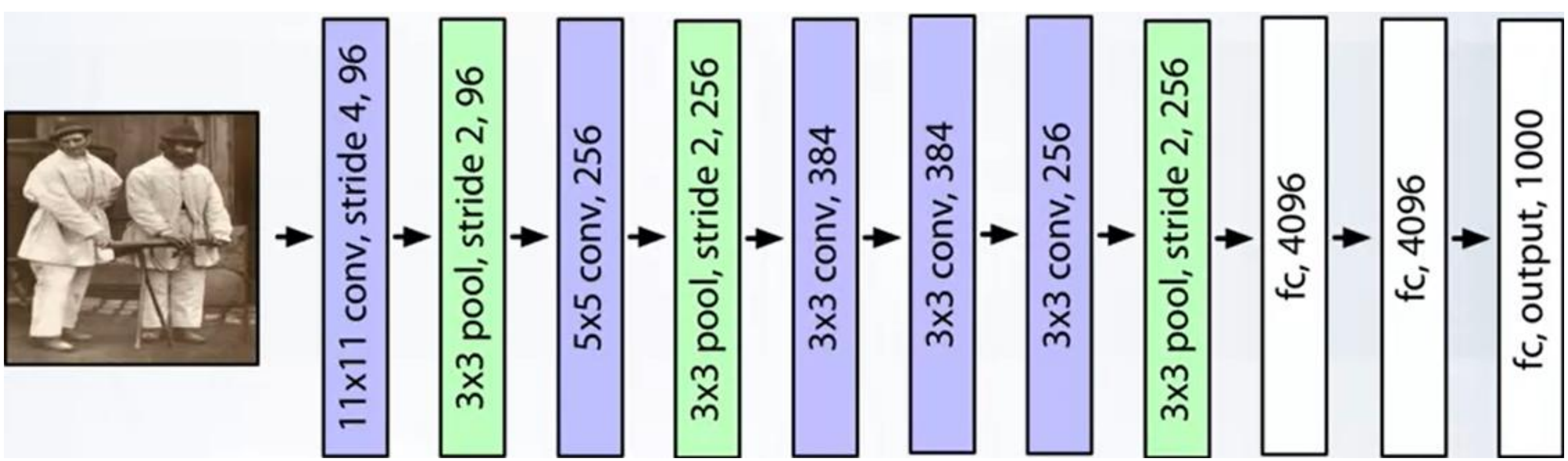
Layer	Layer Type	No. Filters	Filter Size	Layer Size	No. params
Input	Image	-	-	$32 \times 32 \times 1$	-
C1	Conv	6	5×5	$28 \times 28 \times 6$	156
S2	Subsamp	6	2×2	$14 \times 14 \times 6$	0
C3	Conv	16	5×5	$10 \times 10 \times 16$	2416
S4	Subsamp	16	2×2	$5 \times 5 \times 16$	0
C5	Conv+	120	5×5	$1 \times 1 \times 120$	48120
	Flatten	-	$-$	120	0
S6	FC	-	$-$	84	10164
Output	FC			10	850

- C1: No. params: $(F^2 D_1 + 1) * K = (5 * 5 * 1 + 1) * 6 = 156$
- C3: No. params: $(5 * 5 * 6 + 1) * 16 = 2416$
- C5: No. params: $(5 * 5 * 16 + 1) * 120 = 48120$
- S6: No. params: $(120 + 1) * 84 = 10164$
- Output: No. params: $(N_{in} + 1) * N_{out} = (84 + 1) * 10 = 850$
- Total No. params: 61706

Case Study: AlexNet [Krizhevsky et al. 2012]

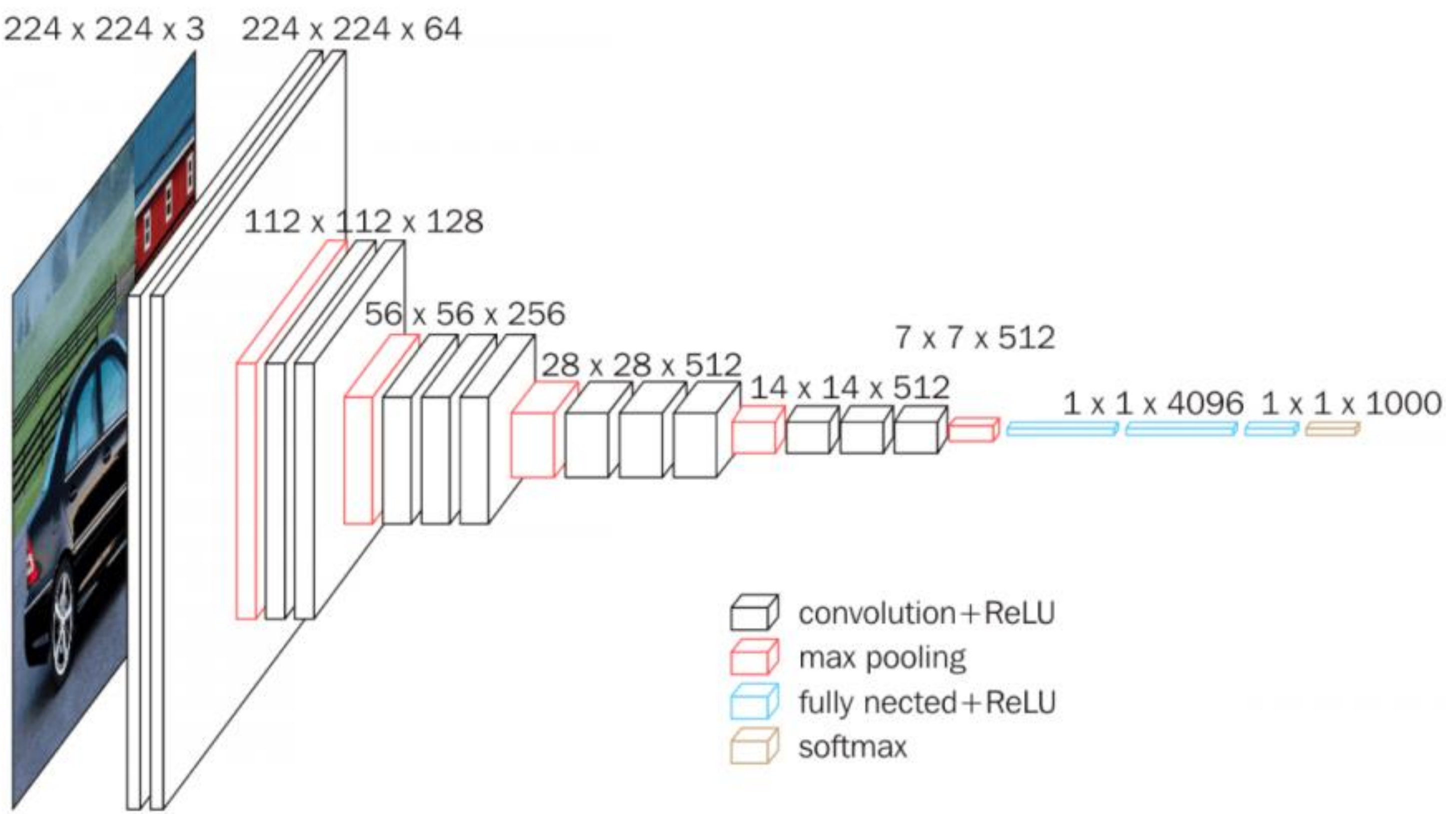
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters w. stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters w. stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters w. stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters w. stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters w. stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters w. stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters w. stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)
ImageNet top 5 error: 15.4%

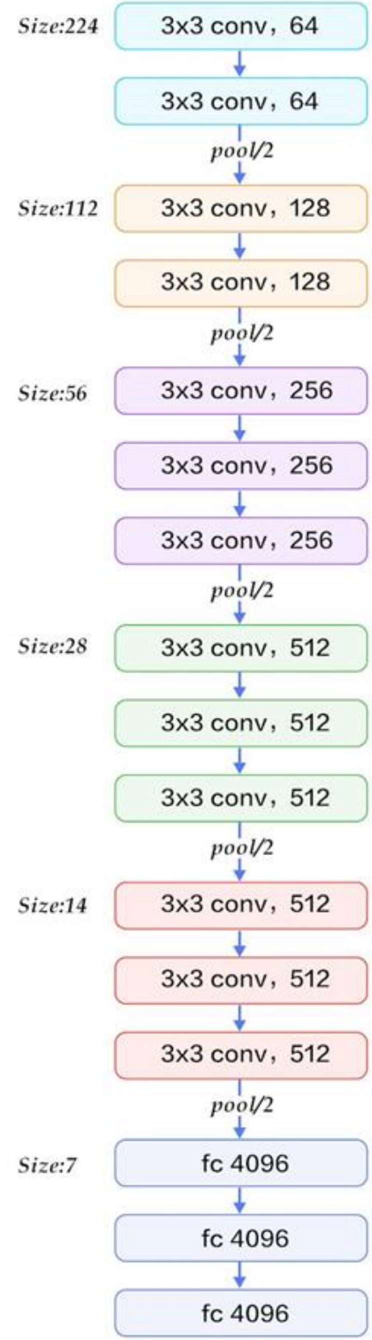
- Input image: $227 \times 227 \times 3$
- 1st layer (CONV1): 96 11×11 filters w. stride $S = 4$, w. ReLU activation function
- Output volume: $55 \times 55 \times 96$ (since $\frac{1}{4}(227 - 11) + 1 = 55$)
  - No. params: $(11 * 11 * 3 + 1) * 96 = 35K$
- 2nd layer (POOL1): 3×3 filters w. stride $S = 2$ (overlapping)
- Output volume: $27 \times 27 \times 96$ (since $\frac{1}{2}(55 - 3) + 1 = 27$)
  - No. params: 0
- …
- Total No. params: 60M



Case Study: VGGNet [Simonyan and Zisserman, 2014]

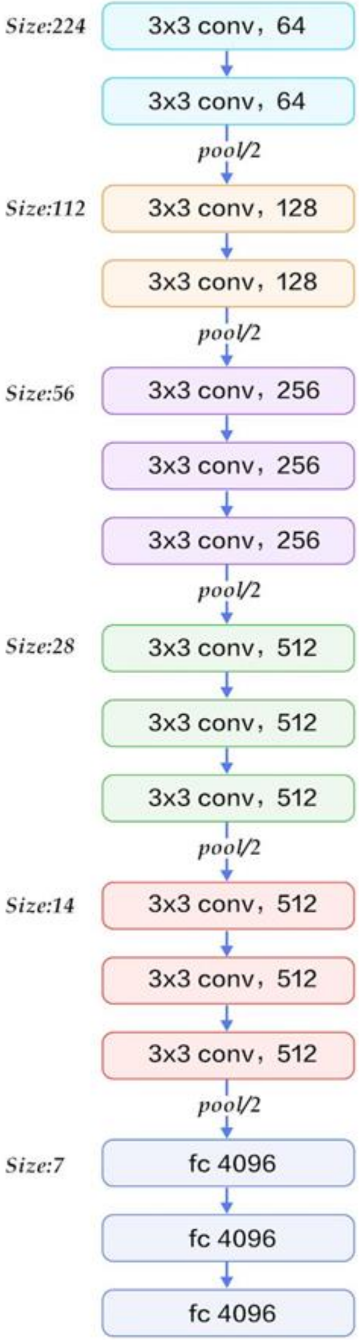
- We show the best performing variant VGG-16





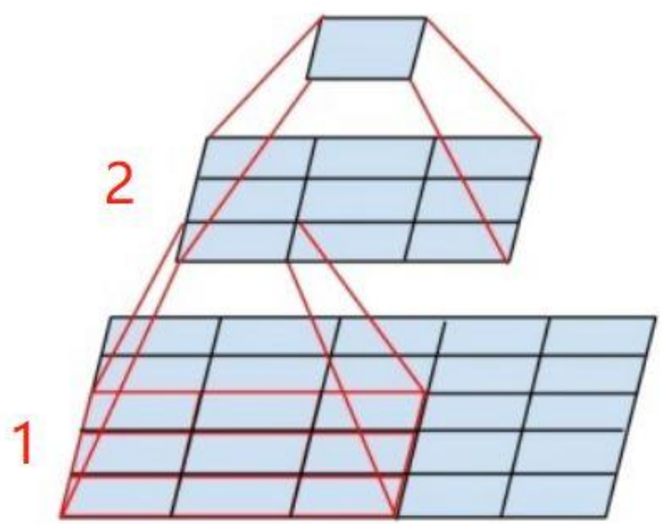
VGG-16 Details

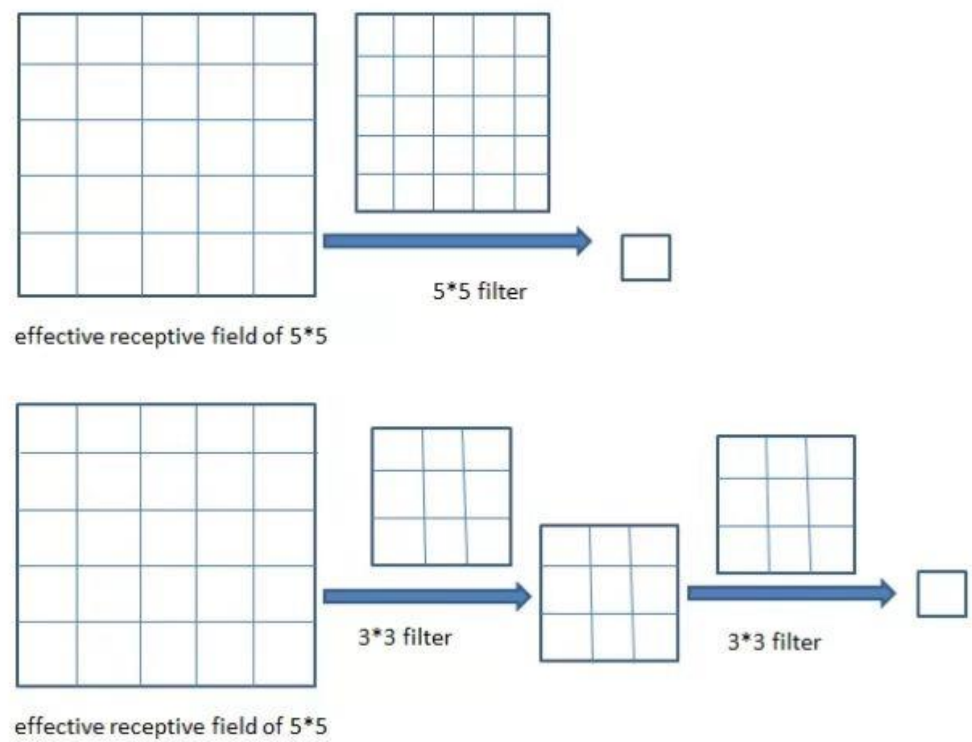
- VGG-16 has 16 weight layers, not including POOL layers w. 0 weight
- Input image: $224 \times 224 \times 3$
- 1st and 2nd CONV layers: 64 3×3 filters w. stride $S = 1$, pad $P = 1$
  - Output volume: $224 \times 224 \times 64$ (since $\frac{1}{1}(224 + 2 * 1 - 3) + 1 = 224$)
- 3rd POOL layer: 2×2 filters w. stride $S = 2$
  - Output volume: $112 \times 112 \times 64$ (since $\frac{1}{2}(224 - 2) + 1 = 112$)
- 4th and 5th CONV layers: 128 3×3 filters w. stride $S = 1$, pad $P = 1$
  - Output volume: $112 \times 112 \times 128$ (since $\frac{1}{1}(112 + 2 * 1 - 3) + 1 = 112$)
- 6th POOL layer: 2×2 filters w. stride $S = 2$
  - Output volume: $56 \times 56 \times 128$ (since $\frac{1}{2}(112 - 2) + 1 = 56$)
- Total No. params: 60M
- ImageNet top 5 error: 7.3%



Stacked 3×3 CONV Layers

- Two stacked 3×3 CONV layers w. pad $P = 1$ have the same effective receptive field as a 5×5 CONV layer. Similarly, three stacked 3×3 CONV layers w. pad $P = 1$ have the same RF as a 7×7 CONV layer
- Benefits:
  - Fewer params. Suppose all volumes have the same depth D, then a 7×7 CONV layer has $(7 * 7 * D + 1) * D \approx 49D^2$ params, while three stacked 3x3 CONV layers have only $(3 * 3 * D + 1) * D * 3) \approx 27D^2$ params
  - Two layers of non-linear activation functions increases CNN depth, hence larger model capacity





https://zhuanlan.zhihu.com/p/79258431

VGGNet No. Params

```
INPUT: [224x224x3]        memory:  224*224*3=150K   weights: 0
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*64)*64 = 36,864
POOL2: [112x112x64]  memory:  112*112*64=800K   weights: 0
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*128)*128 = 147,456
POOL2: [56x56x128]  memory:  56*56*128=400K   weights: 0
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
POOL2: [28x28x256]  memory:  28*28*256=200K   weights: 0
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512]  memory:  14*14*512=100K   weights: 0
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512]  memory:  7*7*512=25K  weights: 0
FC: [1x1x4096]  memory:  4096  weights: 7*7*512*4096 = 102,760,448
FC: [1x1x4096]  memory:  4096  weights: 4096*4096 = 16,777,216
FC: [1x1x1000]  memory:  1000 weights: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters
```

- Memory refers to memory size of activation maps
- For ease of calculation, only the No. weights are counted, not the biases

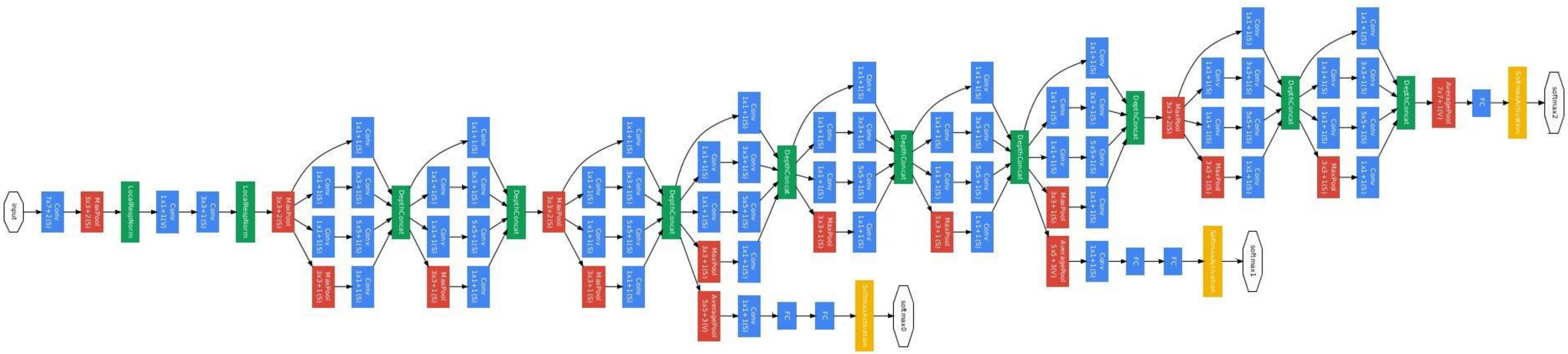
VGGNet Variants

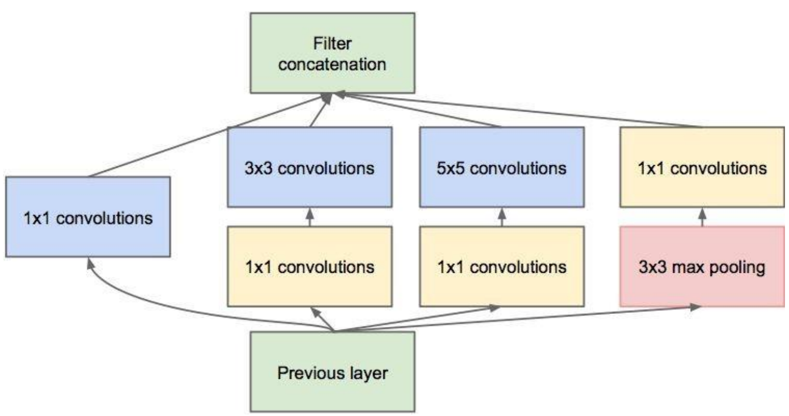
Best performing variant
VGG-16

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Case Study: GoogLeNet [Szegedy et al., 2014]

- ImageNet top 5 error: 6.7%





Inception module

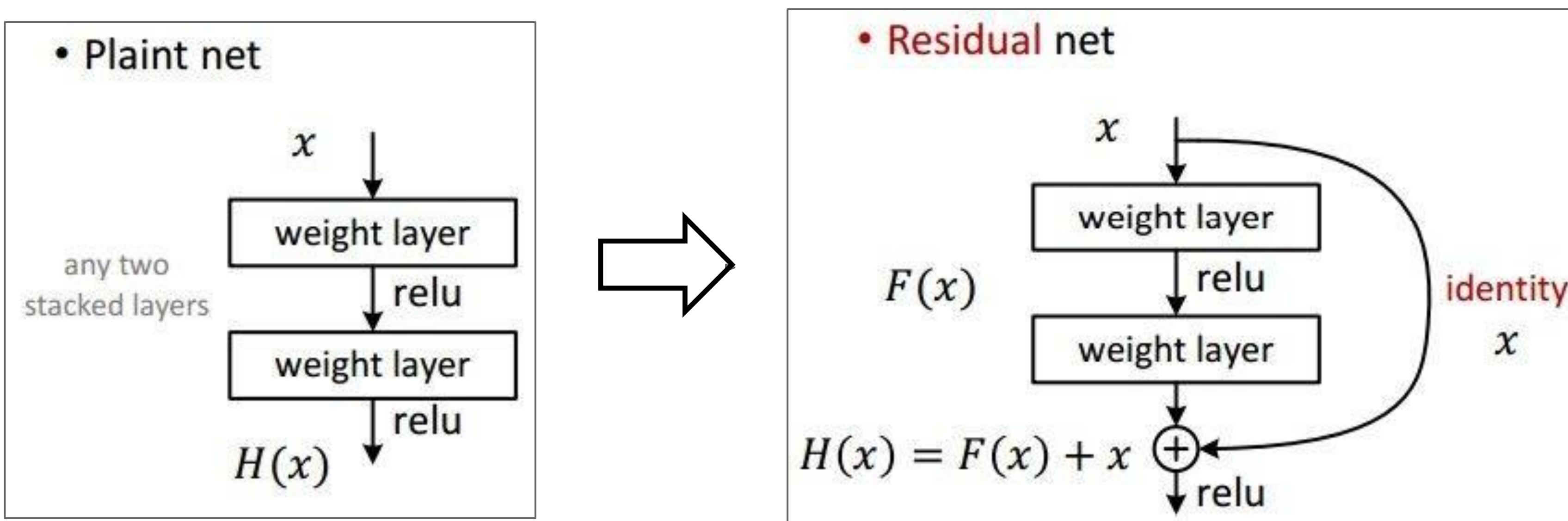
GoogLeNet Size

- Compared to AlexNet:
  - 12x less params (only 5M, due to no FC layers), 2x more compute (due to more CONV layers)

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Case Study: Residual Networks (ResNet) [He et al. 2015]

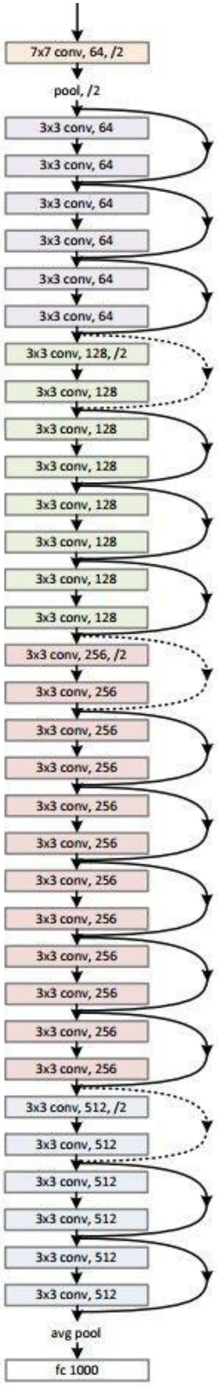
- Based on VGG-19, adding more layers and skip connections
- ImageNet top 5 error: 3.6%



ResNet Variants

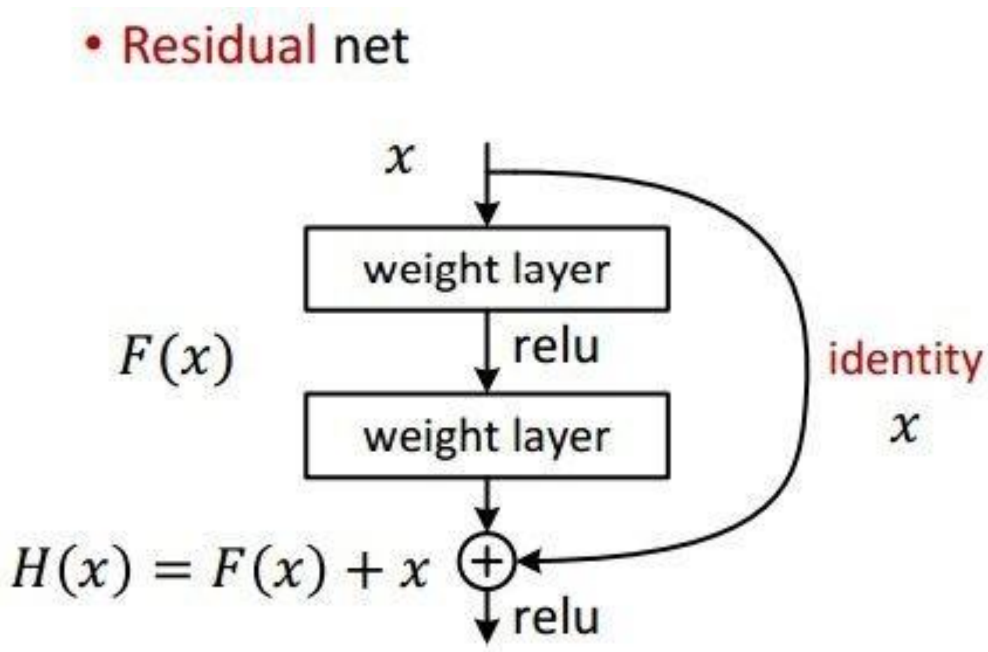
- Right fig shows 34-layer ResNet

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9



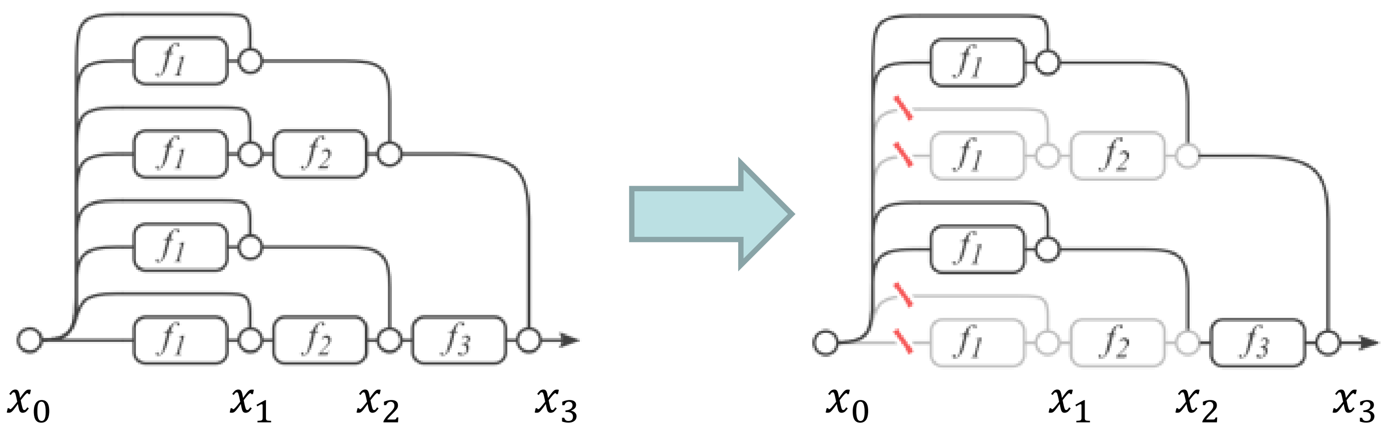
ResNet Skip Connection

- In a standard network, output from a given layer is $F(x)$
- In ResNet w. the identity skip (or short-cut) connection, output from a given layer is $H(x) = F(x) + x$
  - If identify mapping is close to optimal, then weights can be small to capture minor differences only
- Benefits:
  - Residual connections help in handling the vanishing gradient problem in very deep NNs
  - It is safe to train very deep NNs, because “unnecessary layers” can learn to be identity mapping and do no cause overfitting



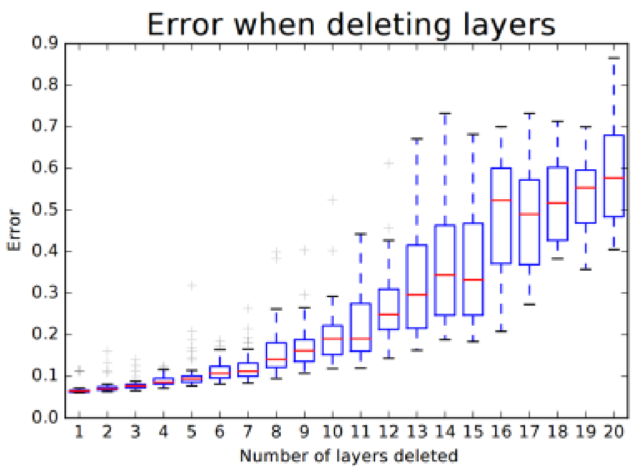
Consider a 3-layer Network

- Standard NN:
  - $x_3 = f_3(f_2(f_1(x_0)))$
- ResNet:
  - $x_1 = f_1(x_0) + x_0$
  - $x_2 = f_2(x_1) + x_1 = f_2(f_1(x_0) + x_0) + f_1(x_0) + x_0$
  - $x_3 = f_3(x_2) + x_2 = f_3(f_2(f_1(x_0) + x_0) + f_1(x_0) + x_0) + f_2(f_1(x_0) + x_0) + f_1(x_0) + x_0$
- Suppose $f_2(x_1)$ is a vector of very small values (layer 2 is "off"/skipped), then it looks like the input x_0 bypassed the second layer completely on its way to the output x_3

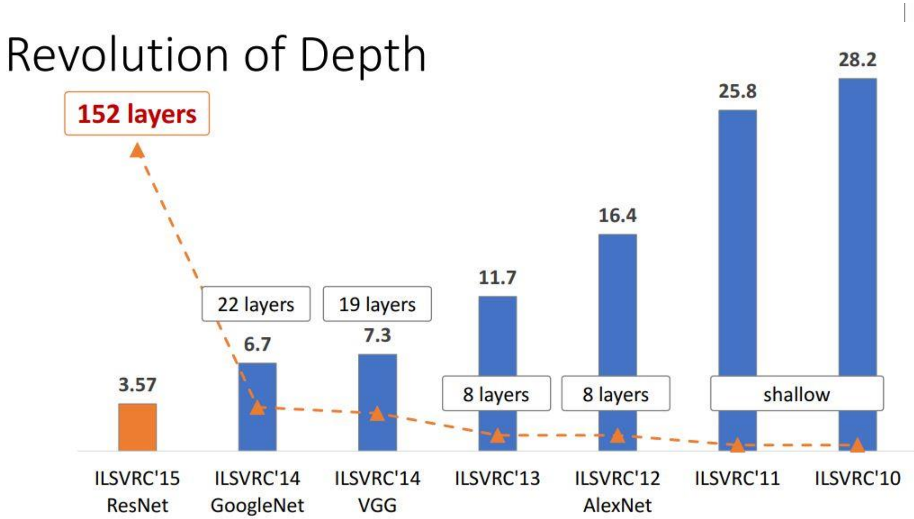


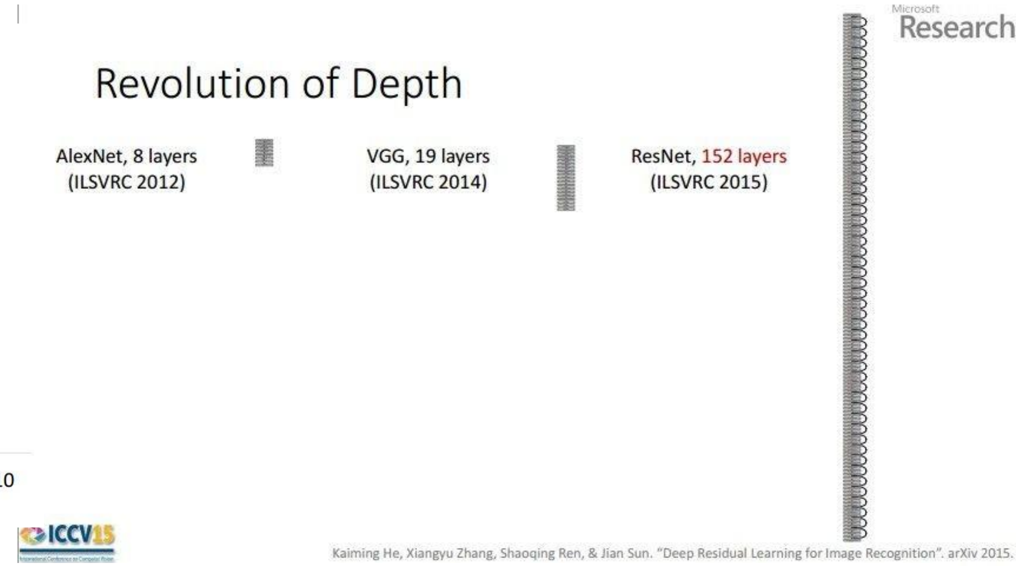
ResNet is Ensemble of Models

- Every input x_0 to ResNet may activate a unique path to the output. Total number of possible paths is 2^N, where N is the total number of layers in the network, since each layer may be either "on" or "off" for a given input x_0
  - Compare w. a standard network, where there is only one single path for any input corresponding to all layers being "on", and no layer is skipped
- Consequences:
  - Resilience to layer deletion: deleting 1-3 layers in a large ResNet introduces only around 6-7% error
  - Shortening of effective paths: w. 152-layer ResNet, most paths are only 20-30 levels deep!

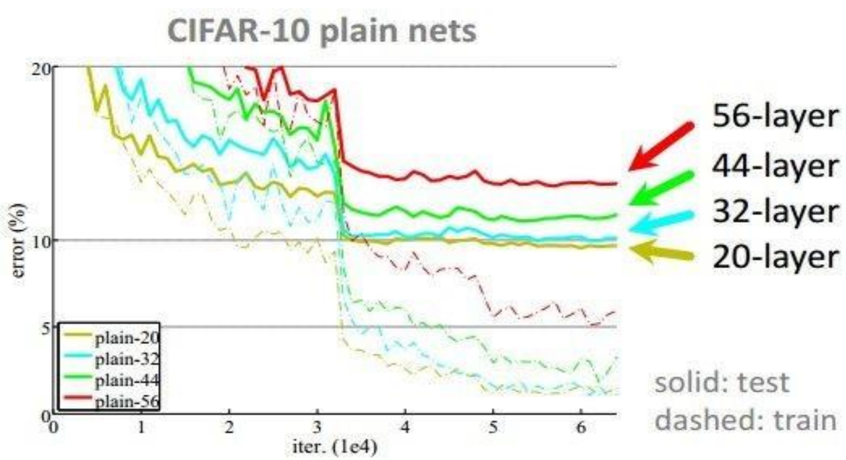


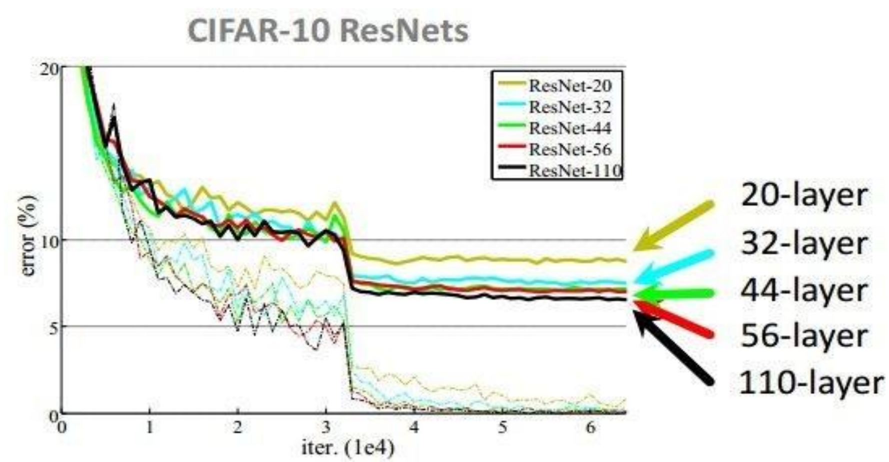
Deeper Nets have Better Performance





CIFAR-10 experiments



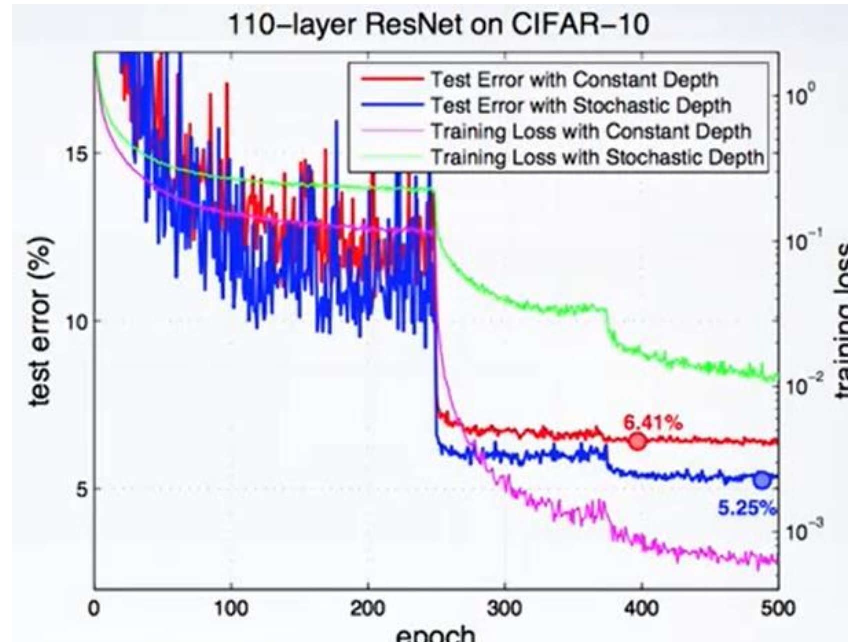


Case Study: Policy Network in AlphaGo

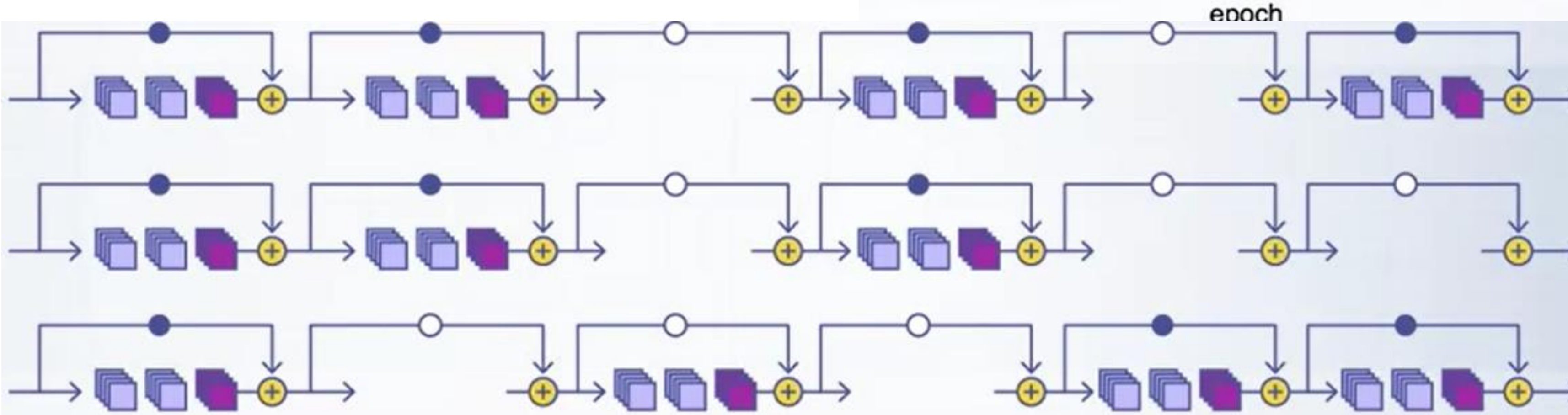
- Input volume: [19x19x48]
- CONV1: 192 5x5 filters, stride 1, pad 2
- Output volume: [19x19x192] (since $\frac{1}{1}(19 + 2 * 2 - 5) + 1 = 19$)
- CONV2..12: 192 3x3 filters, stride 1, pad 1
- Output volume: [19x19x192] (since $\frac{1}{1}(19 + 2 * 1 - 3) + 1 = 19$)
- CONV: 1 1x1 filter, stride 1, pad 0
- Output volume: [19x19] (since $\frac{1}{1}(19 - 1) + 1 = 19$)

Case Study: Stochastic Depth

- For each minibatch of inputs, randomly skip some layers (replaced w. identity mapping)
- Reduced network depth during training; full depth during inference



MB1
MB2
MB3



Layer Sizing Rules-of-Thumb

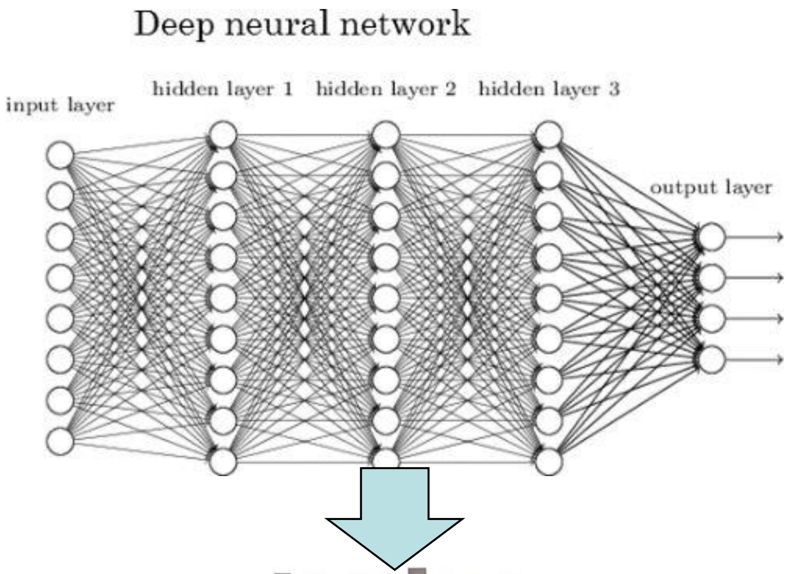
- The input layer (that contains the image) should be divisible by 2 many times. Common numbers include 32 (e.g. CIFAR-10), 64, 96 (e.g. STL-10), or 224 (e.g. ImageNet), 384, and 512.
- The CONV layers should use small filters (e.g. 3x3 or at most 5x5), stride S=1. The input volume should have “same padding”, i.e., the conv layer does not alter the spatial size of the input. For any F, pad $P=(F-1)/2$ preserves the input size, e.g., when F=3, P=1; when F=5, P=2. This means the CONV layers only transform the input volume depth-wise, but do not perform downsampling. (c.f. CONV Example 3 and VGGNet).
- The POOL layers are in charge of downsampling the spatial dimensions of the input. The most common setting is to use max-pooling with 2x2 receptive fields (F=2), with stride of 2 (S=2). A less common setting is to use F=3, S=2. It is uncommon to see receptive field sizes for max pooling that are larger than 3, because the pooling is then too lossy and aggressive.
- In some cases (especially in early layers), the amount of memory can build up very quickly with the rules of thumb presented above. For example, filtering a 224x224x3 image with three 3x3 CONV layers with 64 filters each and padding 1 would create 3 activation volumes, each with size 224x224x64. This amounts to a total of about 10 million activations, or 72MB of memory (per image, for both activations and gradients). Since GPUs are often bottlenecked by memory, it may be necessary to compromise. In practice, make the compromise at only the first CONV layer that is looking at the input image. For example, AlexNet uses filter size of 11x11 and stride of 4 in the first CONV layer.

Memory Size Considerations

- From the intermediate volume sizes:
  - These are the raw number of activations at every layer of the CNN, and also their gradients (of equal size). Usually, most of the activations are on the earlier CONV layers of a CNN. These are kept around because they are needed for backpropagation during training, but for inference, we can store only the current activations at the current layer and discarding the activations from previous layers.
- From the parameter sizes:
  - These are the weights and biases, and their gradients during backpropagation, and also a step cache if the optimization is using momentum, Adagrad, or RMSProp. Therefore, the memory to store the parameter vector alone usually should be multiplied by a factor of at least 3 or so.
- Misc memory, such as the image data batches, perhaps their augmented versions, etc.
- Each number may need 4 Bytes storage space for floating point, 8 Bytes for double, or 1 Bytes or smaller for optimized fixed-point implementations.

Deep Learning on Embedded Systems

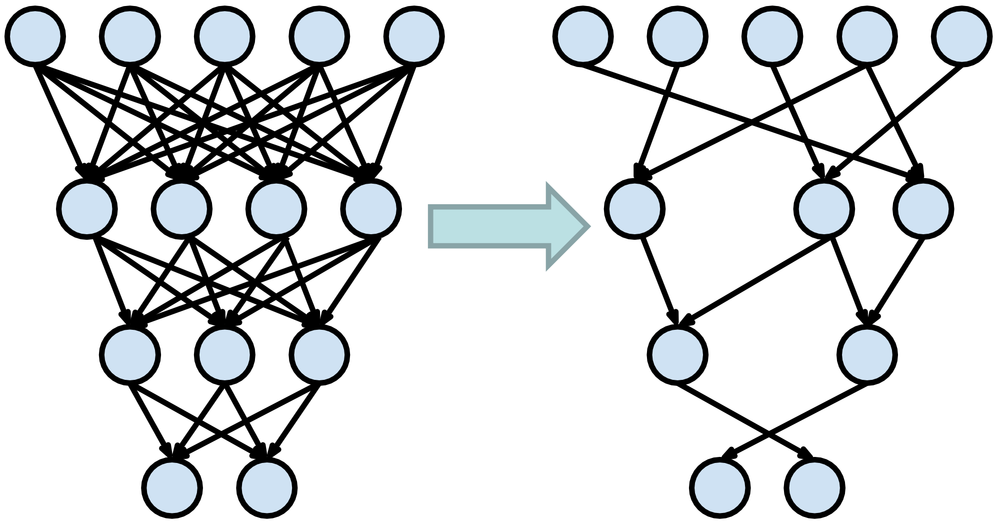
- Large CNN models are memory and computation intensive, even for inference tasks
- Resource constrained embedded devices may have constraints in computational power and battery capacity, and cannot support large DNN inference tasks
  - More applicable to small mobile robots (e.g. drones) than fullsize AVs, which have powerful compute engines
  - Next, we consider running CNN models on resource-constrained platforms.



Weight Pruning

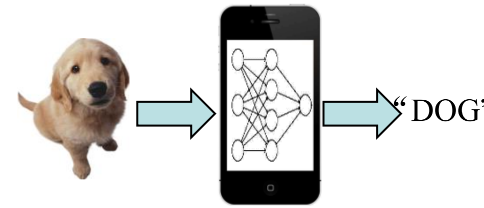
- Reduce the number and/or bit-width of edge weights, especially for the FCLs, since weights of FCLs make up majority of the edge weight parameters of the entire CNN.

	LeNet	AlexNet	OverFeat	VGG-Net
#Weights in CNN	43K	60M	70M	135M
#Weights in FCL	40.5K	58M	54.7M	123M

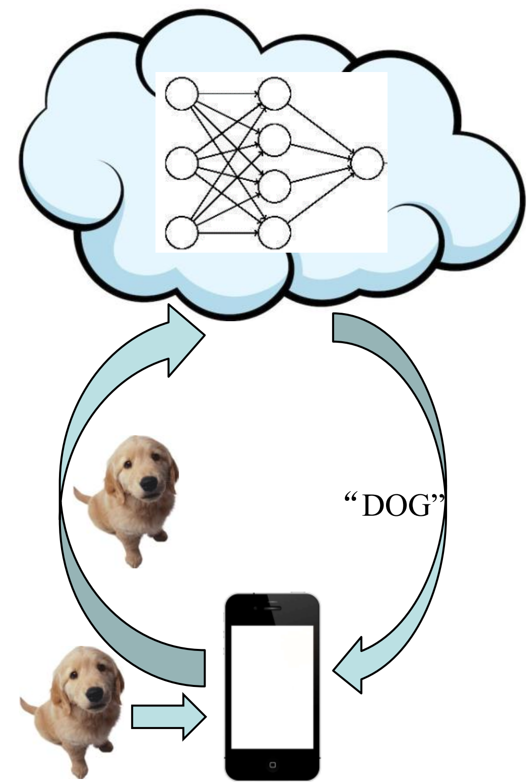


Device vs. Cloud

- On-device execution
  - Computation workload may exceed computing or energy capacity.
  - Feasible for small models, or for devices w. power efficient hardware accelerators.
- Computational offloading to the cloud
  - Network transmission costs time and energy.
  - Quality-of-Service Degradation due to network latencies and disruptions.
- Solutions:
  - Make adaptive decisions based on network condition and device workload (e.g., w. Reinforcement Learning).
  - Place "Edge Servers" in close proximity to the devices, forming a multi-tier hierarchy of device-edge-cloud.



Device execution



Cloud execution

Example Scenario for Computational Offloading

- Different DNNs offer varied compute/accuracy tradeoffs. Mobile-optimized vision DNNs, such as MobileNet and ShuffleNet, sacrifice accuracy to be faster and use less power, compared to the more accurate Mask R-CNN.
- A small robot (e.g., a drone) may not have enough computing power to run Mask R-CNN. So it can either choose to run MobileNet or ShuffleNet locally, or send the images to the cloud, which runs Mask R-CNN and sends back the result.

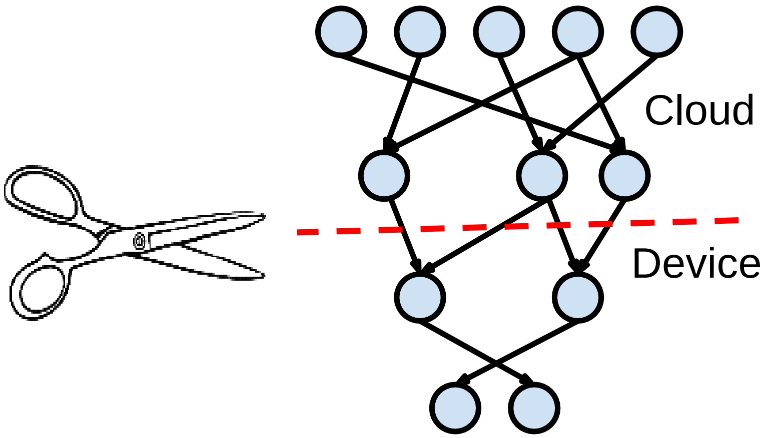
DNN	Accuracy	Size	CPU Infer.	GPU Infer.
MobileNet v1	18	18 MB	270 ms	26 ms
MobileNet v2	22	67 MB	200 ms	29 ms
Mask R-CNN	45.2	1.6GB	325 ms	18 ms

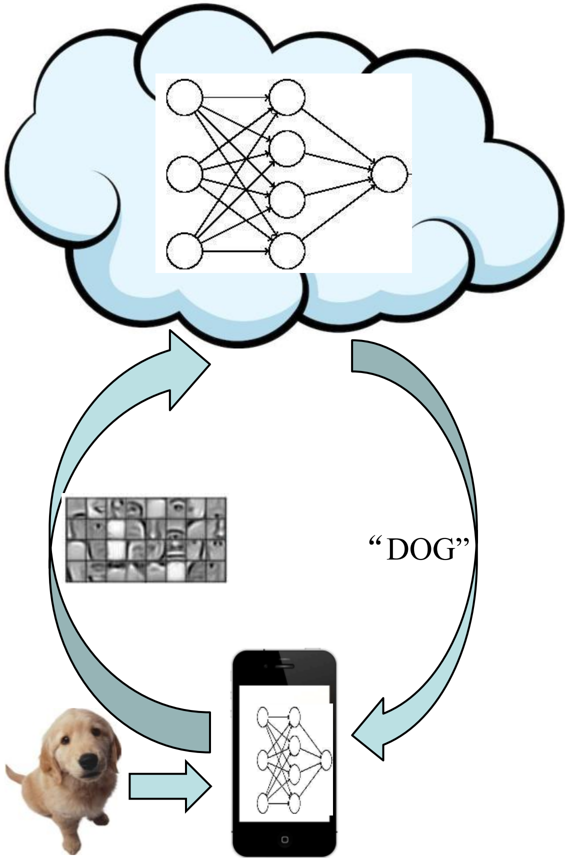
TABLE I: Accuracy, size, and speed tradeoffs of deep neural networks, where accuracy is the standard mean average precision (mAP) metric on the MS-COCO visual dataset [32].

Chinchali S, Sharma A, Harrison J, et al. Network offloading policies for cloud robotics: a learning-based approach[J]. arXiv preprint arXiv:1902.05703, 2019.

Collaborative Processing

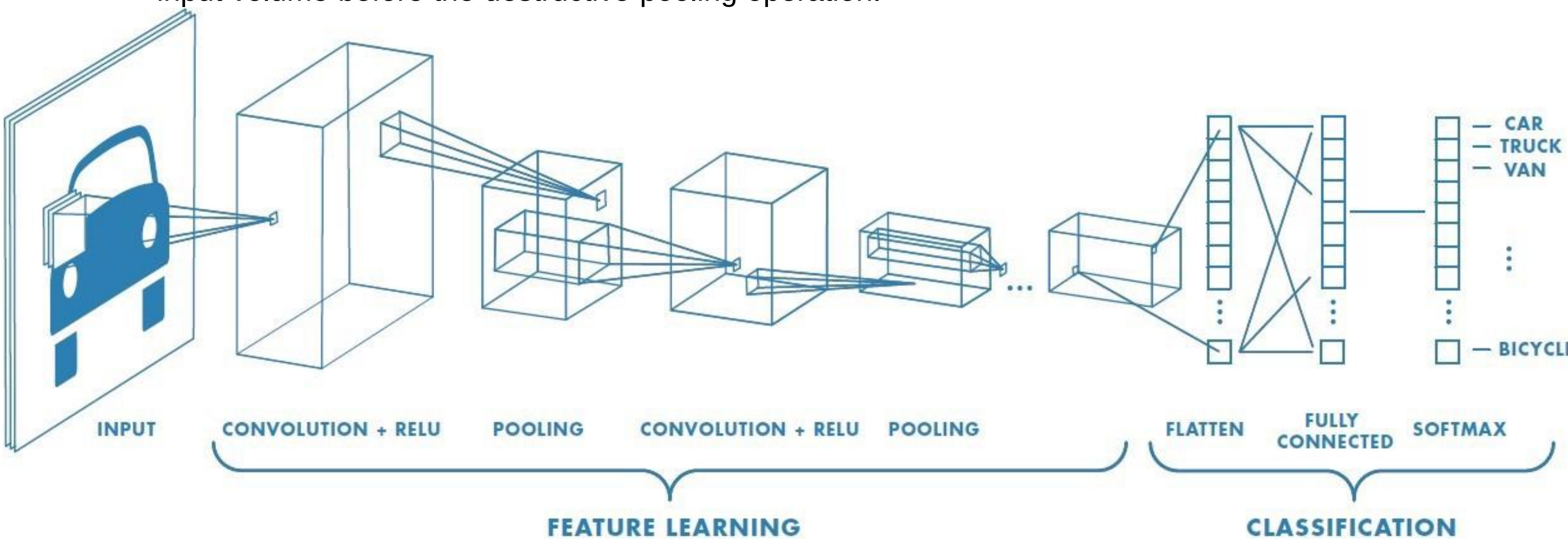
- Partition a DNN model layer-wise.
  - May be multiple layers w. the device-edge-cloud architecture.
- Device executes early layers, and transmits intermediate feature maps to cloud, w. reduced network transmission compared to raw data (pixels).
- “Early exit” is possible: if early layers can produce “good-enough” result, then skip cloud access.





CNN Layer Patterns

- A typical CNN architecture looks like: `INPUT->[[CONV->RELU]*N->POOL?]*M->[FC->RELU]*K->FC`
  - where `*` indicates repetition, and `POOL?` indicates an optional pooling layer. $N \geq 0$ (usually $N \leq 3$), $M \geq 0$, $K \geq 0$ (and usually $K < 3$)
- Some common architectures:
  - `INPUT->FC`, implements a linear classifier. Here N = M = K = 0.
  - `INPUT->CONV->RELU->FC`
  - `INPUT->[CONV->RELU->POOL]*2->FC->RELU->FC` (fig below). There is a single CONV layer between every POOL layer.
  - `INPUT->[CONV->RELU->CONV->RELU->POOL]*3->[FC->RELU]*2->FC` There are two `CONV` layers stacked before every `POOL` layer. This is generally a good idea for larger and deeper networks, because multiple stacked `CONV` layers can develop more complex features of the input volume before the destructive pooling operation.



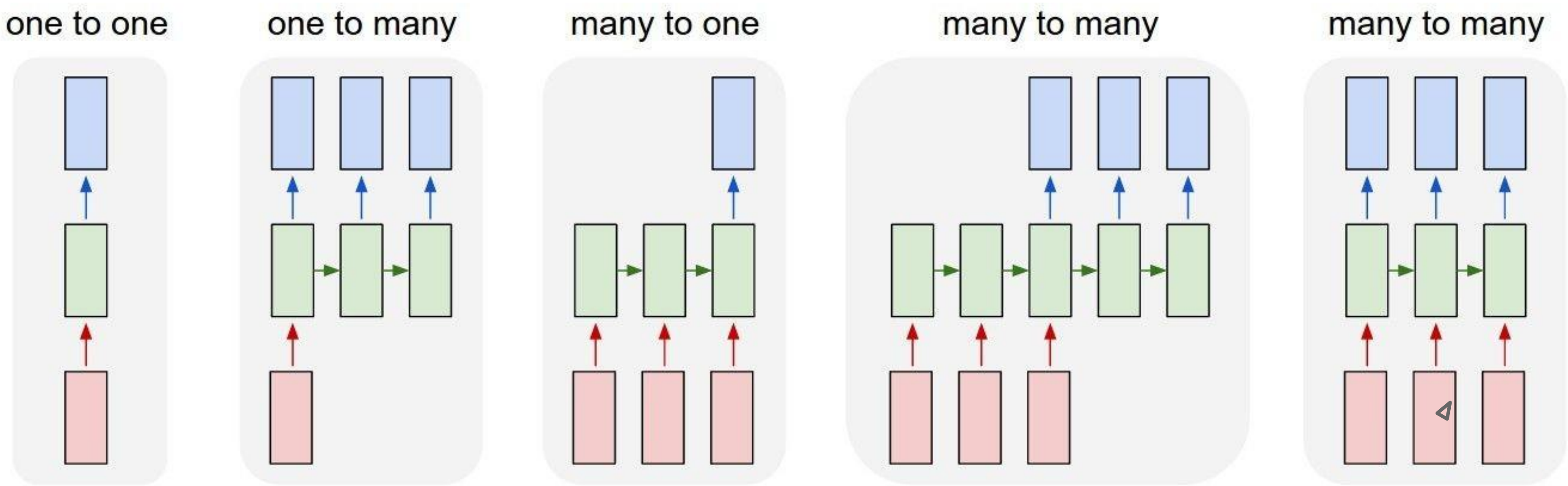
CNN Summary

- CNN is the dominant modeling paradigm for perception tasks in modern CV (detection, classification, tracking, segmentation)
- ConvNets stack multiple CONV,POOL,FC layers
- Recent trend: smaller filters, more layers, no POOL/FC layers (just CONV)

Recurrent Neural Network (RNN)

- An RNN has connections between nodes that form a directed graph along a temporal sequence. This allows it to process variable-length input sequences and take into account dynamic temporal behavior
  - e.g., To take into account temporal sequence of consecutive frames in a video clip, we can either stack together a fixed number of frames as input to a CNN, or we can use an RNN (combined w. CNN) to process any variable-length sequence of frames
  - FYI: Michael Phi, Illustrated Guide to Recurrent Neural Networks: Understanding the Intuition https://www.youtube.com/watch?v=LHXXI4-IEns

RNN Architecture Variants



Regular Feedforward NN

e.g. Image Captioning image -> sequence of words

e.g. Sentiment Classification sequence of words -> sentiment

e.g. Machine Translation seq of words -> seq of words

e.g., video classification on frame level

RNN Many-to-Many Architecture

- RNN can process a sequence of inputs x recurrently at every time step, w. the same activation function and parameters f_W
  - e.g. $h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$, $y_t = W_{hy}h_t$
  - h_t can even be a large CNN (without the last classification layer)

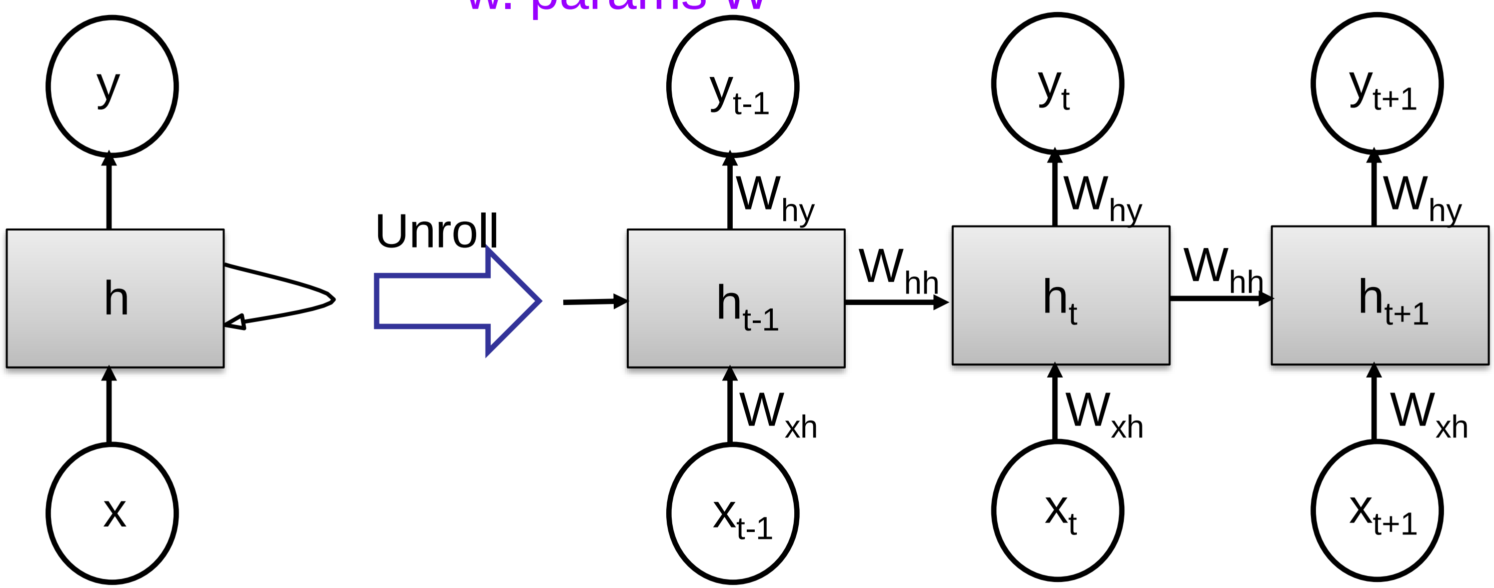
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state at timestep t

old state at $t-1$

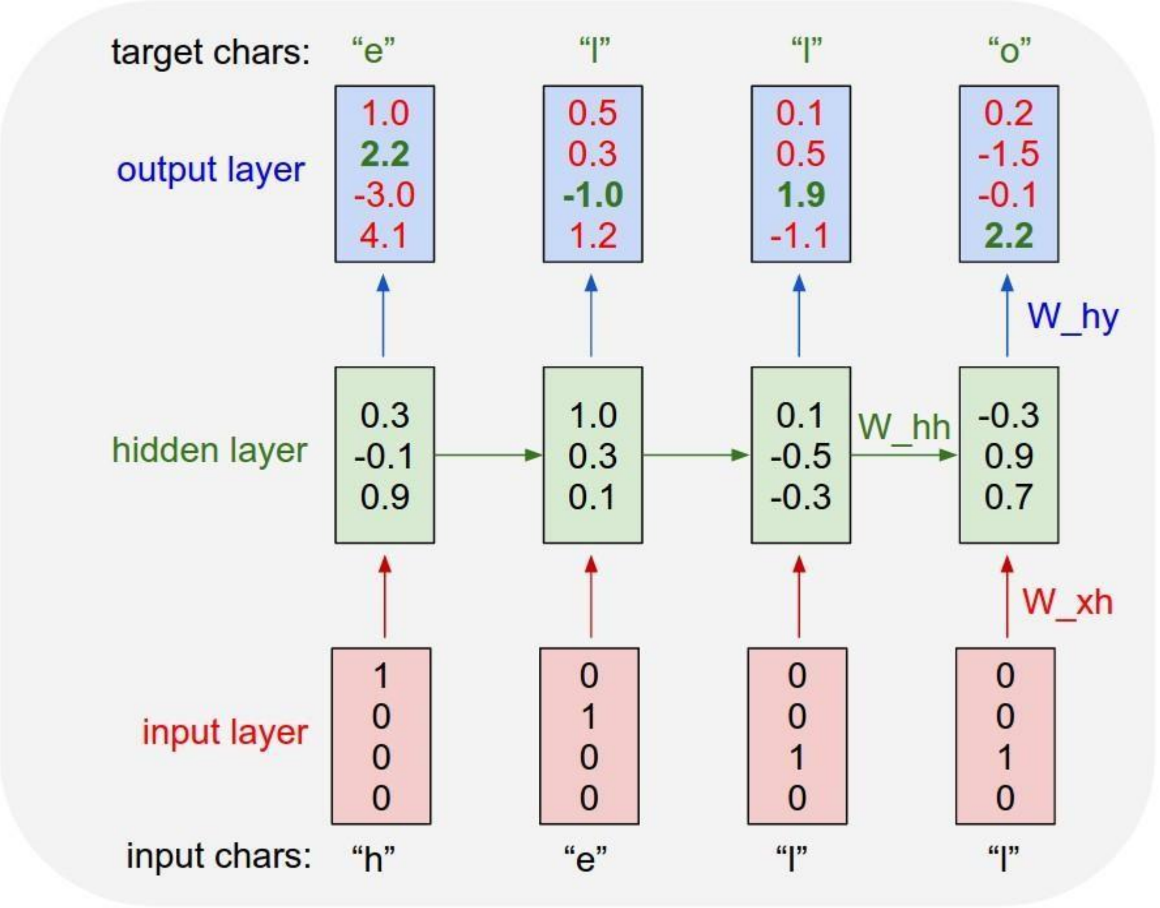
input at timestep t

Activation function w. params W



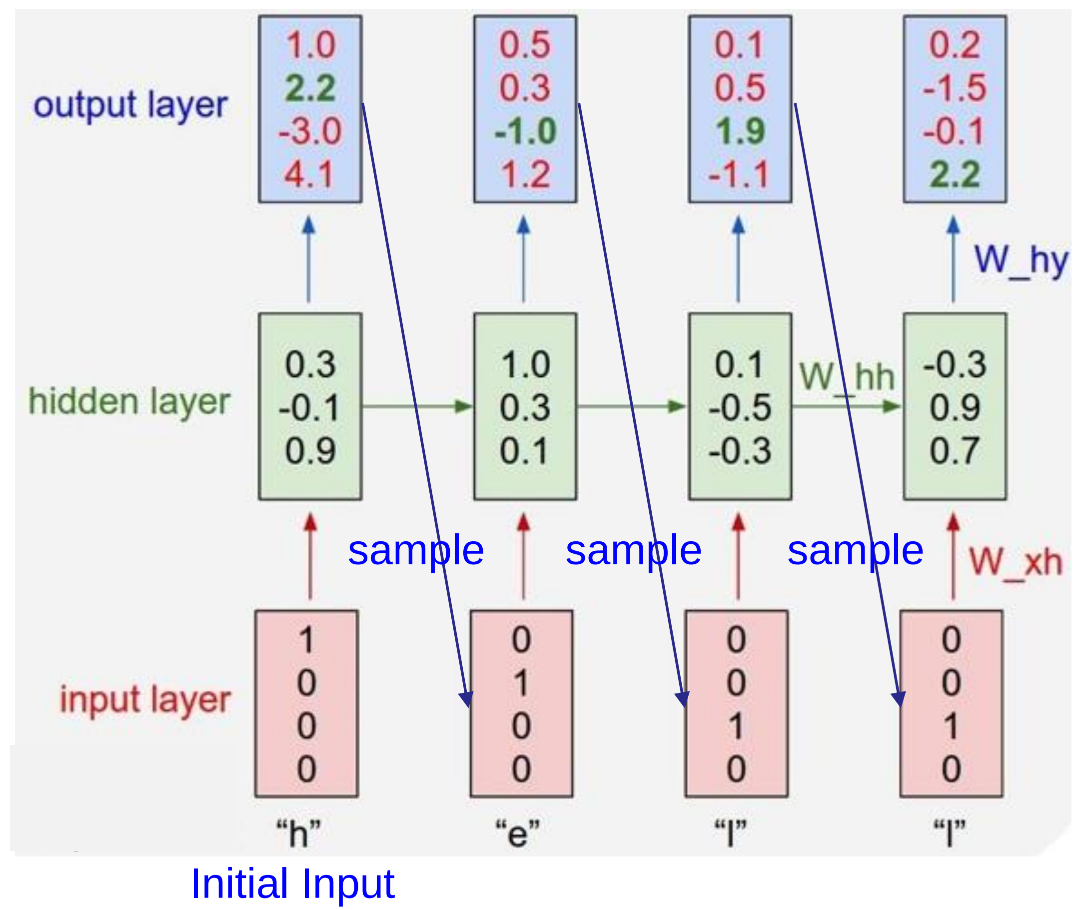
Example: Character-Level Language Model, Training Time

- Task: predict the next char from current char sequence
- Example training sequence: "hello" w. vocabulary: [h,e,l,o]
  - Input is one-hot encoding of each char
  - Hidden layer is learned embedding
  - Output layer is a probability vector w. size 4, denoting prob distribution of next char (Fig shows the activation values before applying the SoftMax function for computing probabilities).



Example: Character-Level Language Model, Inference Time

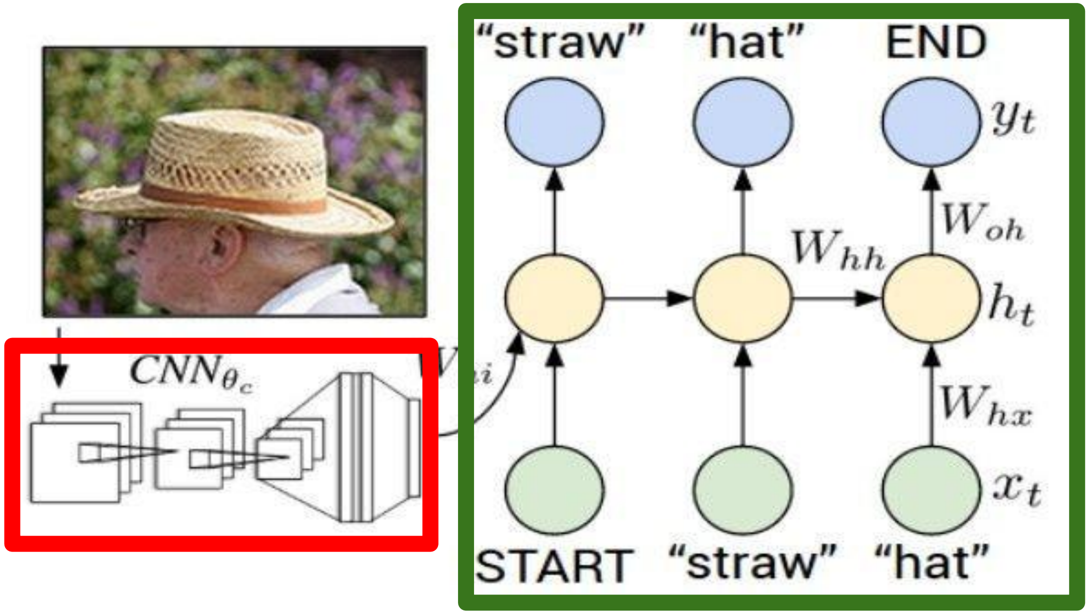
- Initial input is char "h"
- At each timestep, sample from the prob vector of the output y_t to generate the next input char
  - Here we assume the char w. highest prob is always selected as output at each timestep, i.e., "e", "l", "l" in sequence, but it is possible to select the other choices, e.g., "l", "e", "e")



Example: Image Captioning

- CNN processes the input image and generates a feature vector as input to RNN

Recurrent Neural Network



Convolutional Neural Network

Image Captioning: Word-Level Language Model, Inference Time

- The last 2 layers of the CNN for classification (FC-1000 and SoftMax) are not used, since we only need the extracted features from the layer FC-4096
- At each timestep, sample from the prob vector of the output y_t to generate the next input word

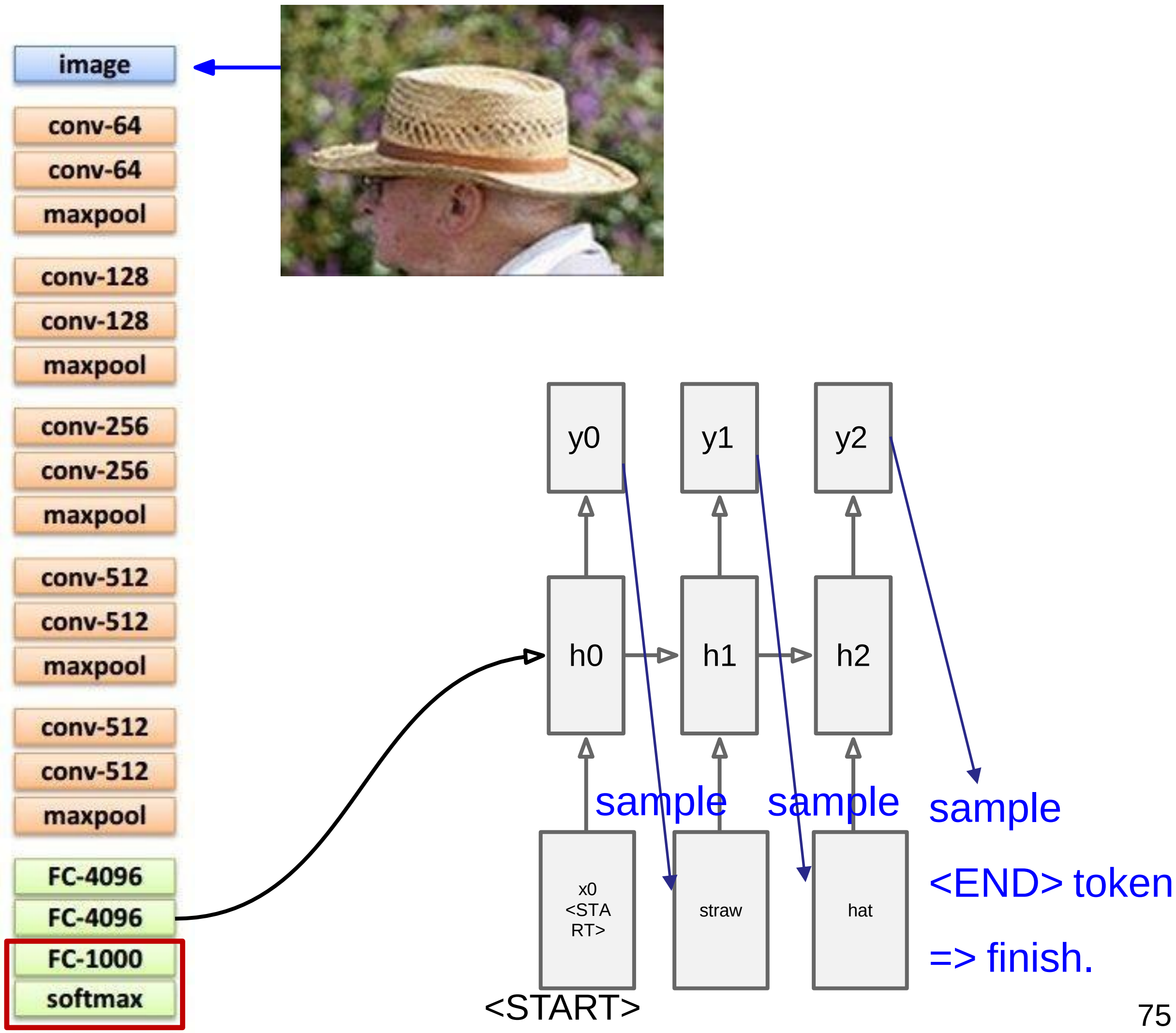


Image Captioning Examples


"man in black shirt is playing guitar."


"construction worker in orange safety vest is working on road."


"two young girls are playing with lego toy."


"boy is doing backflip on wakeboard."


"a young boy is holding a baseball bat."


"a cat is sitting on a couch with a remote control."

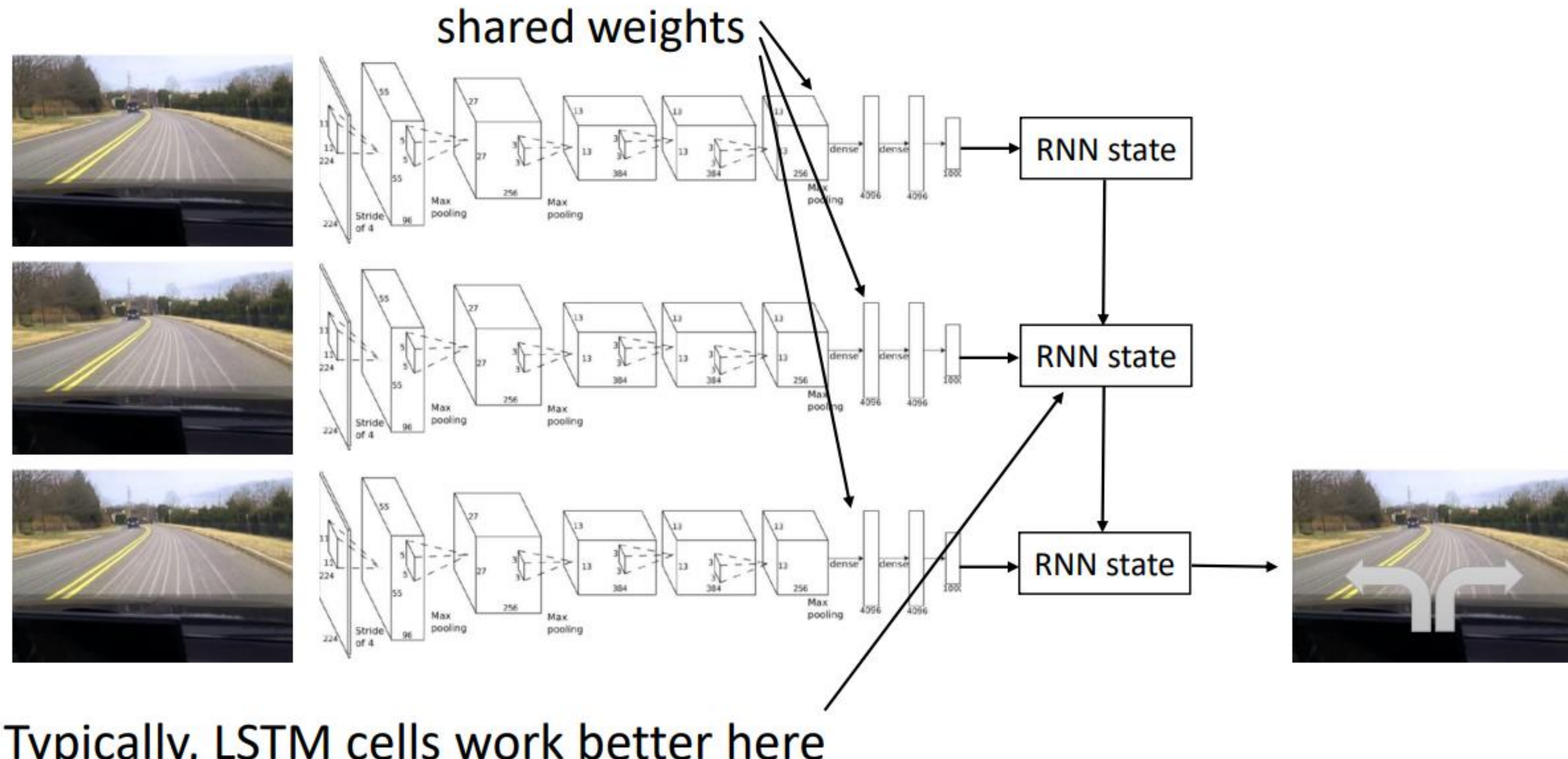
"a woman holding a teddy bear in front of a mirror."


"a horse is standing in the middle of a road."

Bottom row shows failure cases

RNN in AD

- Combined with CNN, RNN can handle Non-Markovian behavior, i.e, the current action depends not just on the current observation (input image), but on a recent history of observations



RNN Summary

- Training of RNNs requires back propagation through time, which may cause exploding or vanishing gradient problems
- More sophisticated architectures are more practical
  - LSTM (Long Short-Term Memory Model) or GRU (Gated Recurrent Unit)
- RNNs are most widely used in Natural Language Processing, but it is also useful for processing videos, w. applications in autonomous driving