CAP 5415: Computer Vision

Deep (Neural) Networks

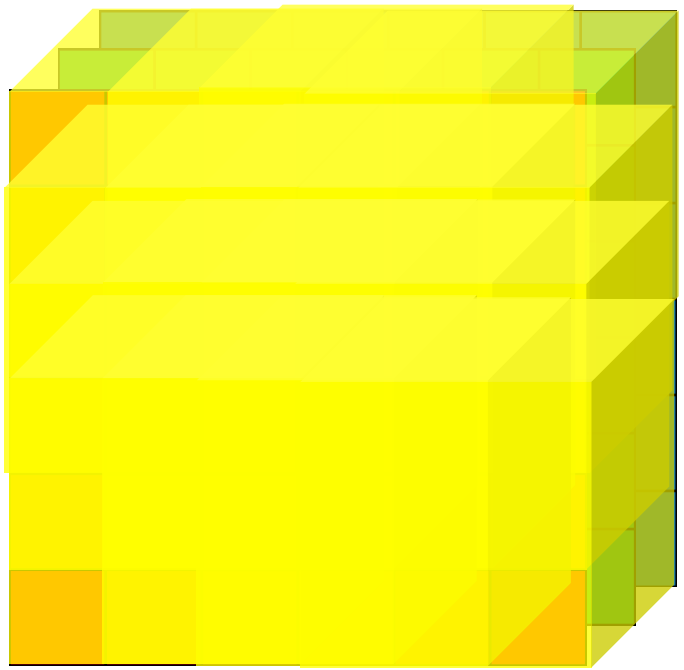
Dr. Sedat Ozer

Announcements:

- Midterm:
  - October 4, 2018, Thursday 3pm-4:15pm
    - Classical: Written, in-class exam.
    - Can include content from all the covered material both in class and in the assignments.
    - May or may not have multiple choice questions.
    - You can bring one page hand written cheat-sheet.

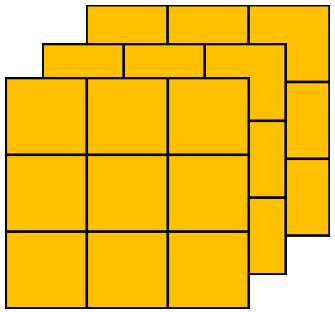
- **Non-Existing** Final exam schedule:
  - **Non-existing** Final exam time: **Thursday, December 6, 2018 1:00 PM – 3:50 PM**
  - (scheduled automatically :)

Convolutions on RGB image



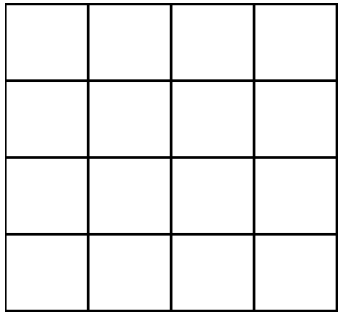
6x6x3

*



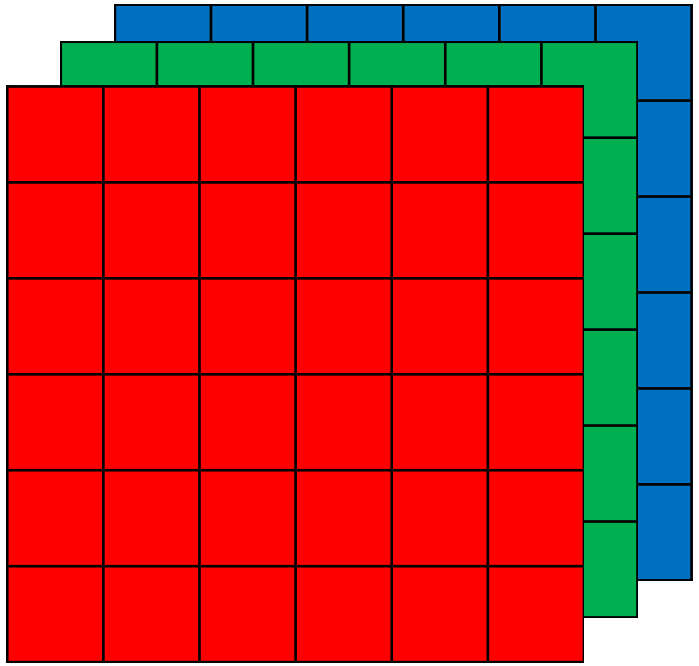
3x3x3

=



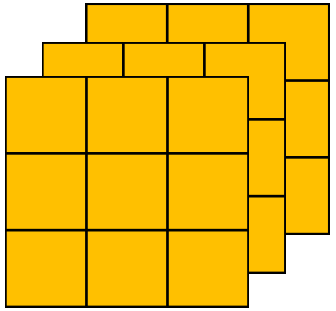
4 x 4

Multiple filters



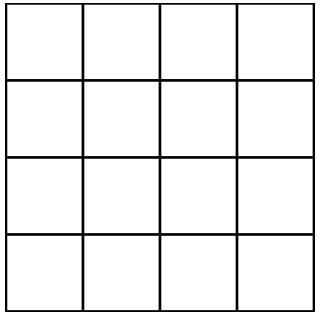
6 x 6 x 3

*



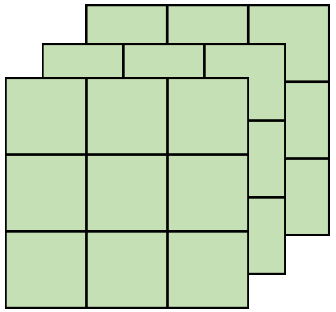
3 x 3 x 3

=



4 x 4

*



3 x 3 x 3

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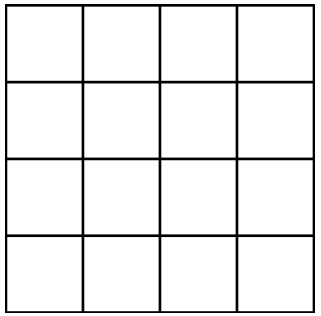


4 x 4

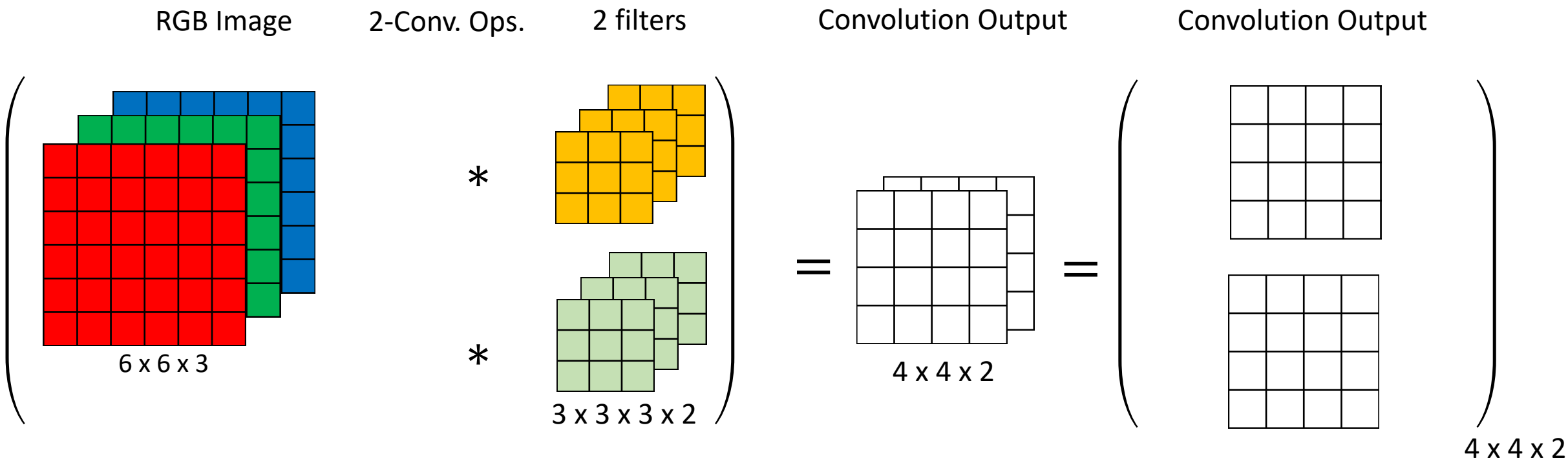
Number of channels

$n \times n \times n_c$ * $f \times f \times n_c \times 2$ = $(n- f +1) \times (n-f+1) \times 2$

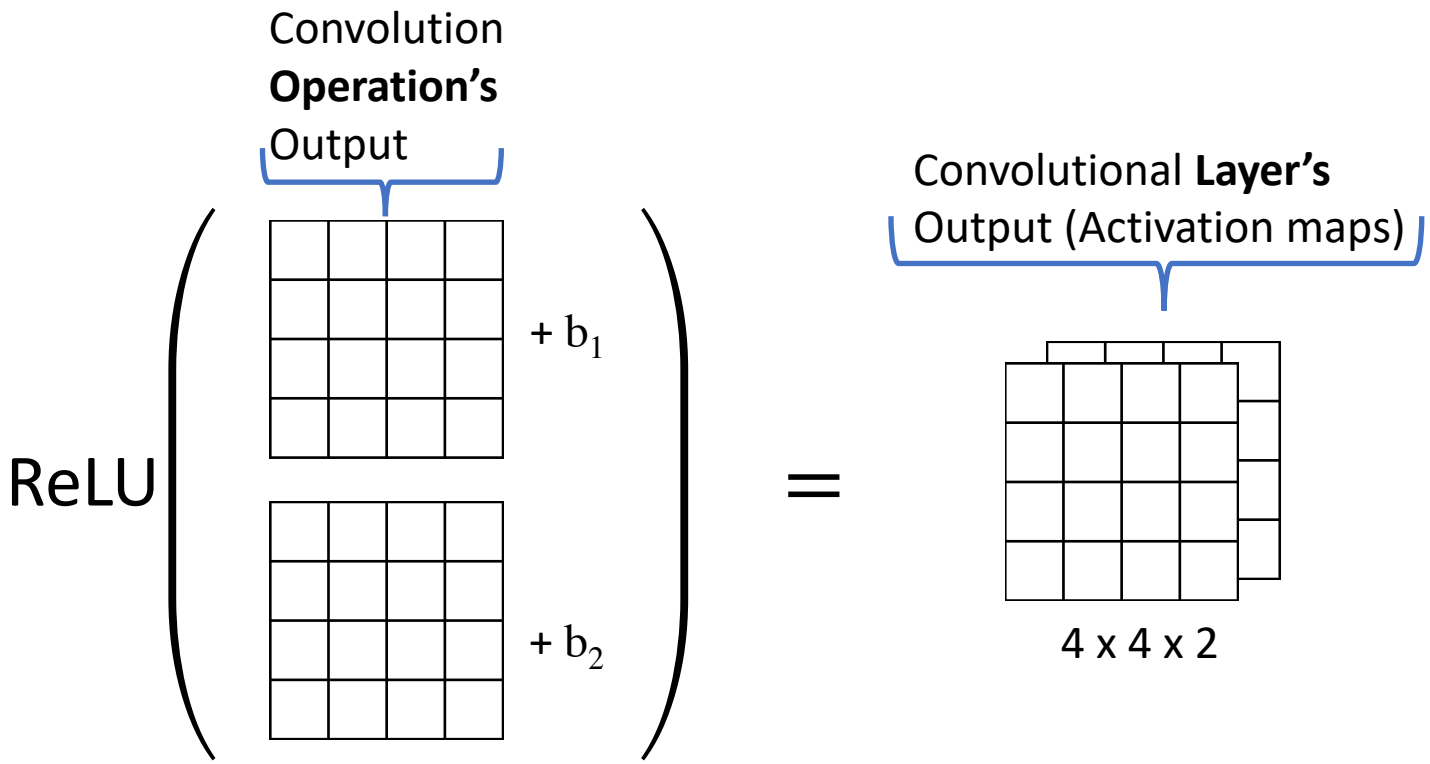
Number of filters

Number of filters

Multiple filters



A Convolutional Layer of CNN (ConvNet)



Convolutional Layer Output: Activation_map = ReLU ($(RGBImage * filter) + b$)

Output of a neuron in a FC NN: a = ReLU ($\mathbf{w}^{\mathrm{T}}\mathbf{x} + b$) in FC NN

Similar notation! (but not equal)

Input – Output Dimensions for l^{th} Convolutional Layer

Input (One image): $n_H^{[l-1]}$ x $n_W^{[l-1]}$ x $n_C^{[l-1]}$ ⟶ Output: $n_H^{[l]}$ x $n_W^{[l]}$ x $n_C^{[l]}$

Padding size: $p^{[l]}$ x $p^{[l]}$

Stride size: $s^{[l]}$ x $s^{[l]}$

Filter size: $f^{[l]} \times f^{[l]} \times n_C^{[l-1]} \times n_C^{[l]} = One\_Filter_{Dims} \times n_C^{[l]}$

(Number of Weights = Filter size, Bias size: $n_C^{[l]}$)

Output dims (for one image) : $\left\lfloor \frac{n_H^{[l-1]} + 2p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor \times \left\lfloor \frac{n_W^{[l-1]} + 2p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor \times n_C^{[l]}$

$n_H^{[l]}$ x $n_W^{[l]}$ x $n_C^{[l]}$

The output dimensions for m input samples $A^{[l]}$: m x $n_H^{[l]}$ x $n_W^{[l]}$ x $n_C^{[l]}$

Common Layer Types in a ConvNet

- Convolutional Layer (CONV)
- Fully Connected (FC, Dense)
- Locally Connected (not so commonly used!)

These three layers have parameters to be learned!

- Pooling (POOL)
- Activation Layer
  - (Sometimes, activation function is considered as a separate layer)

…

No learned parameters for these layers!

We have already seen both CONV and FC layers!

For now, we will use only those two layer types mentioned above.

Pooling layer: Max pooling

Input

1	3	2	1
2	7	1	0
2	3	4	3
5	6	1	2

Filter size: f =2

Stride size: s=2

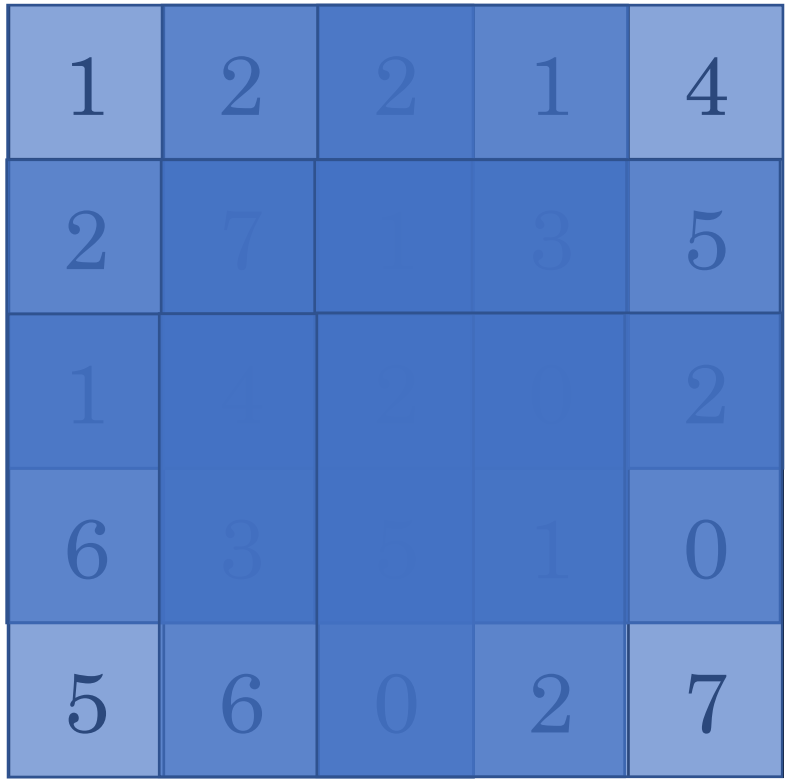
Output

7	2
6	4

Pooling is typically applied on each channel separately.

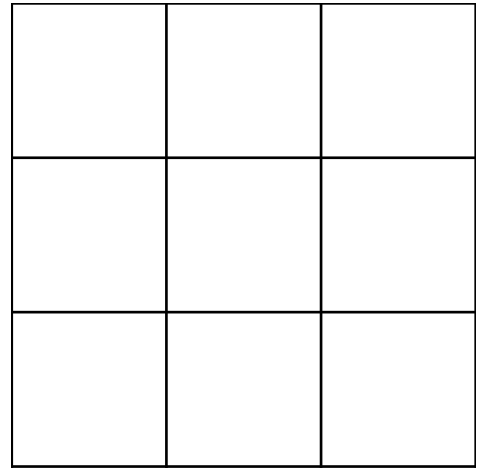
Pooling layer: Max pooling

Input



f=3
s=1

Output

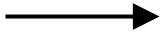


Pooling layer: Average pooling

Input

1	0	2	1
2	9	1	1
2	3	2	2
5	6	2	2

Filter size= 2 x 2
Stride: s = 2

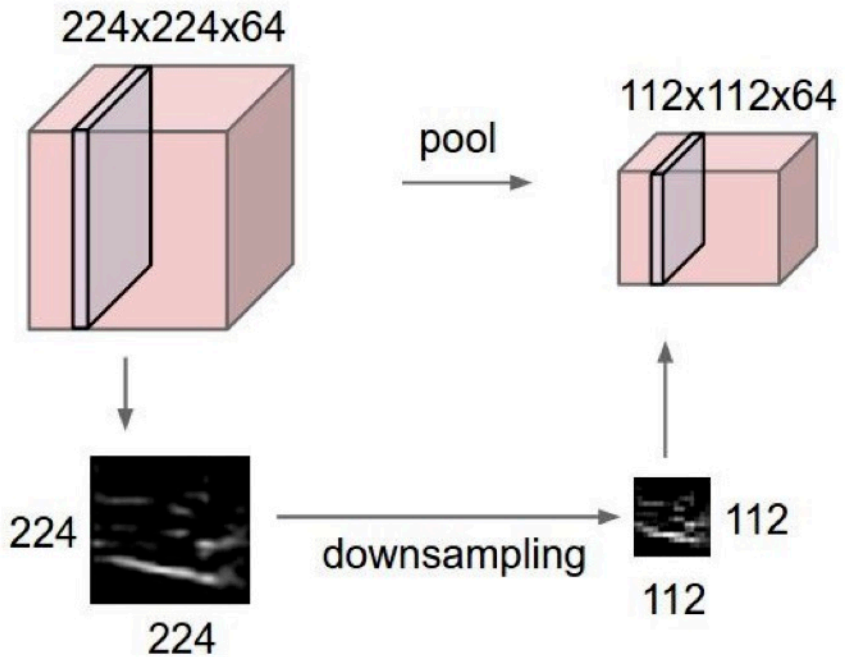


Output

3	1.25
4	2

Pooling layer

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



Source: Fei-Feli Li & Justin Johnson & Serena Yeung

Summary of pooling

Hyperparameters:

f : filter size

s : stride

Max or **Average** pooling

f=2, s=2

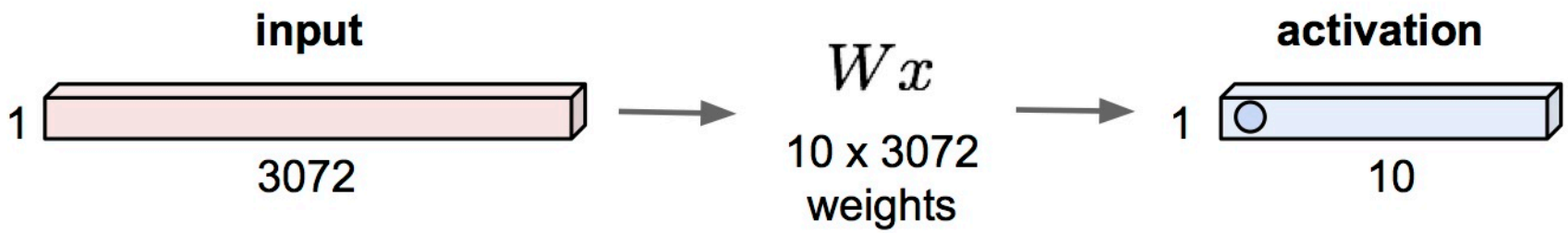
f=3, s=2

p = 0

Input: n_H x n_W x n_C Output: $\left\lfloor \frac{n_H - f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n_W - f}{s} + 1 \right\rfloor \times n_C$

Fully Connected Layer

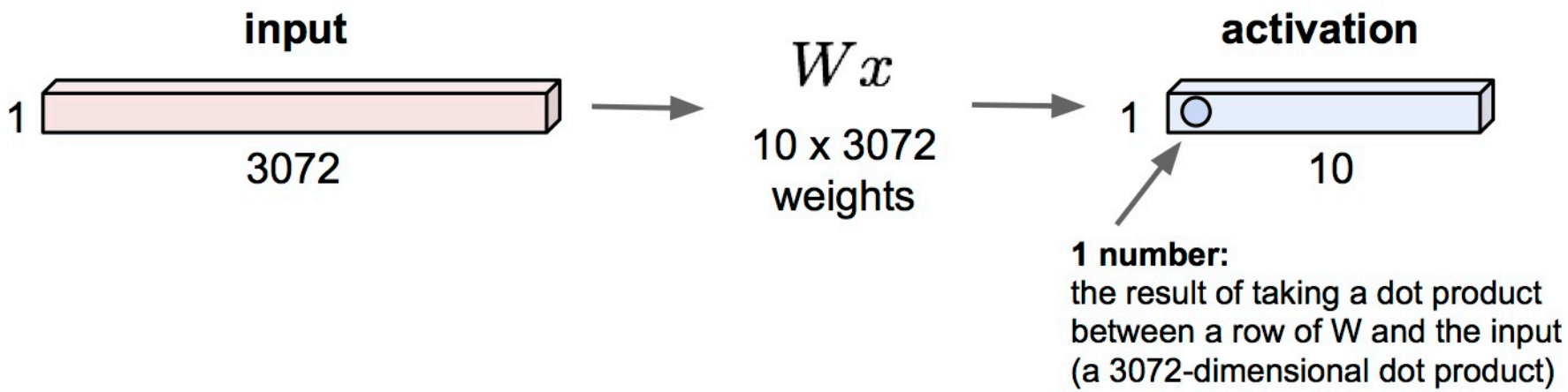
32x32x3 image -> stretch to 3072 x 1



Source: Fei-Feli Li & Justin Johnson & Serena Yeung

Fully Connected Layer

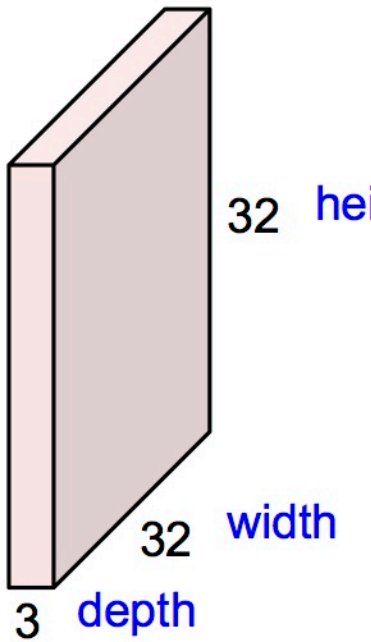
32x32x3 image -> stretch to 3072 x 1



Source: Fei-Feli Li & Justin Johnson & Serena Yeung

Convolution Layer

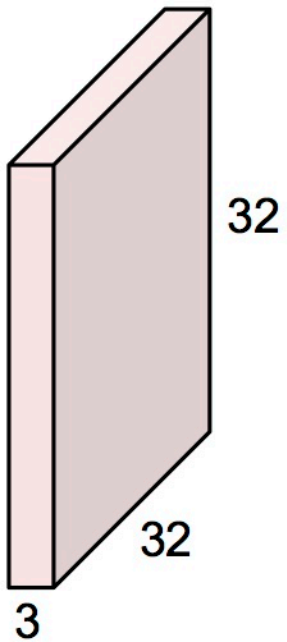
32x32x3 image -> preserve spatial structure



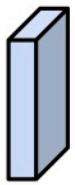
Source: Fei-Feli Li & Justin Johnson & Serena Yeung

Convolution Layer

32x32x3 image



5x5x3 filter



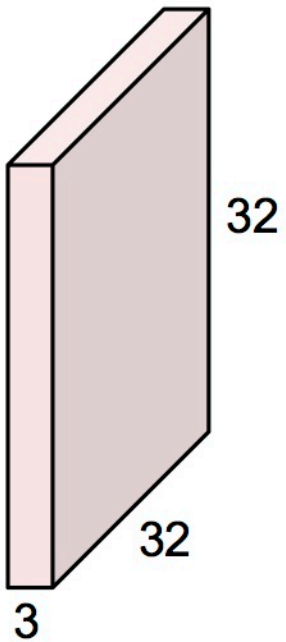
Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Source: Fei-Feli Li & Justin Johnson & Serena Yeung

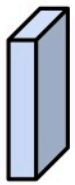
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



5x5x3 filter



Convolve the filter with the image
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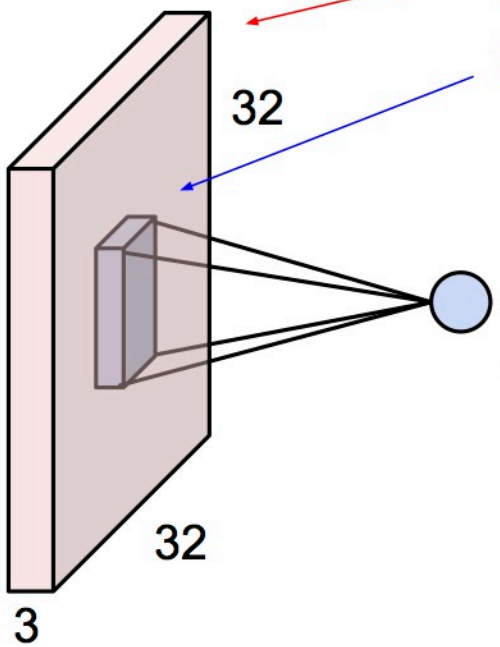
Convolution Layer



32x32x3 image

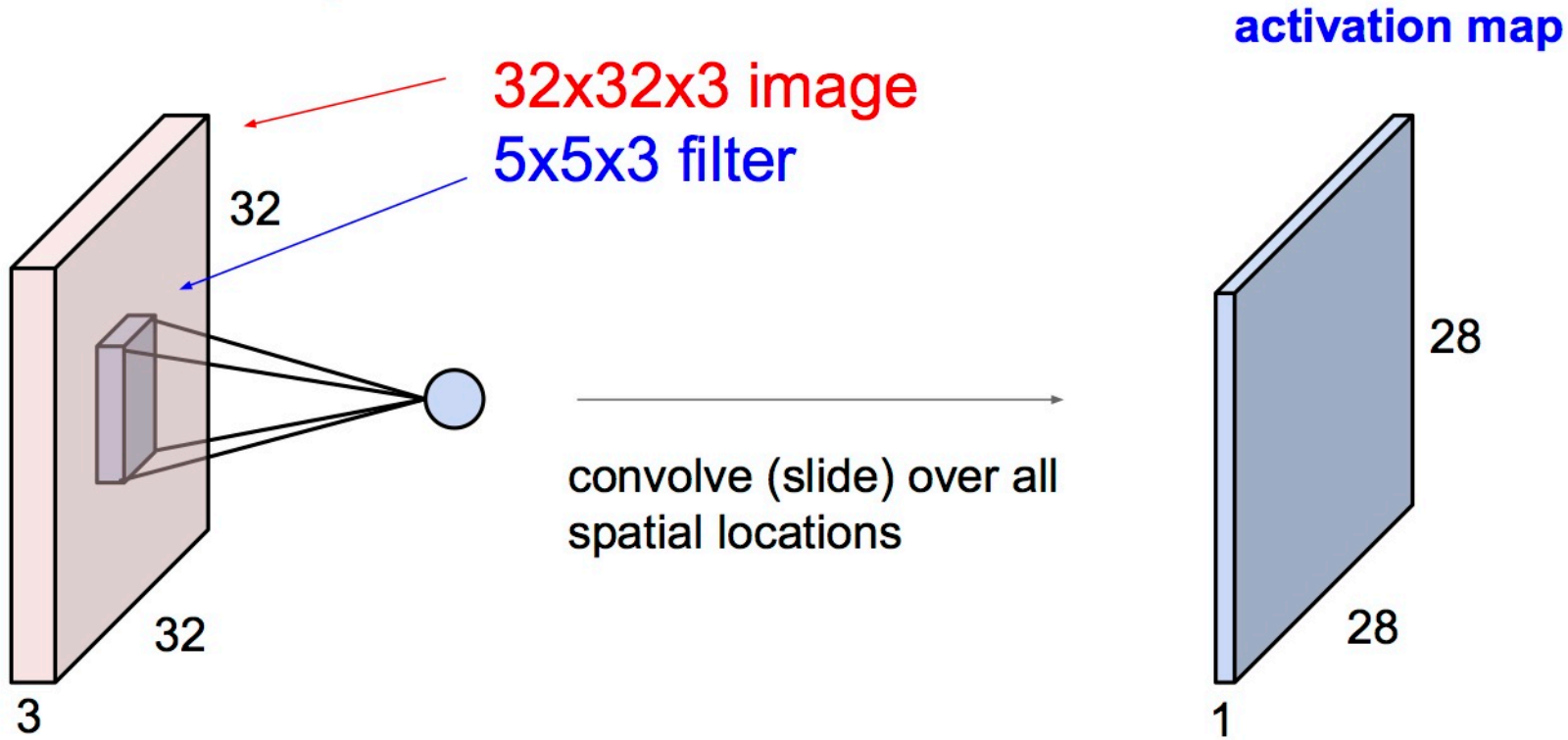
5x5x3 filter w

1 number:
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)

$$w^T x + b$$

Source: Fei-Feli Li & Justin Johnson & Serena Yeung

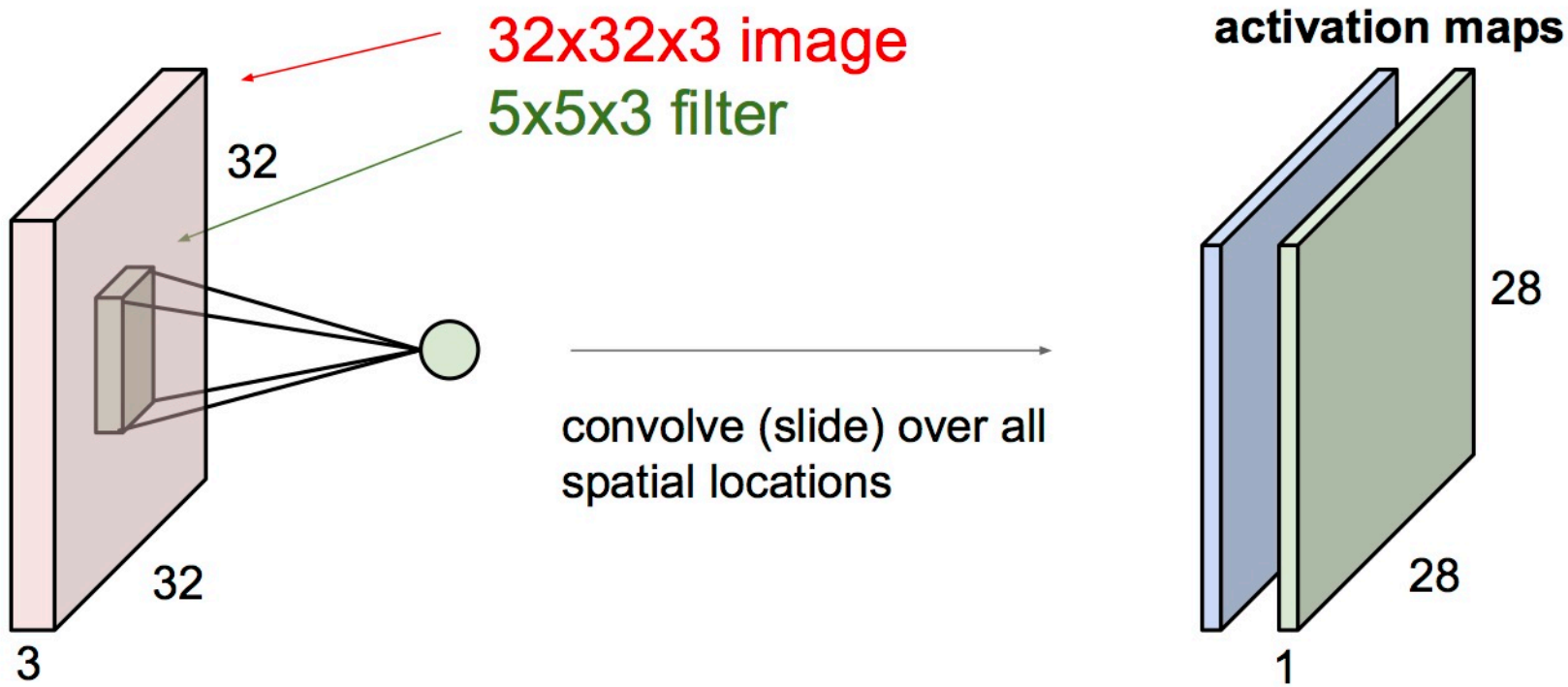
Convolution Layer



Source: Fei-Feli Li & Justin Johnson & Serena Yeung

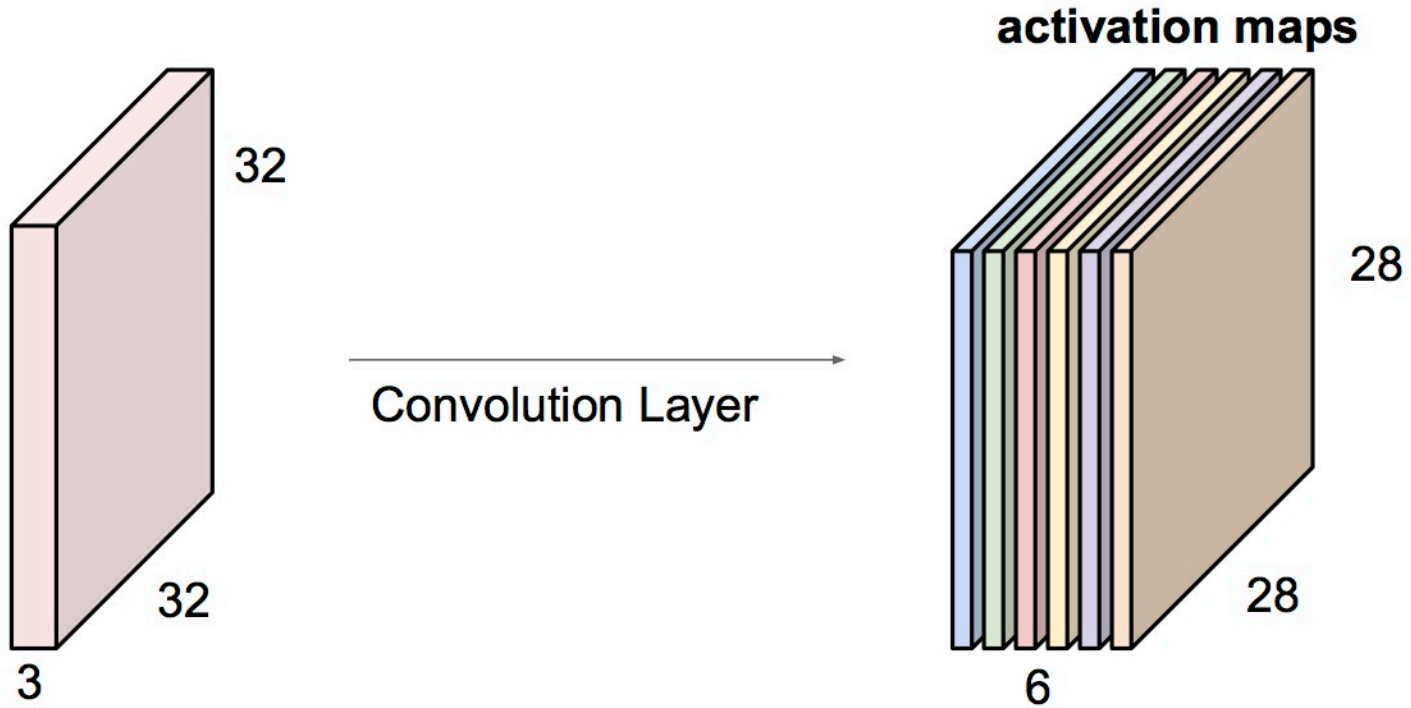
Convolution Layer

consider a second, green filter



Source: Fei-Feli Li & Justin Johnson & Serena Yeung

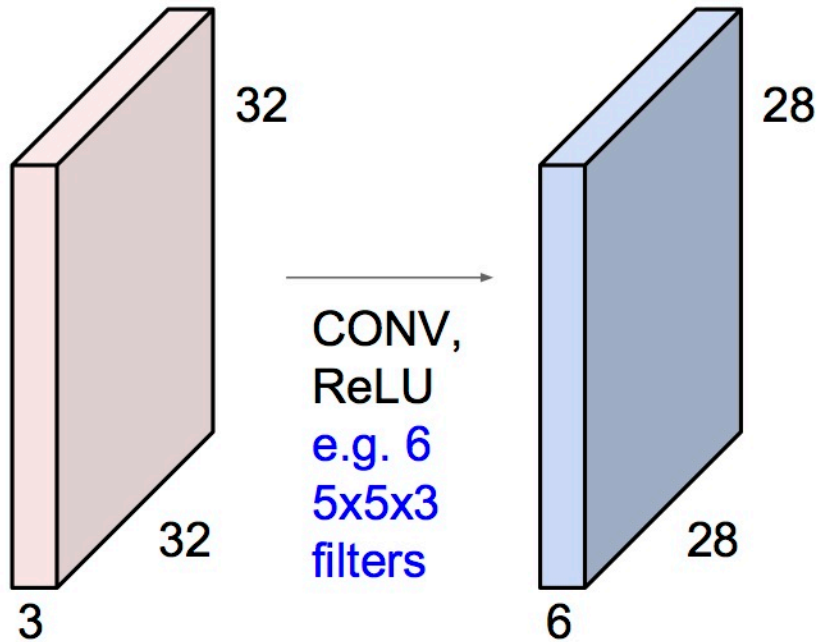
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

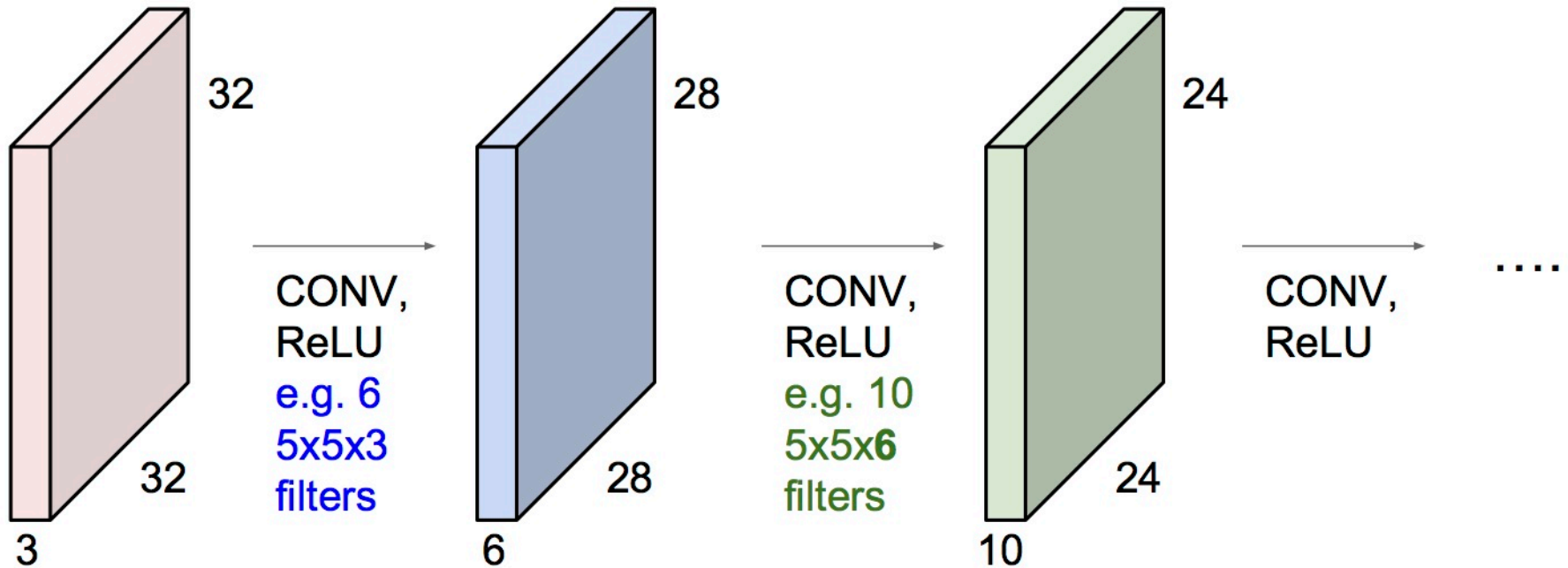
Source: Fei-Feli Li & Justin Johnson & Serena Yeung

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



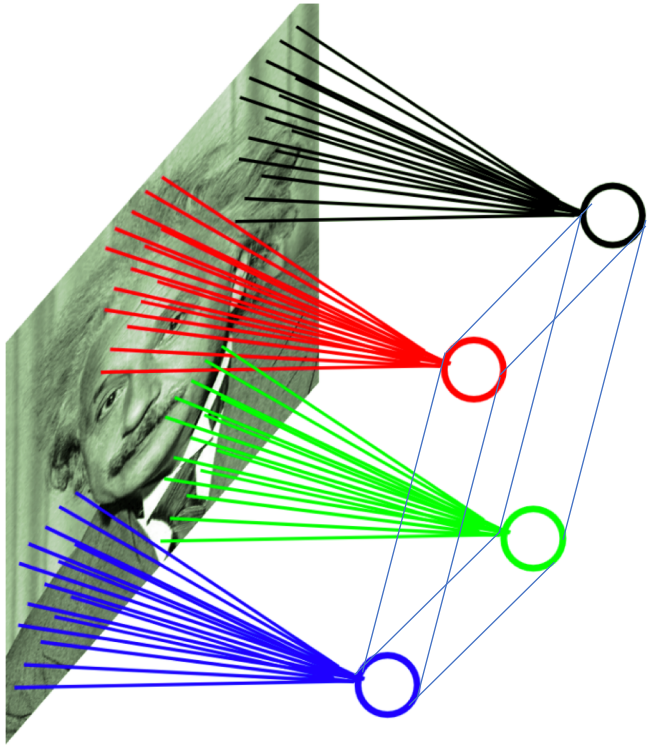
Source: Fei-Feli Li & Justin Johnson & Serena Yeung

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



Source: Fei-Feli Li & Justin Johnson & Serena Yeung

Parameter Sharing



One filter to rule them all!

- Image Classification & Recognition: A main task in computer vision
  - PASCAL
  - IMAGENET

Pop Quiz

- How many parameters do we have in a conv layer with 100 filters that are 3x3x3 dimensional each?

- For one filter: we have 3x3x3 = 27 filter weights; and + 1 bias = **28** parameters.
- For all 100 filters: we have **28** x 100 = **2800 parameters** to learn for that layer!

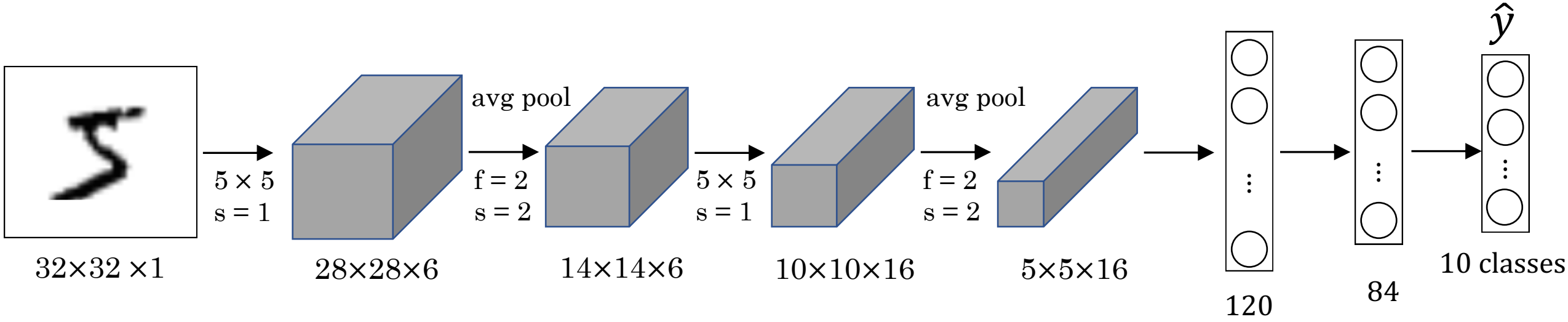
Pop Quiz

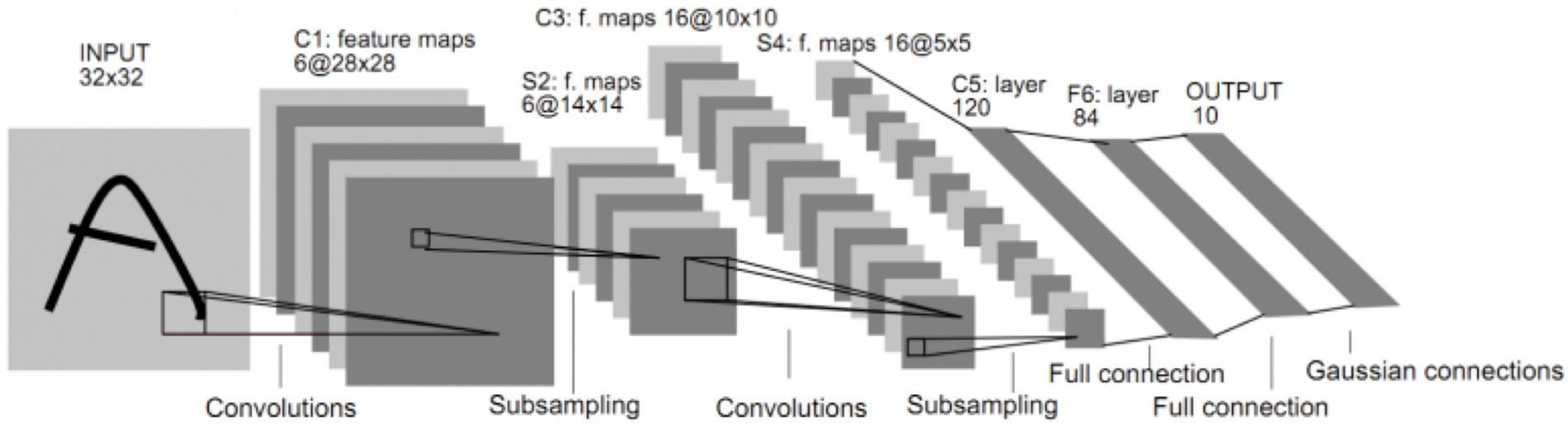
- Imagine that you are designing a CNN with 5 layers. The first 4 layers are convolutional and the last layer is FC layer with one neuron (using logistic reg).
  - The input dims are: 600x600x3.
  - In each of the 4 conv. layers:
    - We have 10 filters (for each, f = 3)
    - Stride is 2
    - Padding is “valid”.

What is the output dims at the end of the 5^{th} layer?

30 seconds to return your answers! ☺

(Slightly Modified) LeNet-5

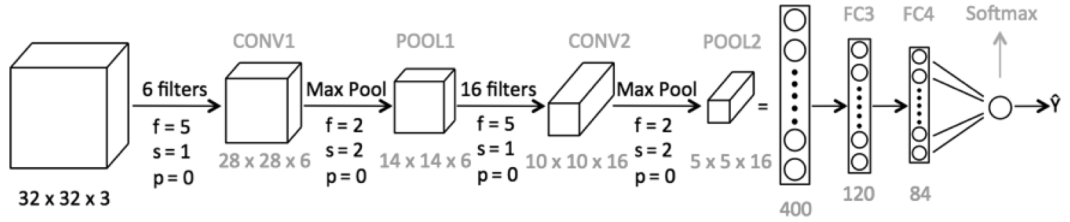




Original LeNet-5

[LeCun et al., 1998. Gradient-based learning applied to document recognition]

(Slightly Modified) LeNet-5



For: Grayscale image (single channel)

	Activation shape	Activation Size	# parameters
Input:	(32,32,**1**)	1,024	0
CONV1 (f=5, s=1)	(28,28,6)	4,704	150 + 6 bias = **156**
POOL1	(14,14,6)	1,176	0
CONV2 (f=5, s=1)	(10,10,16)	1,600	(5x5x6) x 16= 2400 2400 + 16 = **2416**
POOL2	(5,5,16)	400	0
FC3	(120,1)	120	48,000 + 120 = **48,120**
FC4	(84,1)	84	10,080 + 84 = **10,164**
Softmax	(10,1)	10	84x10 + 10 = **850**

For: Colored (RGB) image

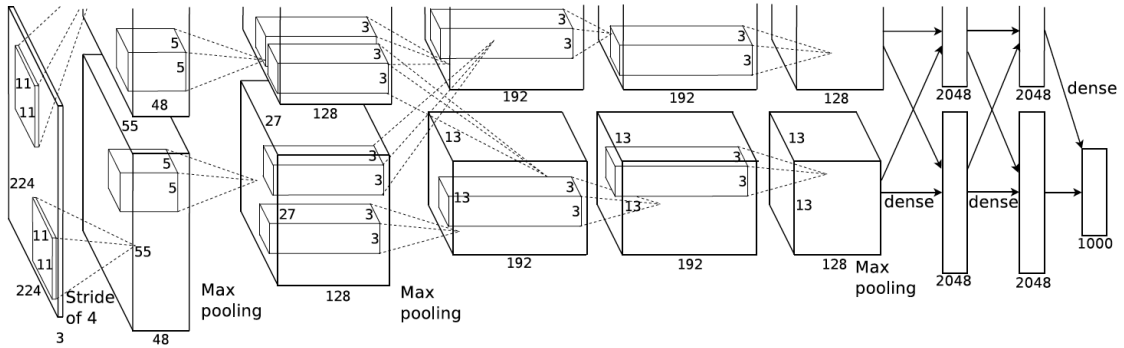
	Activation shape	Activation Size	# parameters
Input:	(32,32,**3**)	3,072	0
CONV1 (f=5, s=1)	(28,28,6)	4,704	450 + 6 bias = **456**
POOL1	(14,14,6)	1,176	0
CONV2 (f=5, s=1)	(10,10,16)	1,600	(5x5x6) x 16= 2400 2400 + 16 = **2416**
POOL2	(5,5,16)	400	0
FC3	(120,1)	120	48,000 + 120 = **48,120**
FC4	(84,1)	84	10,080 + 84 = **10,164**
Softmax	(10,1)	10	84x10 + 10 = **850**

Tensorflow output for the (grayscale) model summarizing the model parameters:

```
Variables: name (type shape) [size]
---------
Variable:0 (float32_ref 5x5x1x6) [150, bytes: 600]
conv1_biases:0 (float32_ref 6) [6, bytes: 24]
Variable_1:0 (float32_ref 5x5x6x16) [2400, bytes: 9600]
conv2_biases:0 (float32_ref 16) [16, bytes: 64]
Variable_2:0 (float32_ref 400x120) [48000, bytes: 192000]
fc1_biases:0 (float32_ref 120) [120, bytes: 480]
Variable_3:0 (float32_ref 120x84) [10080, bytes: 40320]
fc2_biases:0 (float32_ref 84) [84, bytes: 336]
Variable_4:0 (float32_ref 84x10) [840, bytes: 3360]
fc3_biases:0 (float32_ref 10) [10, bytes: 40]
Total size of variables: 61706
Total bytes of variables: 246824
sedat@sedat-ThinkPad-P50:~/
```

(Slightly modified) AlexNet

Original



227×227 ×3

11 × 11
s = 4

55×55 ×96

MAX-POOL

3 × 3
s = 2

27×27 ×96

5 × 5
same

27×27 ×256

MAX-POOL

3 × 3
s = 2

13×13 ×256

3 × 3
same

13×13 ×384

3 × 3
same

13×13 ×384

3 × 3
same

13×13 ×256

MAX-POOL

3 × 3
s = 2

6×6 ×256

=

9216

4096

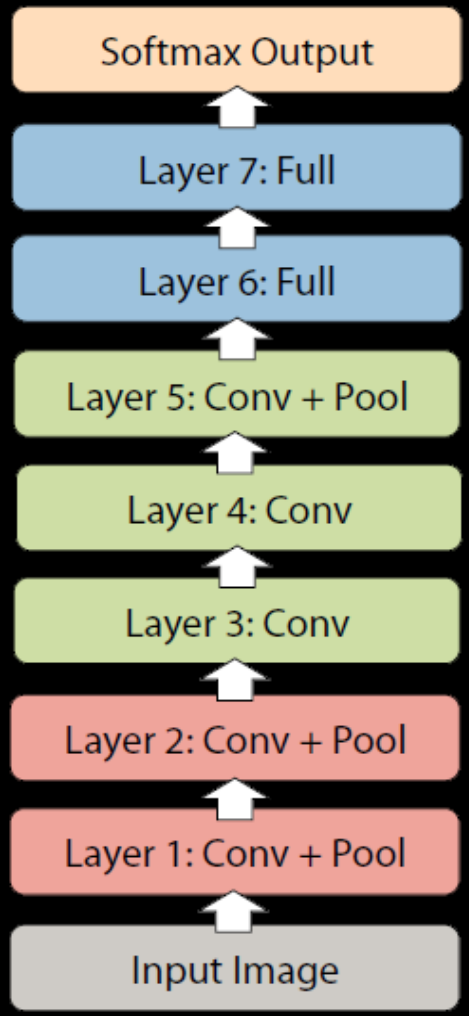
4096

Softmax
1000

[Krizhevsky et al., 2012. ImageNet classification with deep convolutional neural networks]

Why ConvNet should be Deep?

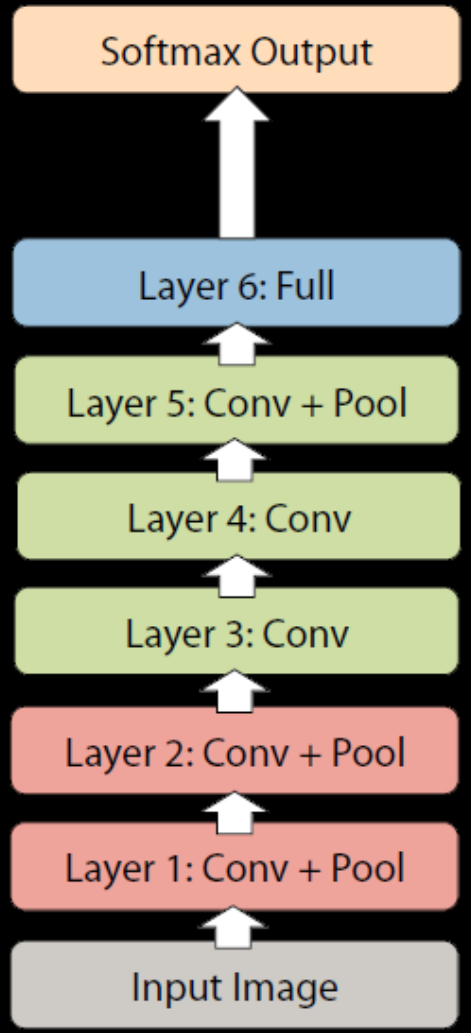
- 8 layers total
- Trained on Imagenet dataset [Deng et al. CVPR'09]
- 18.2% top-5 error
- Our reimplementation:
  18.1% top-5 error



Rob Fergus, NIPS 2013

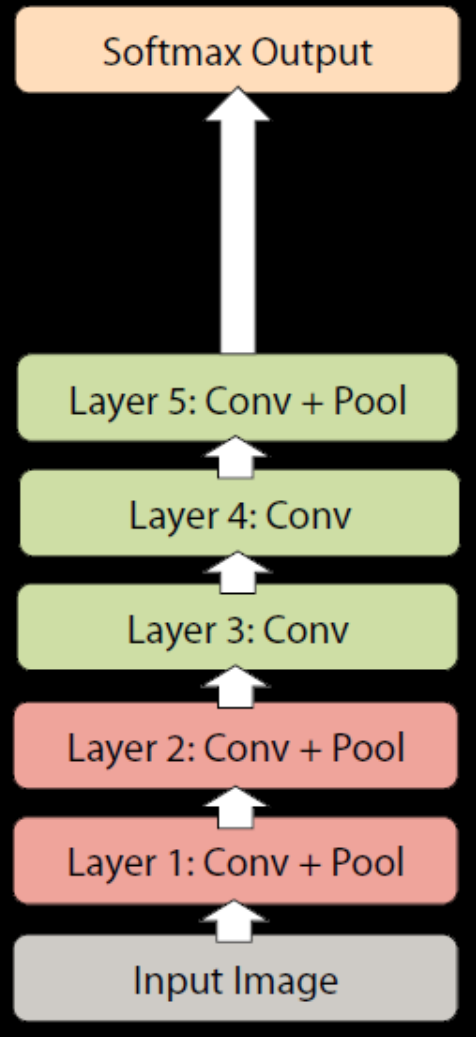
Why ConvNet should be Deep?

- Remove top fully connected layer
  - Layer 7
- Drop 16 million parameters
- Only 1.1% drop in performance!



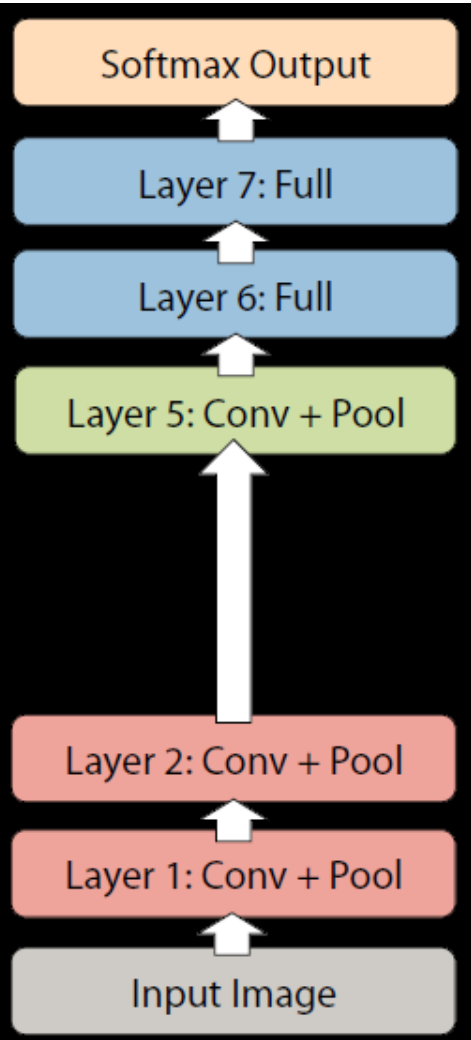
Why ConvNet should be Deep?

- Remove both fully connected layers
  - Layer 6 & 7
- Drop ~50 million parameters
- 5.7% drop in performance



Why ConvNet should be Deep?

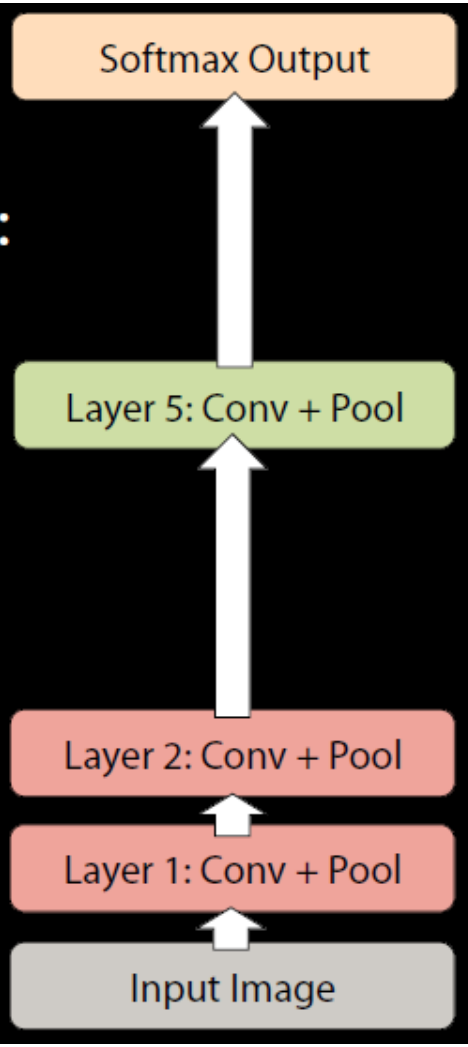
- Now try removing upper feature extractor layers:
  - Layers 3 & 4
- Drop ~1 million parameters
- 3.0% drop in performance



Why ConvNet should be Deep?

- Now try removing upper feature extractor layers & fully connected:
  - Layers 3, 4, 6 ,7
- Now only 4 layers
- 33.5% drop in performance

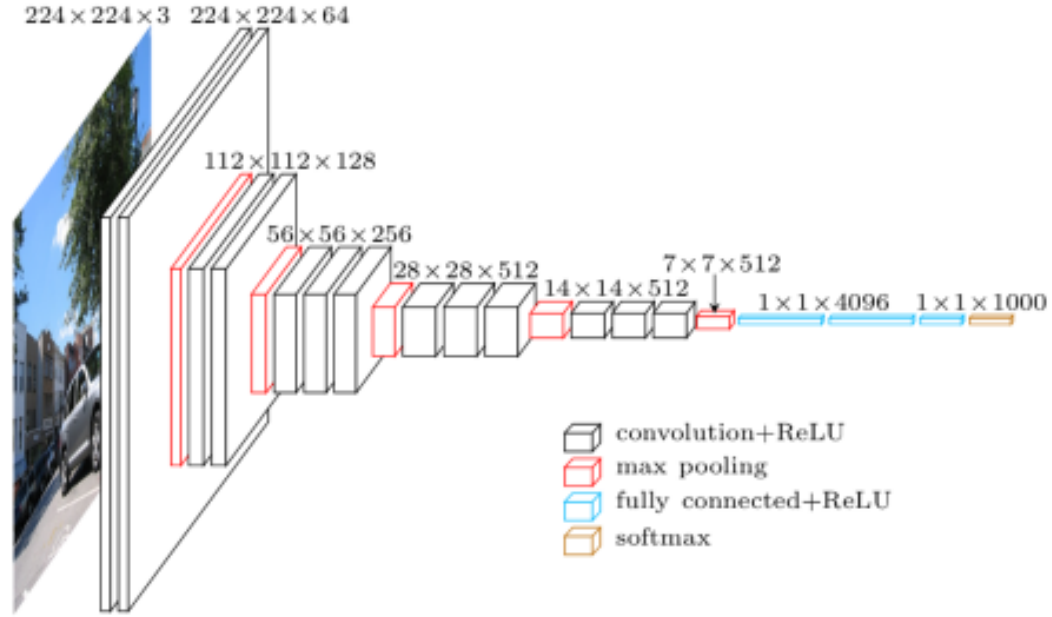
→Depth of network is key

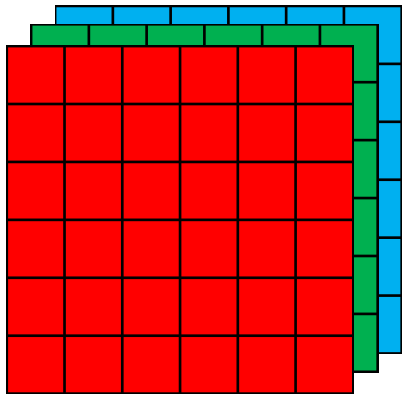


VGG – 16 (16 layers)

CONV = 3×3 filter, s = 1, “**same” padding**

MAX-POOL = 2×2 , s = 2





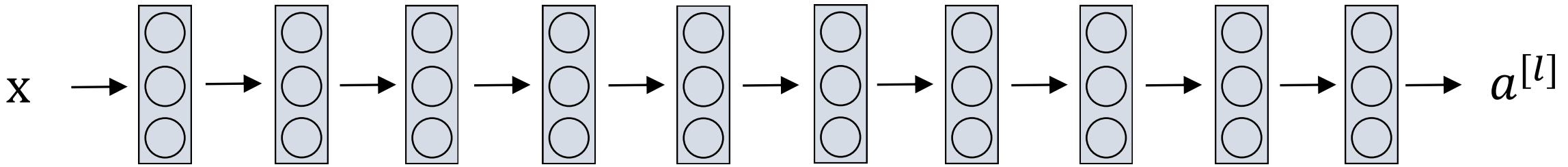
224×224 ×3 → [CONV: 64] ×2 layers → 224×224×64 → POOL → 112×112 ×64 → [CONV: 128] ×2 layers → 112×112 ×128 → POOL → 56×56 ×128

→ [CONV: 256] ×3 layers → 56×56 ×256 → POOL → 28×28 ×256 → [CONV: 512] ×3 layers → 28×28 ×512 → POOL → 14×14×512

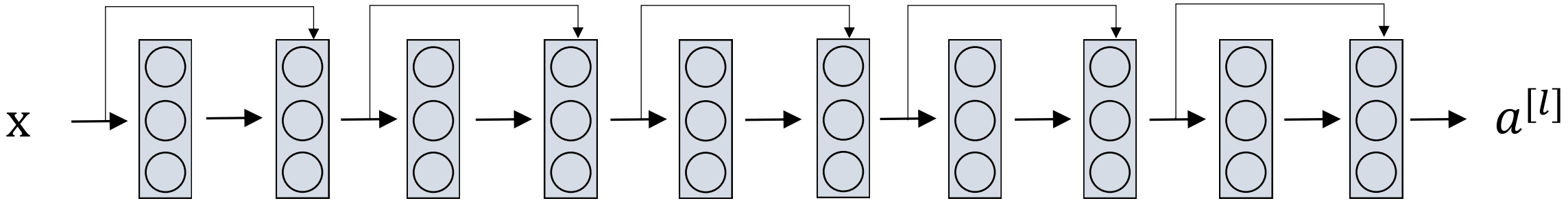
→ [CONV: 512] ×3 layers → 14×14 ×512 → POOL → 7×7×512 → FC 4096 → FC 4096 → Softmax 1000

[Simonyan & Zisserman 2015. Very deep convolutional networks for large-scale image recognition]

Residual Network - ResNet (Microsoft)



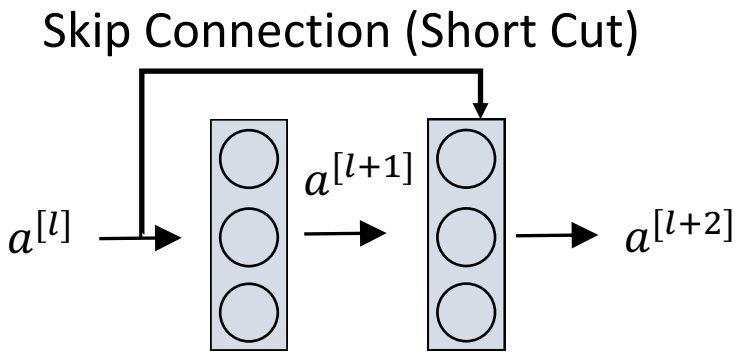
A “plain” (deep) network

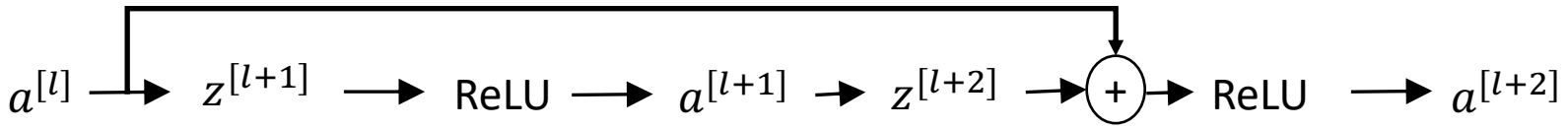


A residual network (with 5 residual blocks)

[He et al., 2015. Deep residual networks for image recognition]

Residual Building Block



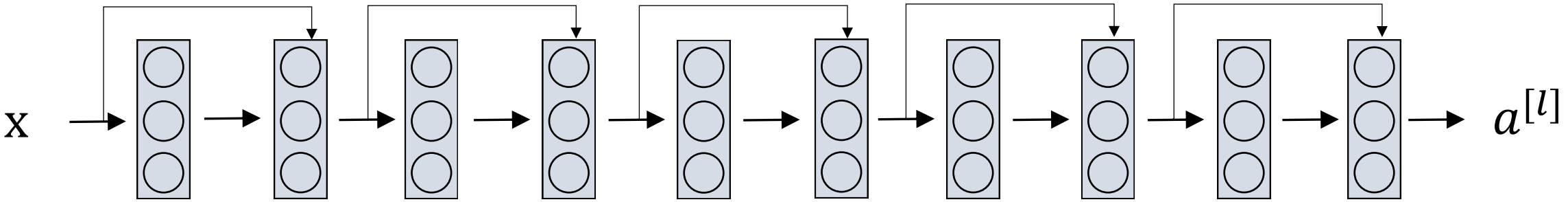


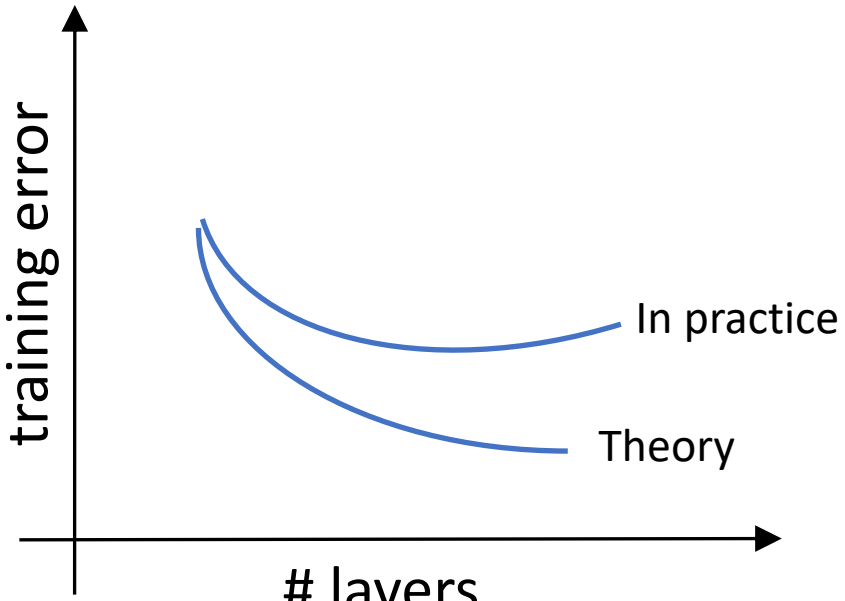
$$z^{[l+1]} = W^{[l+1]}\, a^{[l]} + b^{[l+1]} \qquad a^{[l+1]} = g(z^{[l+1]}) \qquad z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]} \qquad a^{[l+2]} = g(z^{[l+2]})$$

With skip connection: $a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$

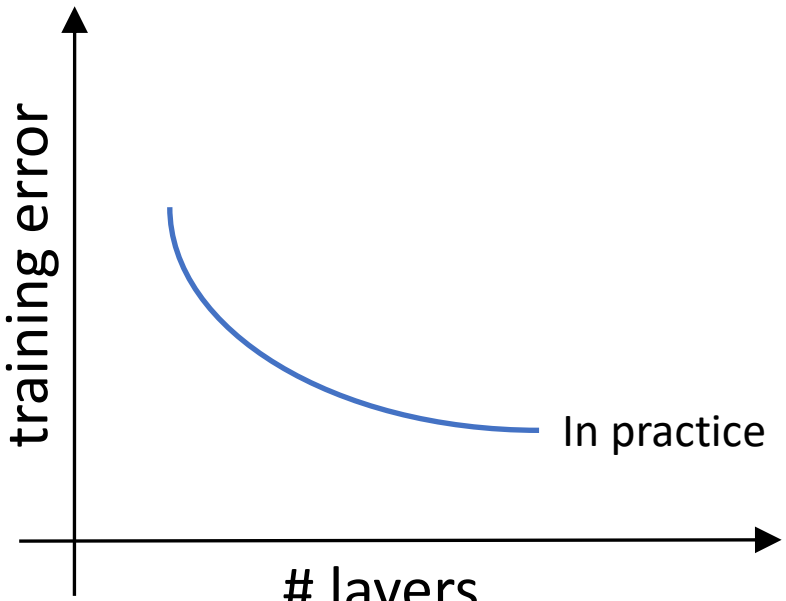
[He et al., 2015. Deep residual networks for image recognition]

Residual Network





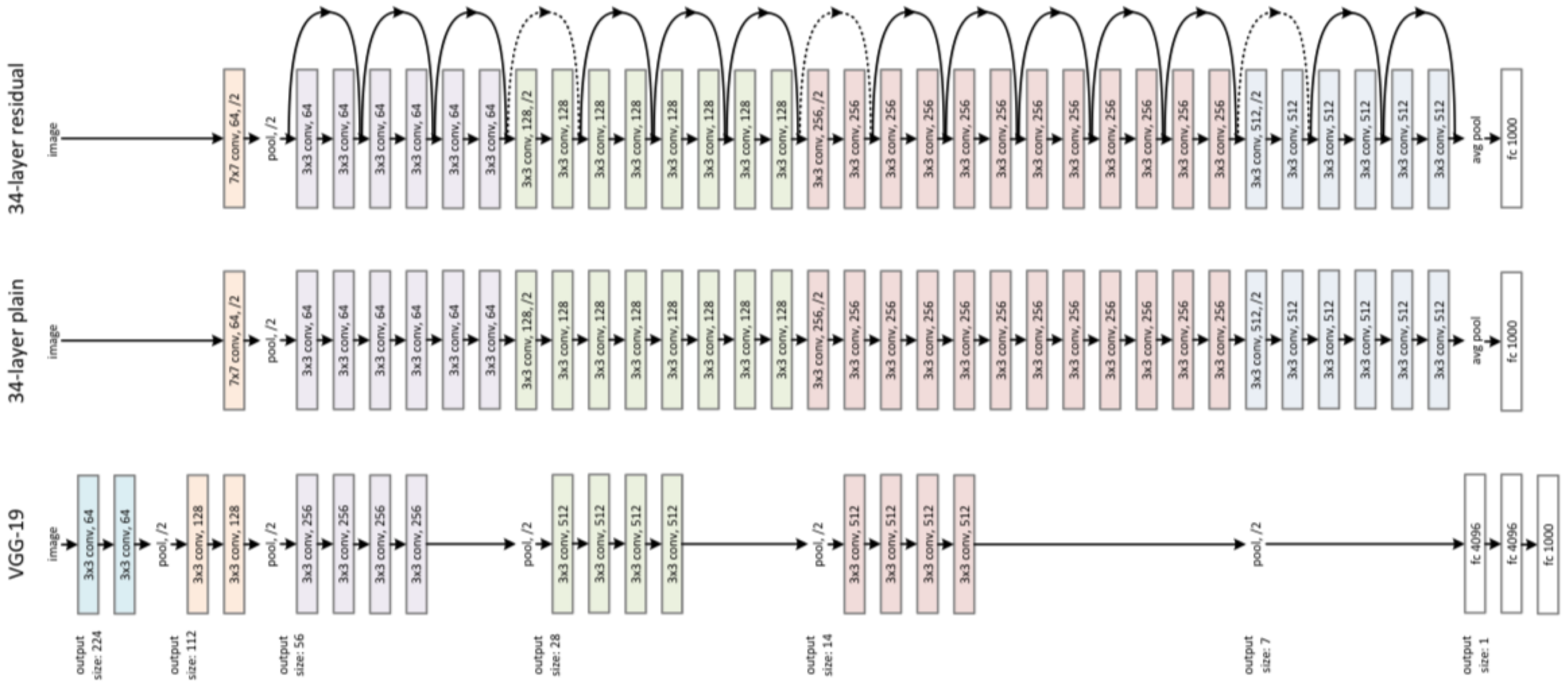
Plain



ResNet

[He et al., 2015. Deep residual networks for image recognition]

ResNet



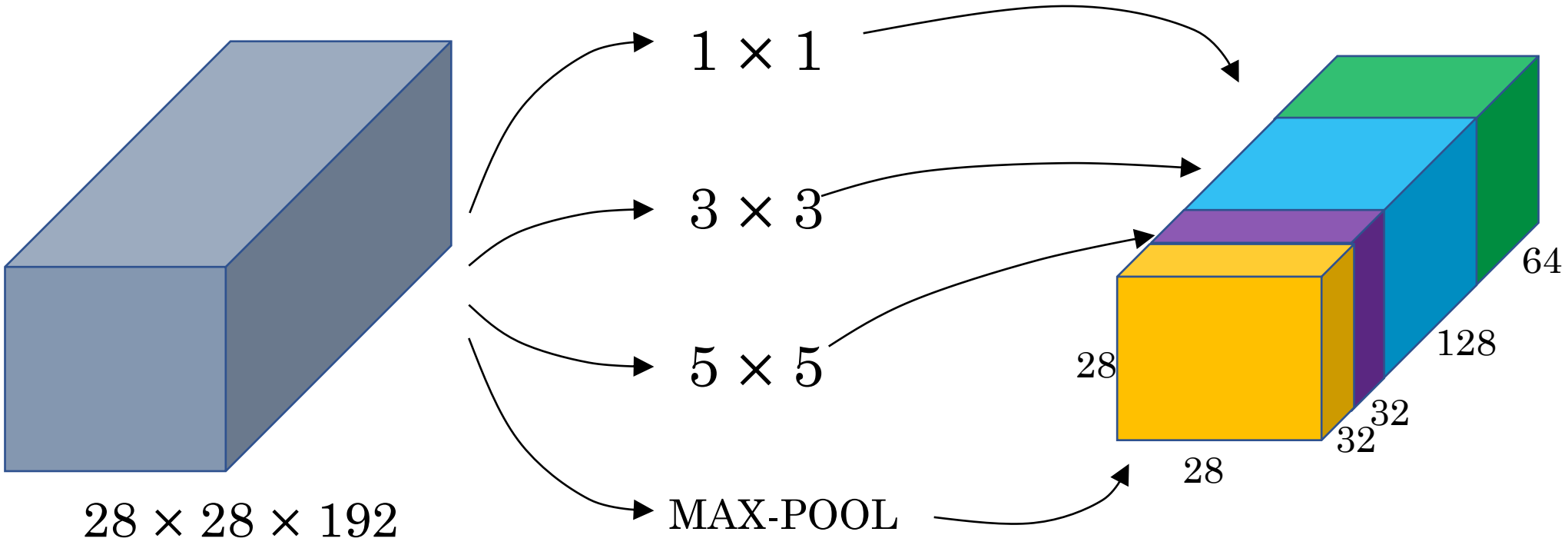
[Source: He et al., 2015. Deep residual networks for image recognition]

Inception Network

(GoogleNet)

http://knowyourmeme.com/memes/we-need-to-go-deeper

Main motivation for inception network



[Szegedy et al. 2014. Going deeper with convolutions]

What does a 1 × 1 convolution do?

3	1	3	6	5	8
3	2	4	1	3	4
2	1	3	4	9	2
4	5	8	1	7	9
1	5	3	3	4	3
5	4	4	8	3	1

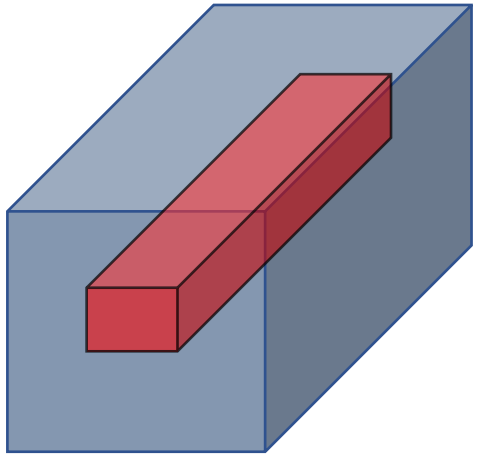
6 × 6

*

2

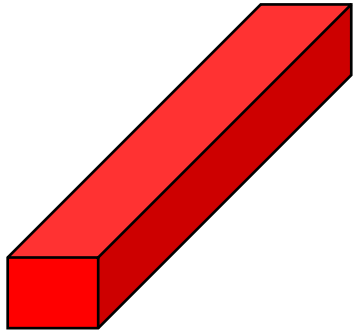
=

6	2	6	.	.	.
6	4	8	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.



6 × 6 × 32

*



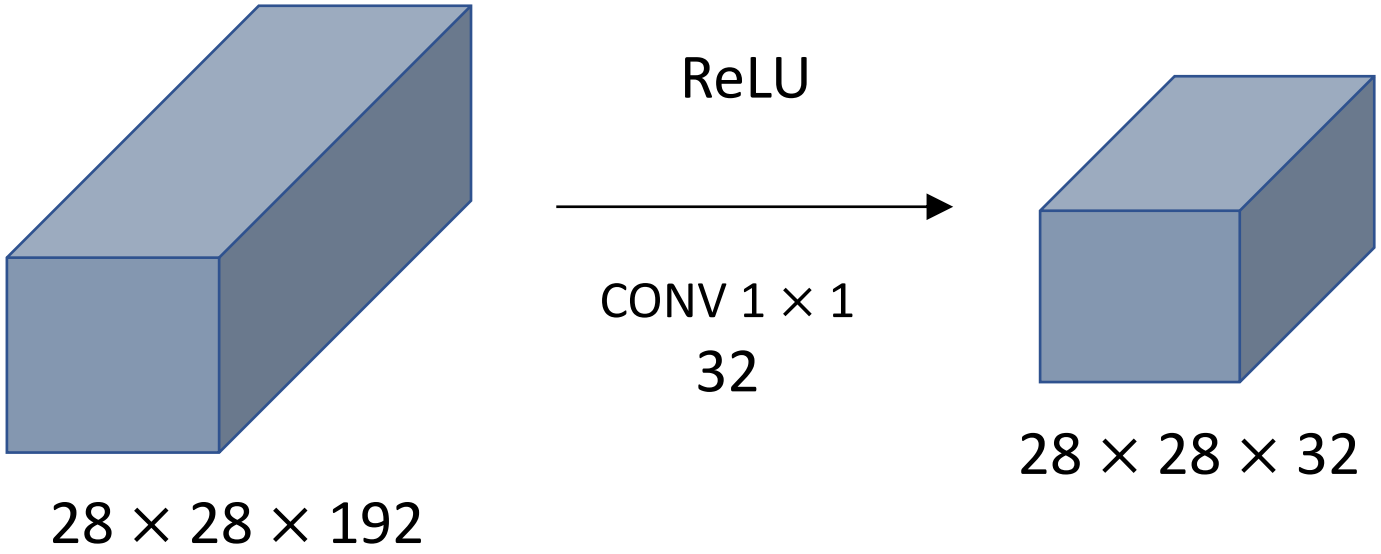
1 × 1 × 32

=

6 × 6 × # filters

[Lin et al., 2013. Network in network]

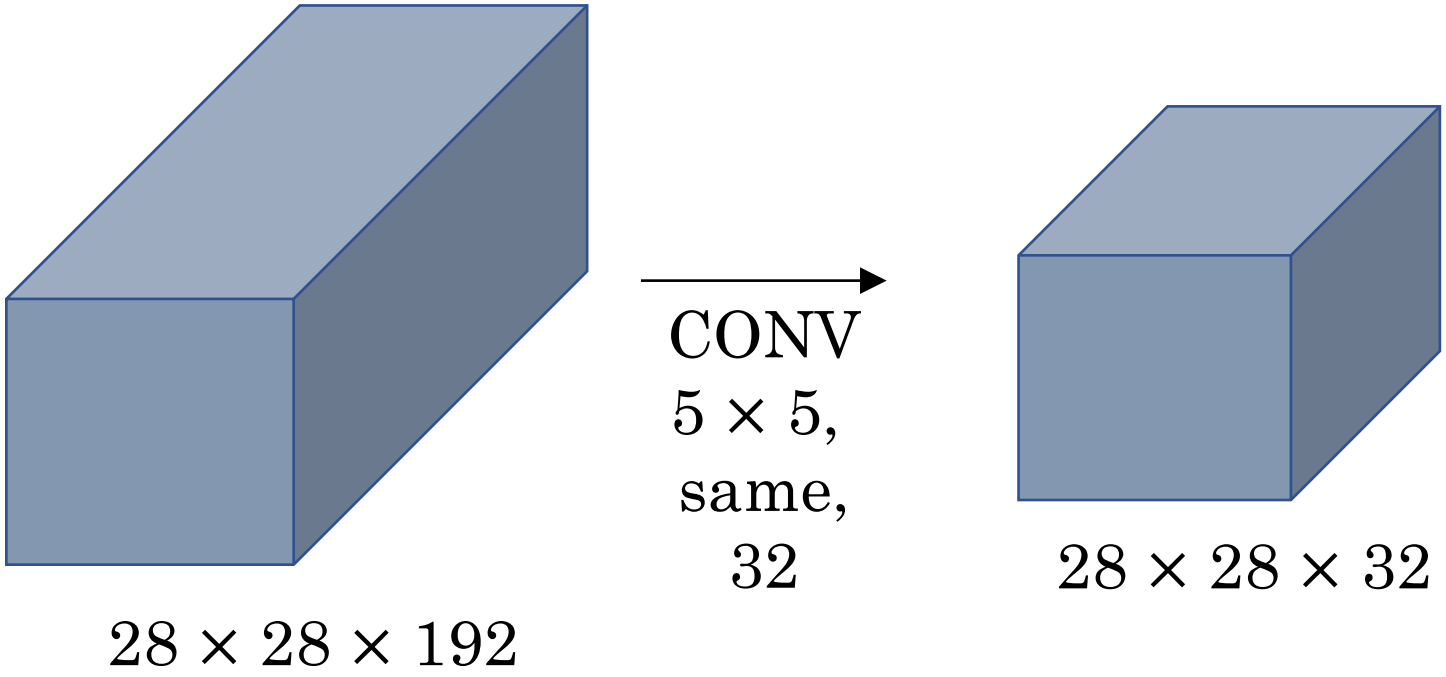
1×1 convolutions can shrink the layer dims



Helps reducing the number of parameters!

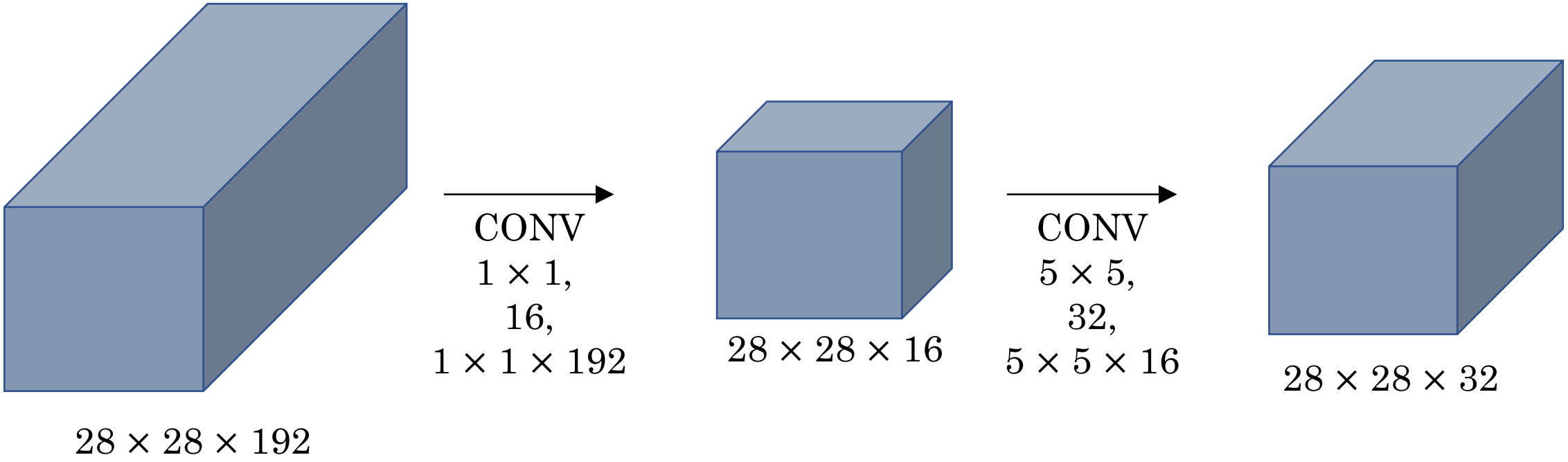
[Lin et al., 2013. Network in network]

The problem of computational cost



- One filter volume: 5x5x192 for one voxel in the output volume (in the activation map).
- Since we have 28x28x32 dimensional volume at the output, we need:
  (5x5x192) x (28x28x32) multiplications! (~120Million)

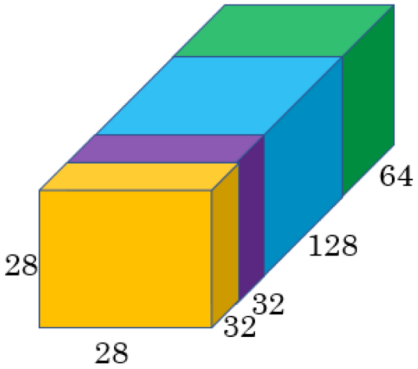
Using 1×1 convolution for reducing the computation



Multiplications needed: (28x28x16) x (1x1x192) = ~ 2.4 Million (28x28x32) x (5x5x16) = ~ 10 Million

Total: 12.4 Million << 120Million

Inception module



Previous Activation

1 × 1 CONV

1 × 1 CONV

3 × 3 CONV

1 × 1 CONV

5 × 5 CONV

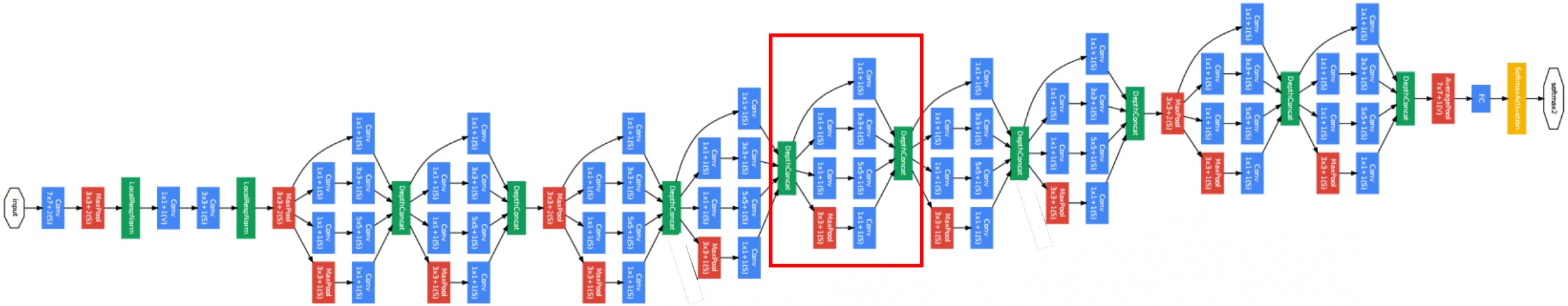
MAXPOOL 3 × 3,s = 1 same

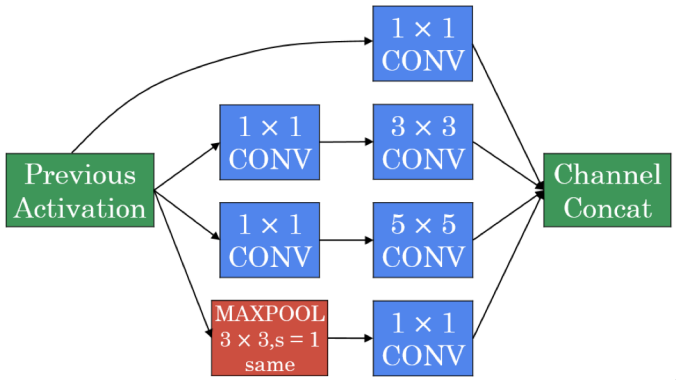
1 × 1 CONV

Channel Concat

Inception Network (Google)

GooLeNet or GoogLeNet





Local Response Normalization (LRN)

[Szegedy et al., 2014, Going Deeper with Convolutions]

- This lecture has materials from CS231n (Stanford), Andrew Ng and Ulas Bagci.