

#### Introduction to Machine Learning (CS419M)

#### Lecture 13:

- Convolutional Neural Networks

- Fully connected (dense) layers have no awareness of spatial information
- Key concept behind convolutional layers is that of kernels or filters
- Filters slide across an input space to detect spatial patterns (translation invariance) in local regions (locality)

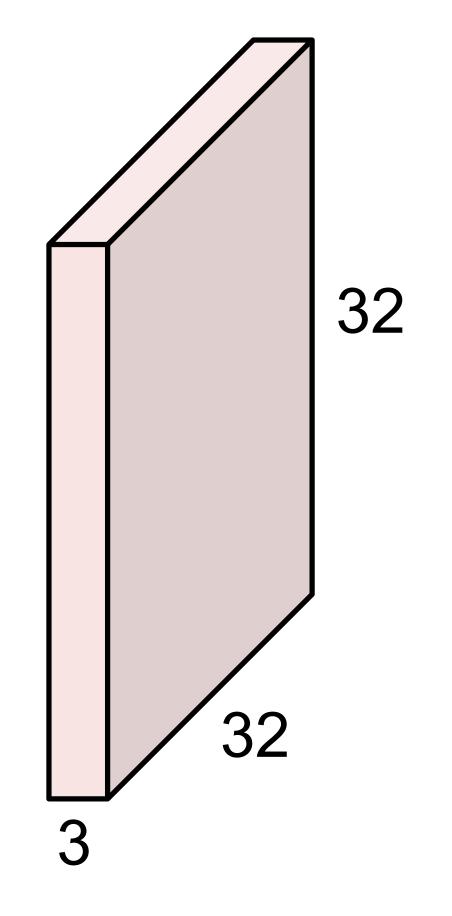
<b>1</b> <sub>×1</sub>	<b>1</b> <sub>×0</sub>	<b>1</b> <sub>×1</sub>	0	0
<b>O</b> <sub>×0</sub>	1 <sub>×1</sub>	1 <sub>×0</sub>	1	0
<b>0</b> <sub>×1</sub>	<b>O</b> <sub>×0</sub>	1 <sub>×1</sub>	1	1
0	0	1	1	0
0	1	1	0	0

4

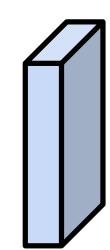
Image

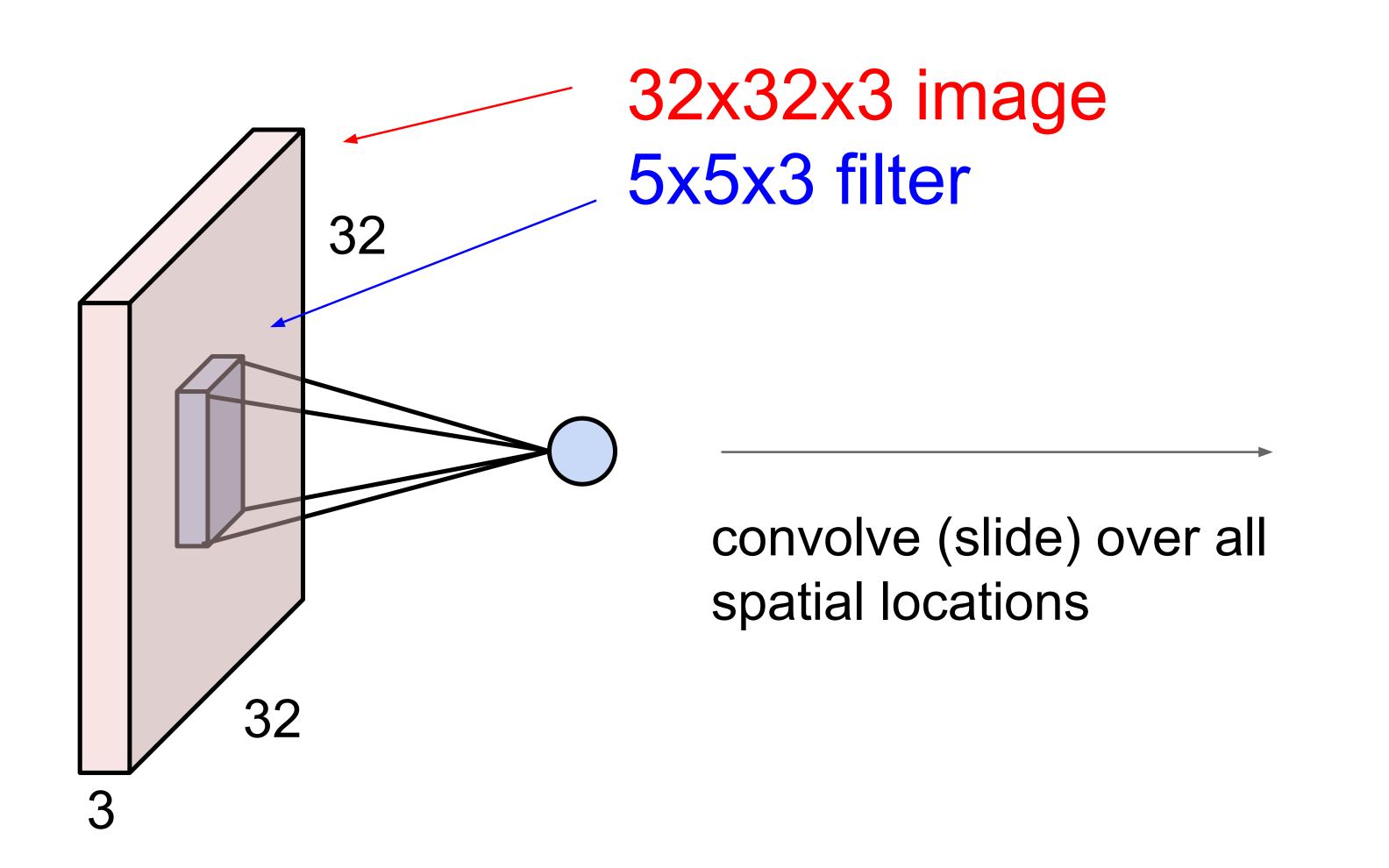
Convolved Feature

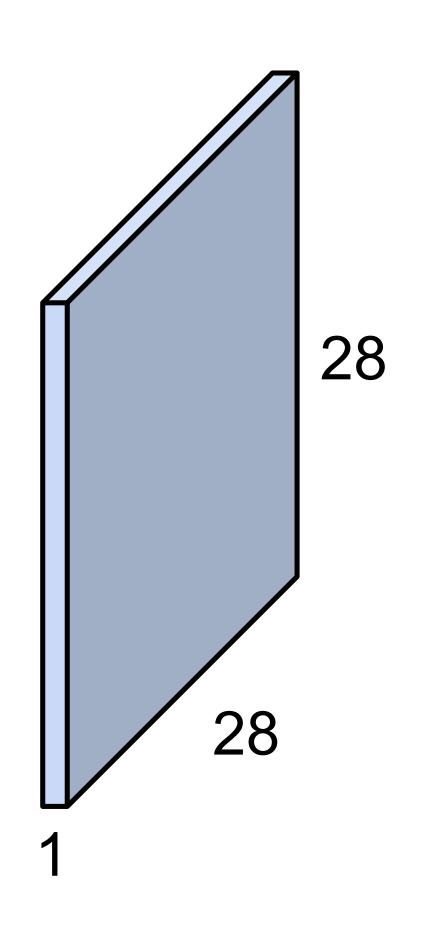
32x32x3 image

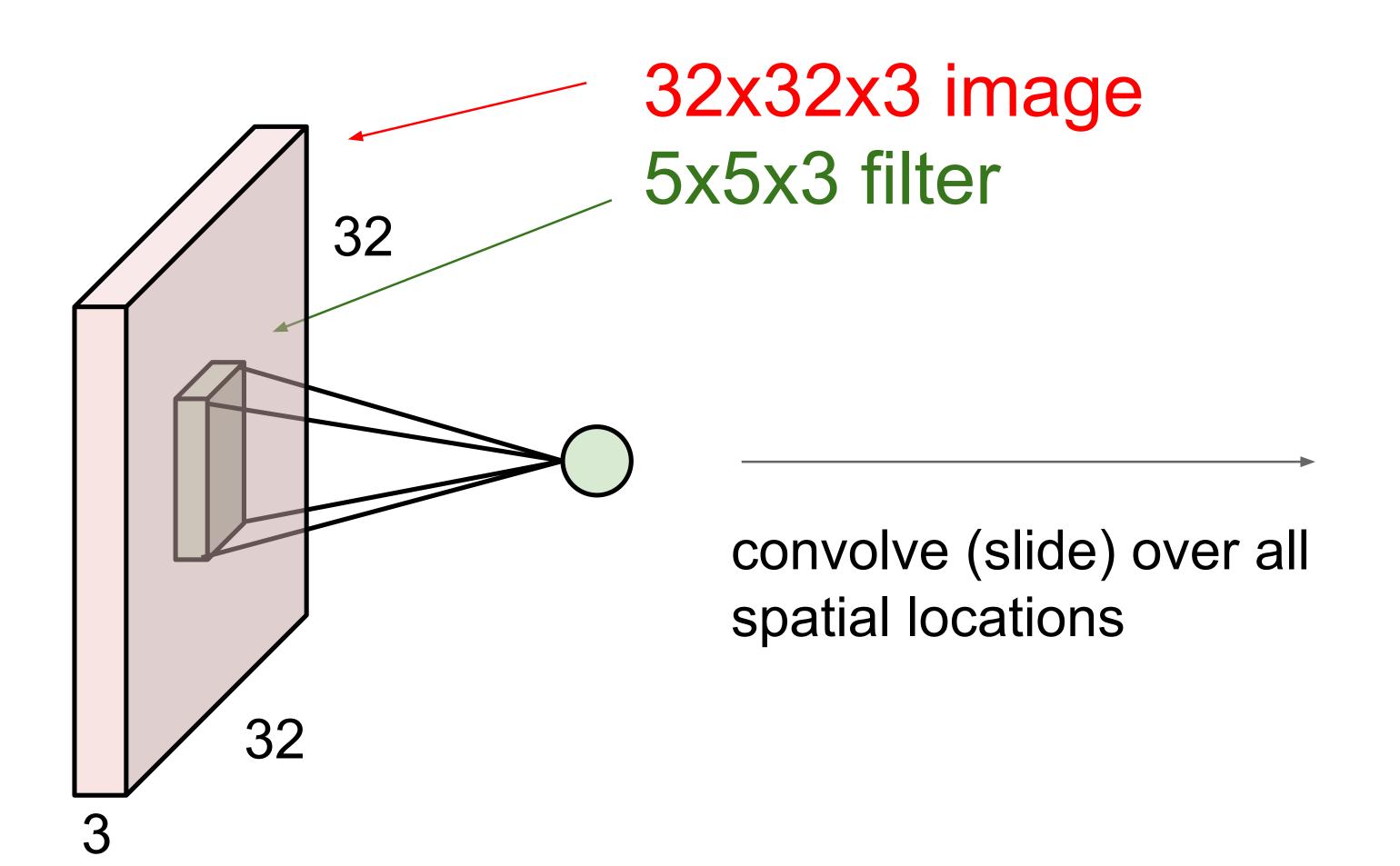


5x5x3 filter

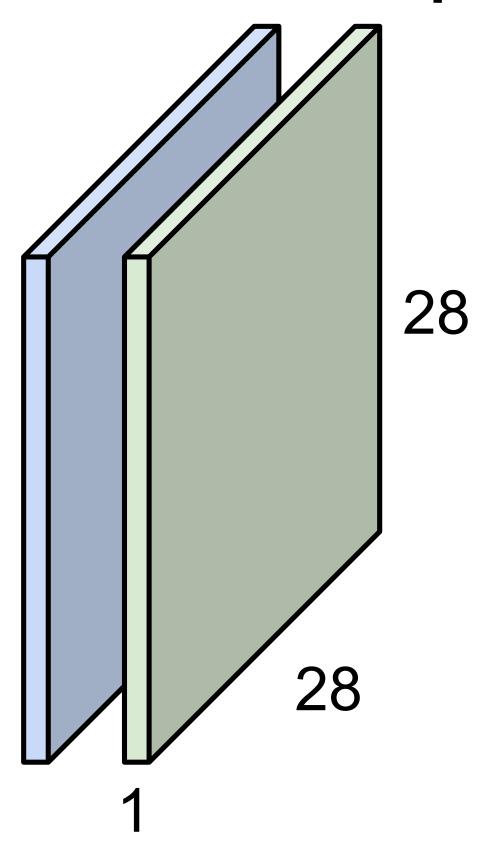


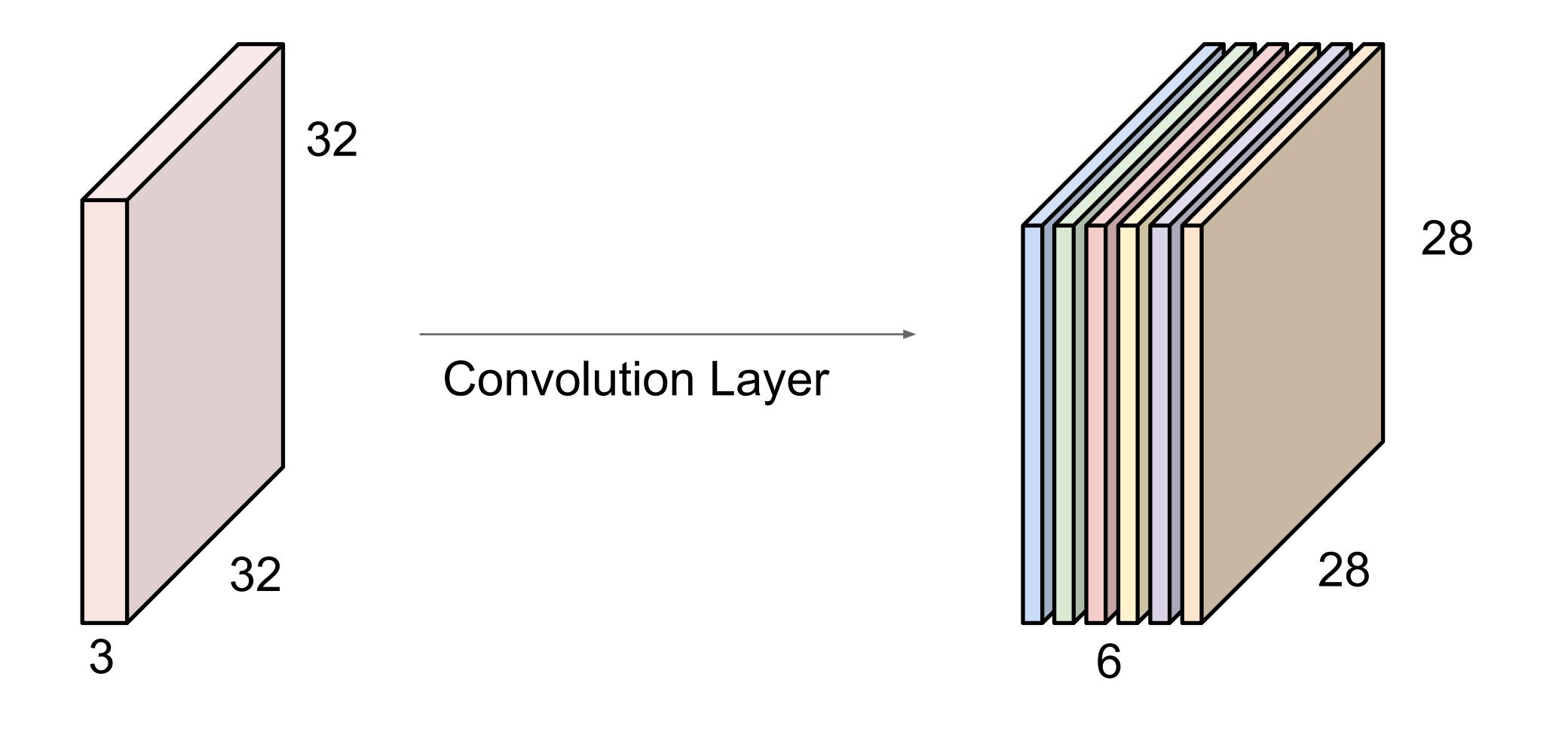




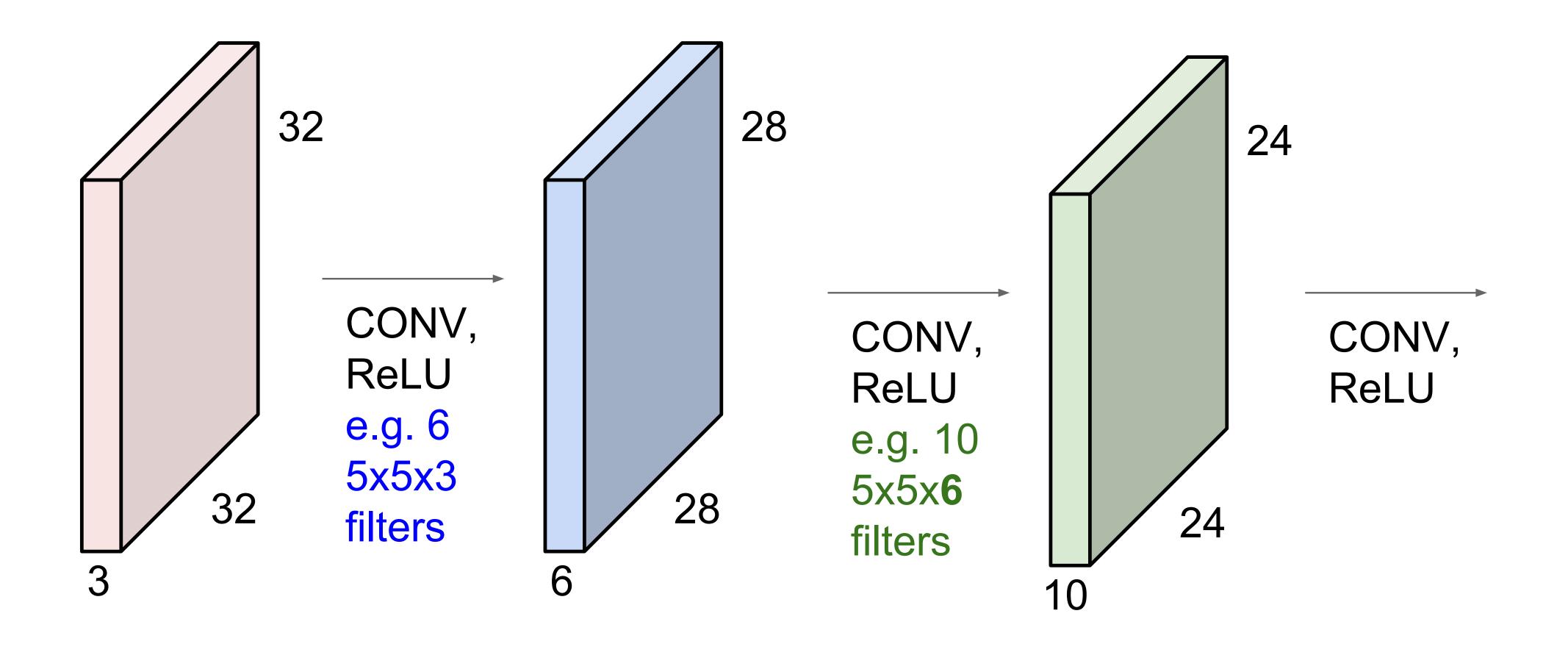


#### activation maps

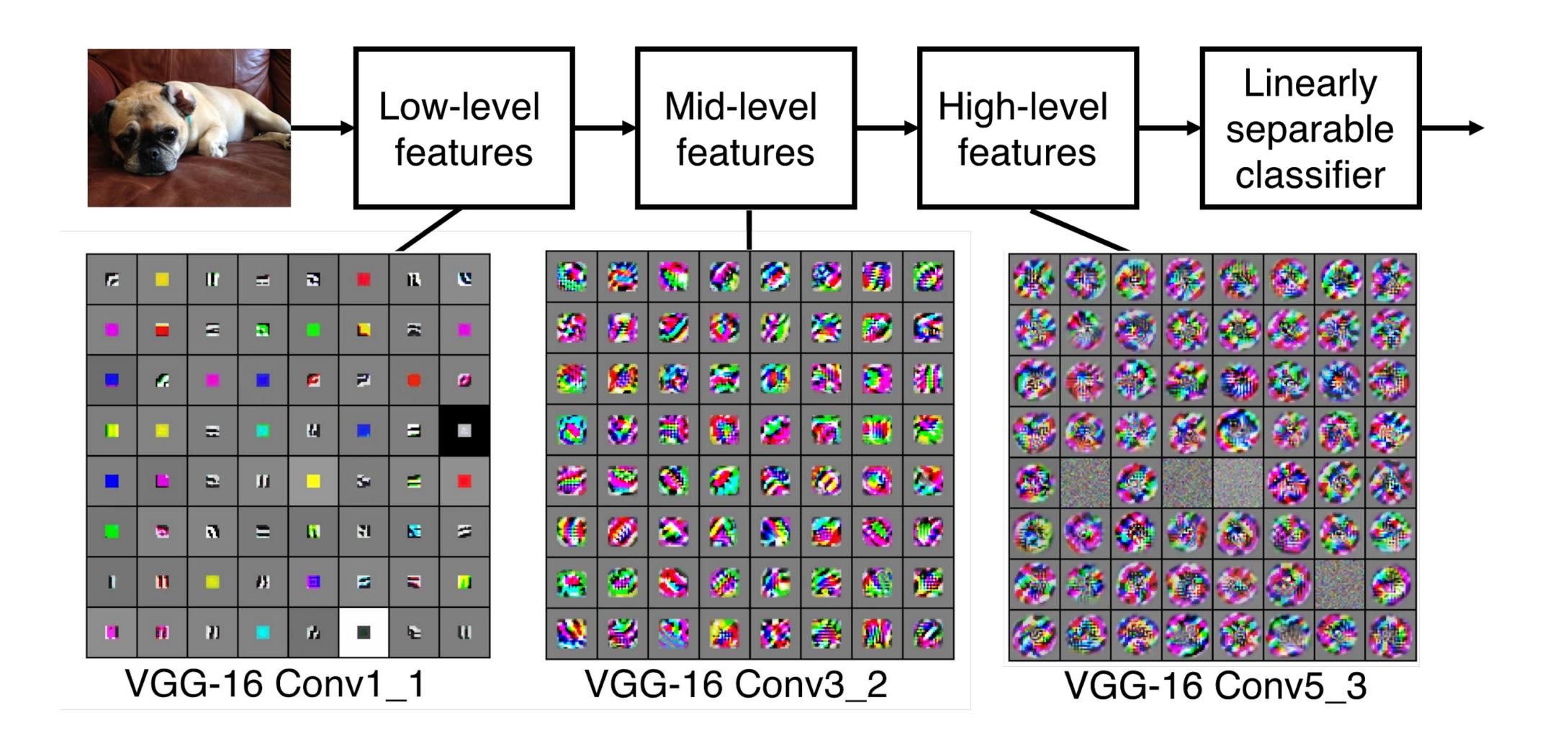


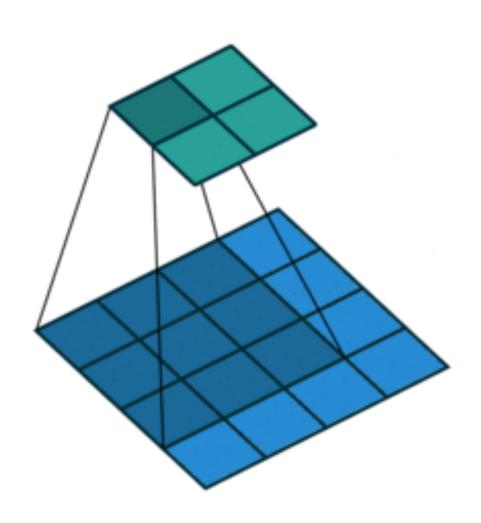


#### **Convolutional Neural Network**

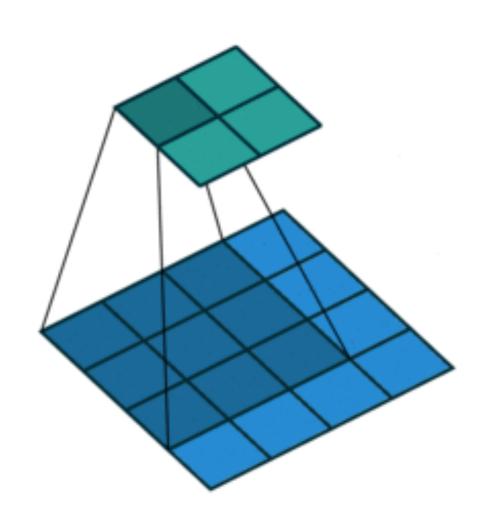


#### What do these layers learn?

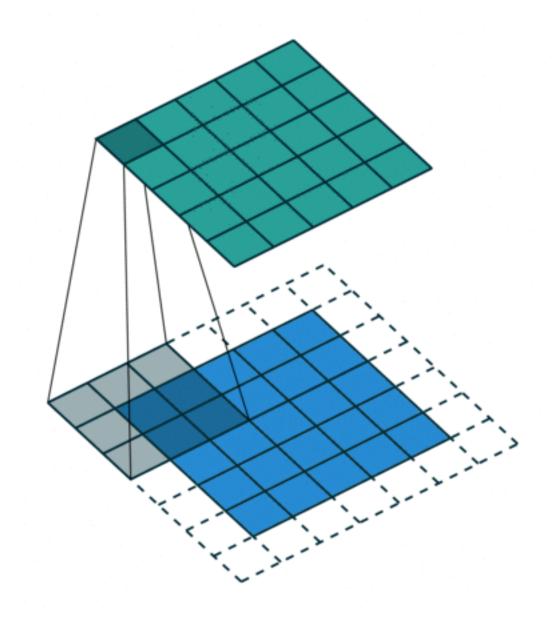




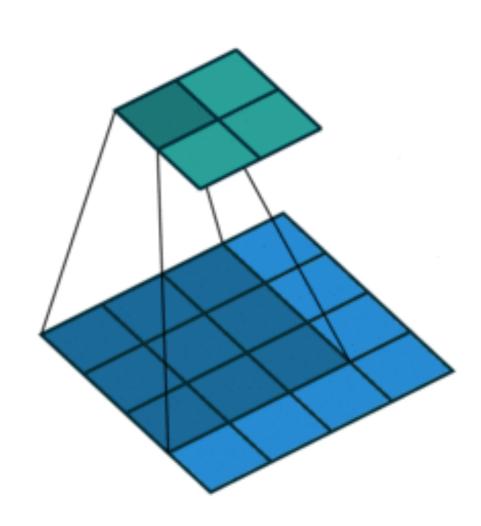
Stride=1, No padding



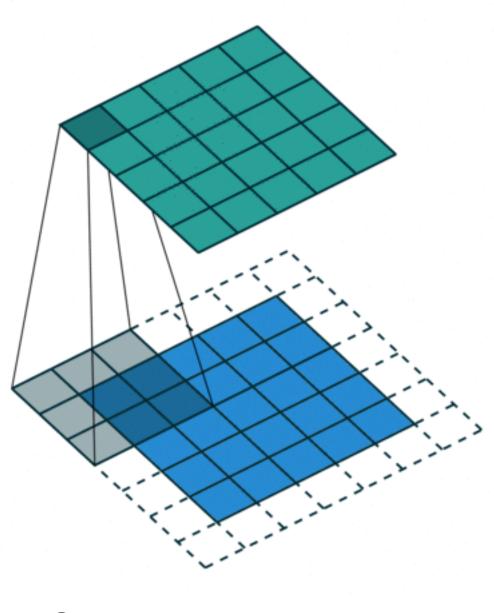
Stride=1, No padding



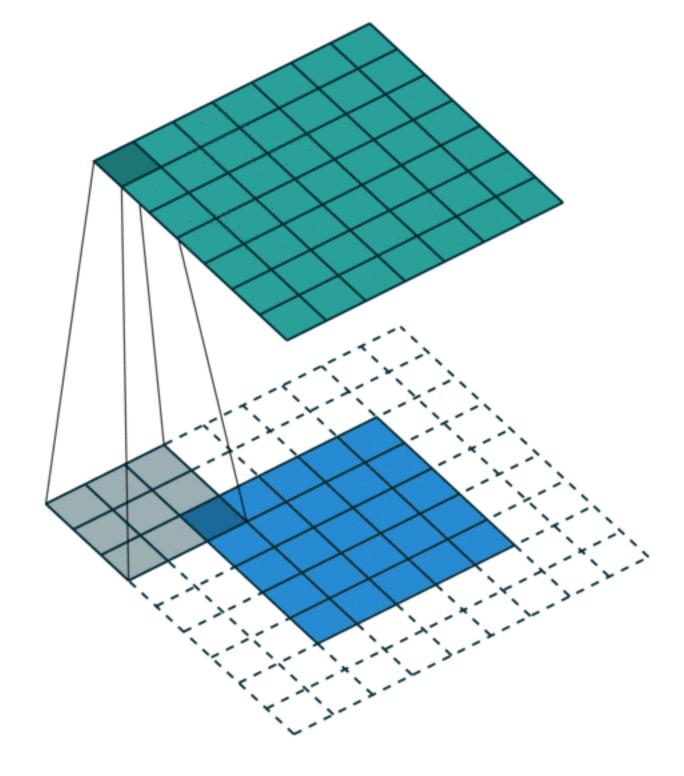
Stride=1, Padding, P=1



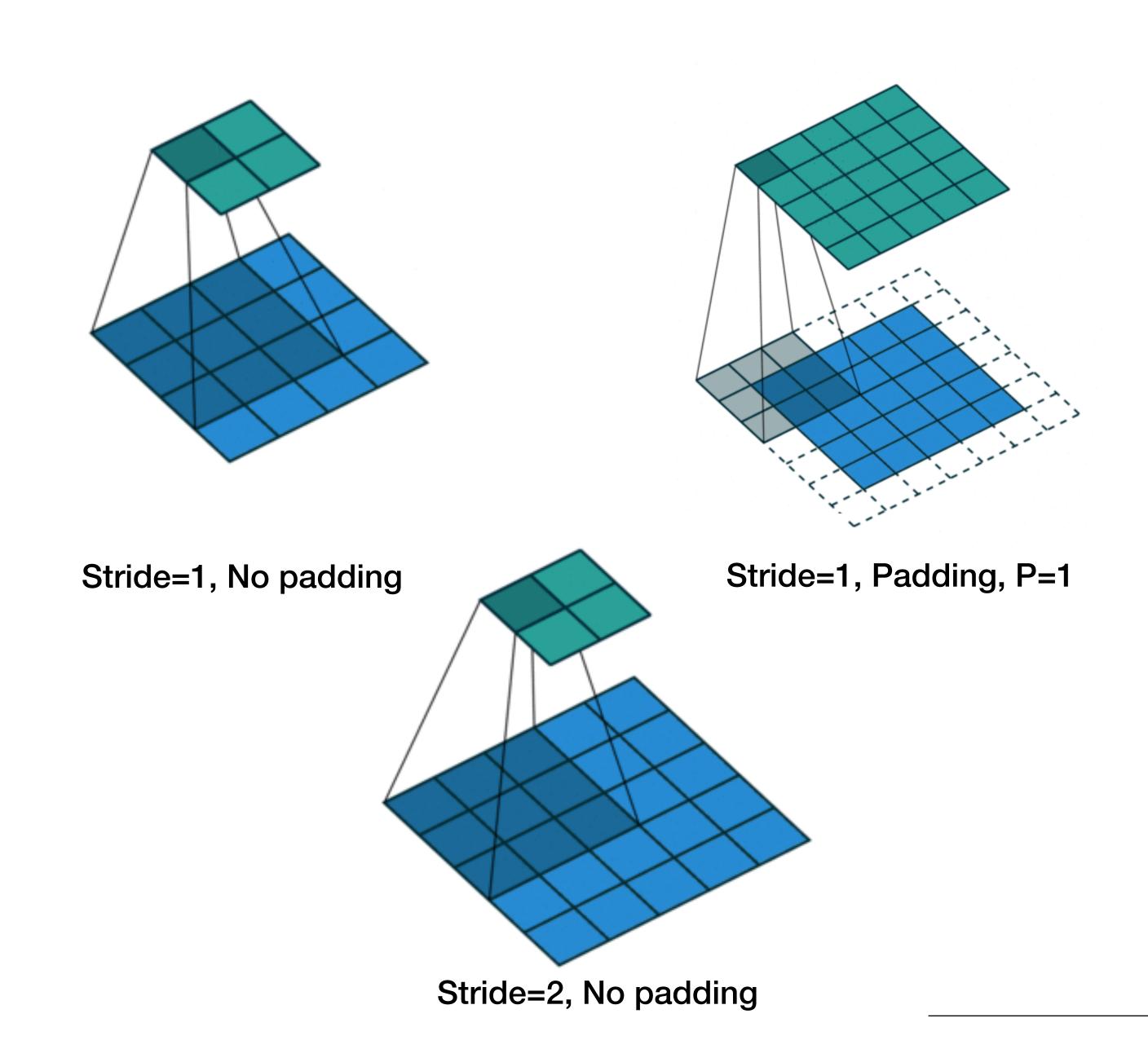
Stride=1, No padding

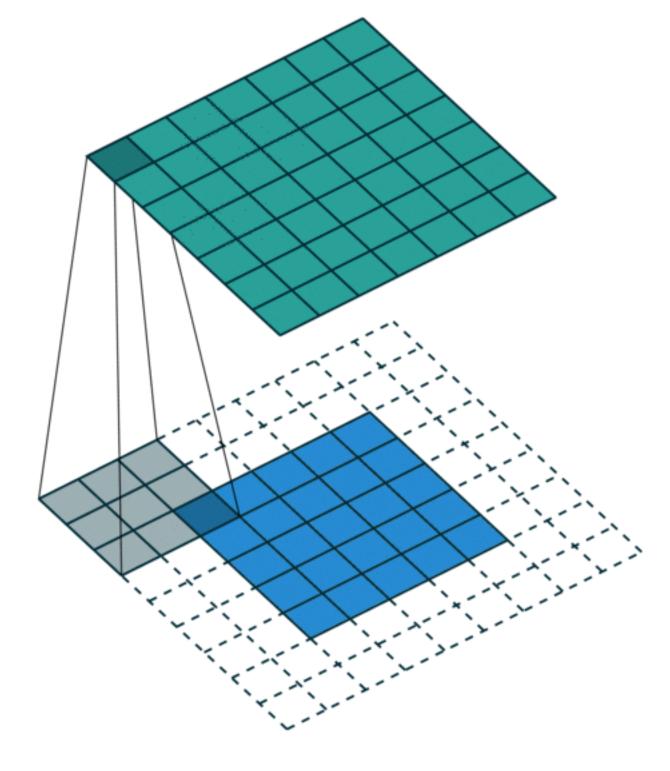


Stride=1, Padding, P=1

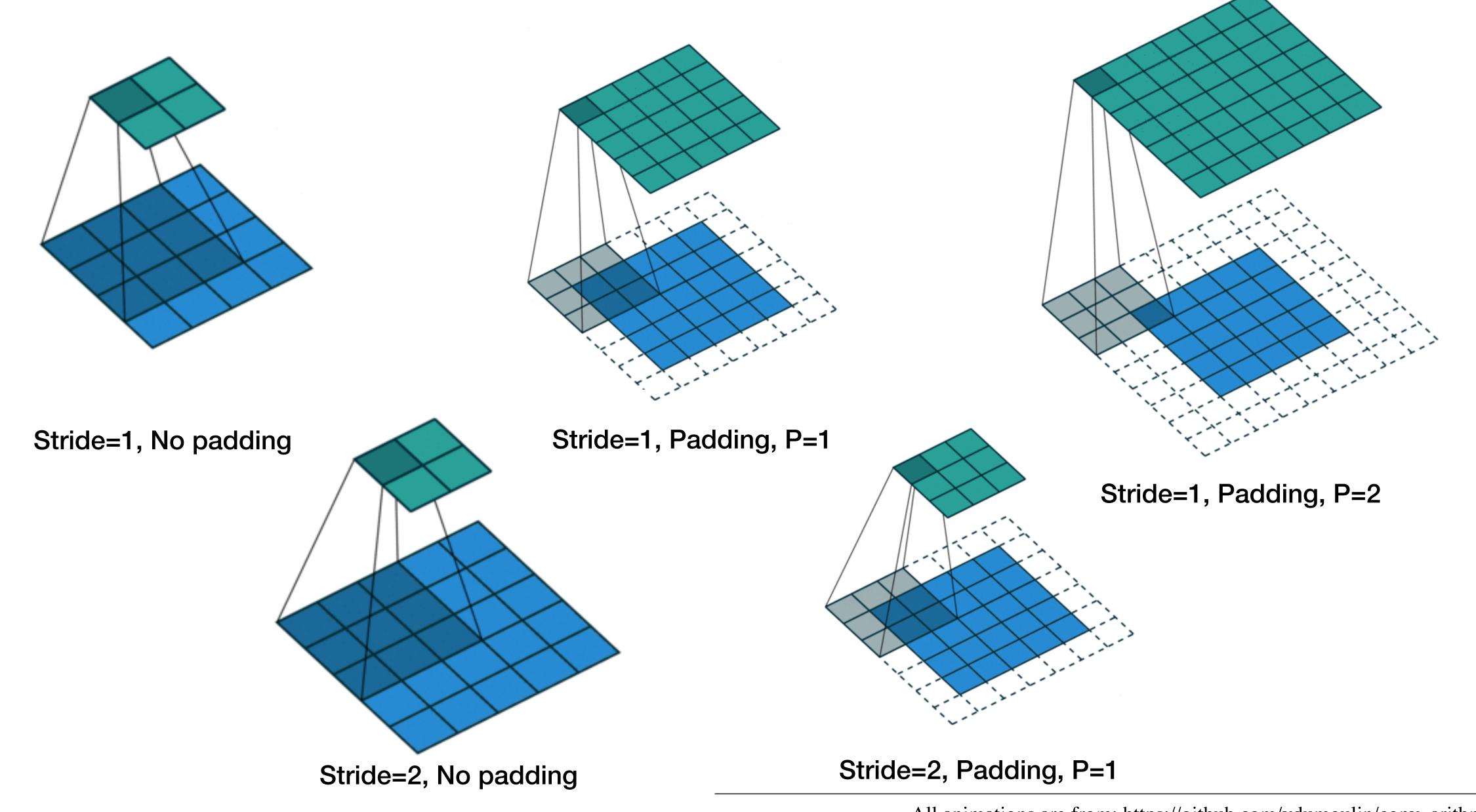


Stride=1, Padding, P=2





Stride=1, Padding, P=2

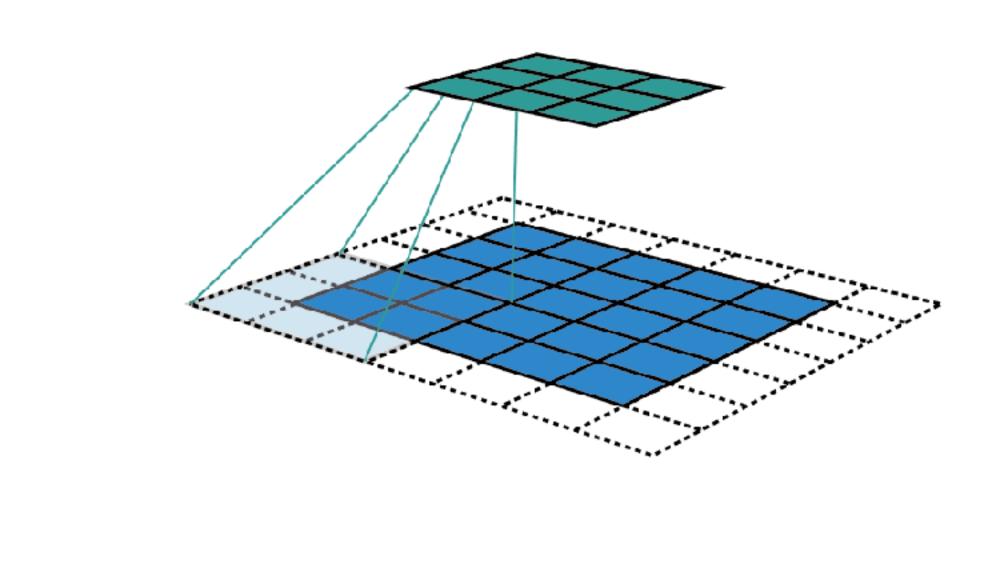


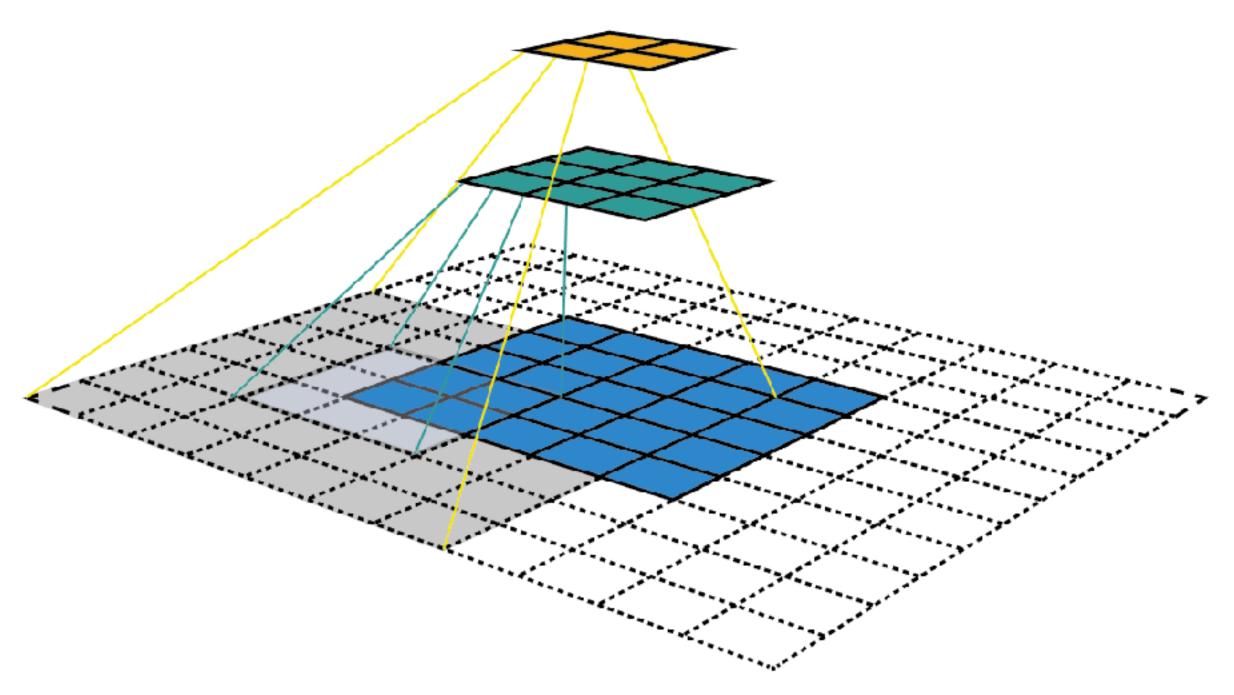
#### **Convolution Layers: Summary**

- Accepts a volume of size  $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - $\circ$  Number of filters K,
  - $\circ$  their spatial extent F,
  - $\circ$  the stride S,
  - $\circ$  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)
  - $O D_2 = K$
- 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.

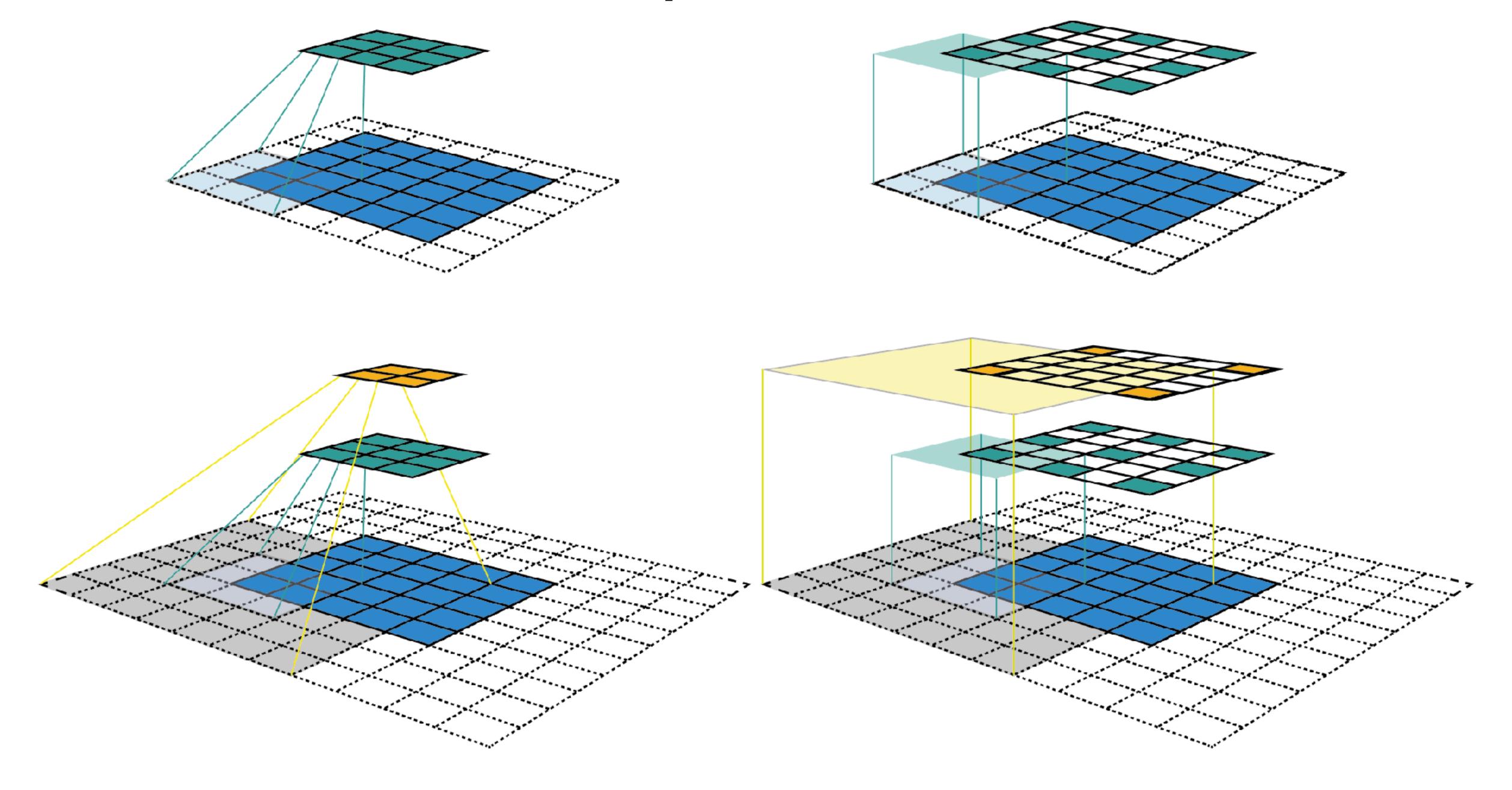
Summary from: http://cs231n.github.io/convolutional-networks/

# **Receptive Field**

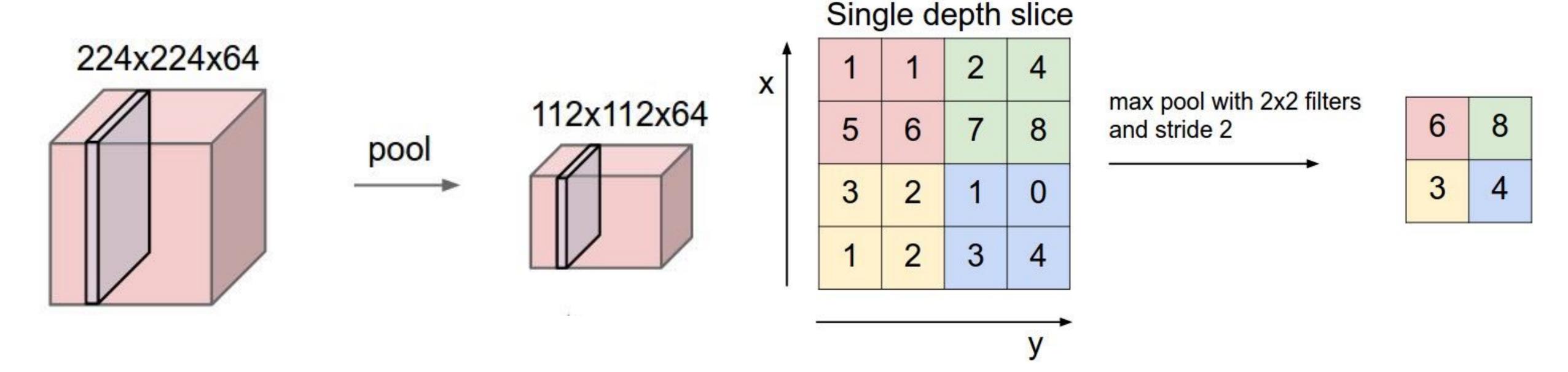




# Receptive Field



#### **Pooling Layer**



- Why pooling?
  Reduce the size of the representation, speed up the computations and make the features a little more robust.
- Max pooling is popularly used in CNNs.

#### **Pooling Layer**

- Accepts a volume of size  $W_1 \times H_1 \times D_1$
- Requires two hyperparameters:
  - $\circ$  their spatial extent F,
  - $\circ$  the stride S,
- Produces a volume of size  $W_2 \times H_2 \times D_2$  where:

$$W_2 = (W_1 - F)/S + 1$$

$$H_2 = (H_1 - F)/S + 1$$

$$D_2 = D_1$$

#### **Batch Normalization**

Input: Values of x over a mini-batch:  $\mathcal{B} = \{x_{1...m}\}$ ; Parameters to be learned:  $\gamma$ ,  $\beta$ 

Output: 
$$\{y_i = BN_{\gamma,\beta}(x_i)\}$$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^{m} x_i$$
 // mini-batch mean

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2$$
 // mini-batch variance

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}}$$
 // normalize

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv BN_{\gamma,\beta}(x_i)$$
 // scale and shift

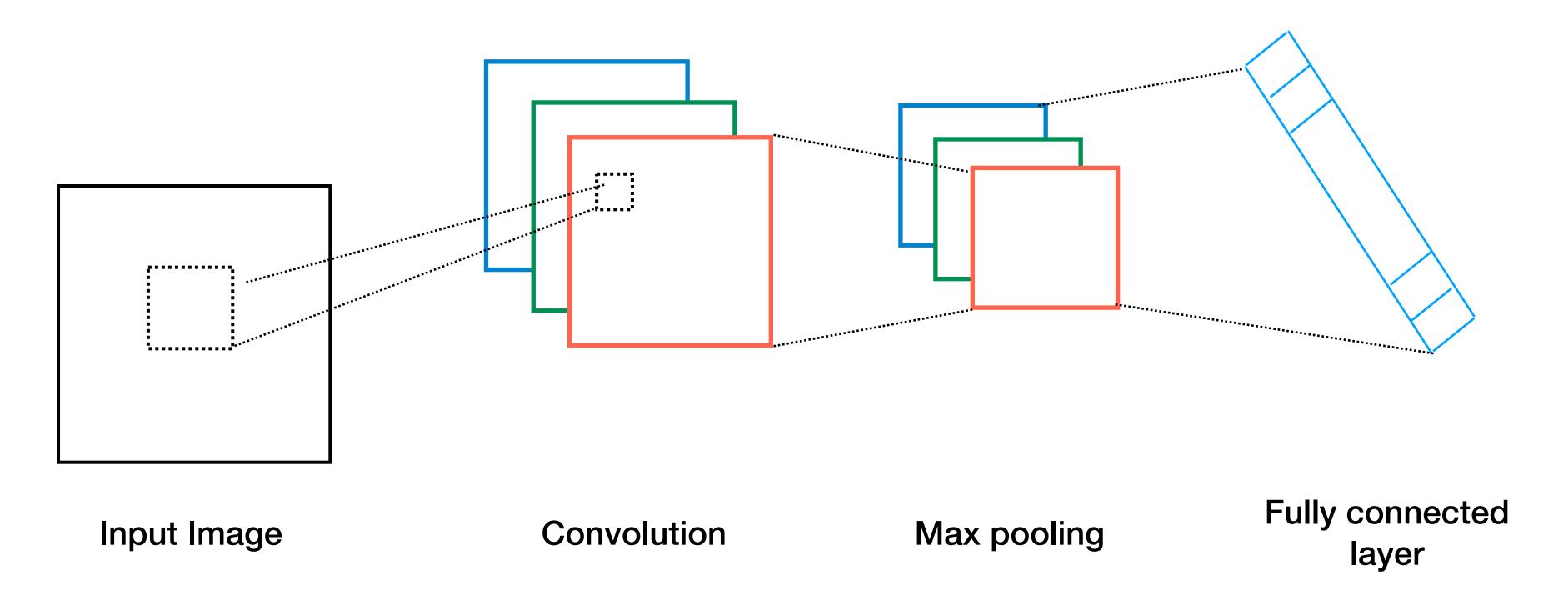
- $\gamma$  and  $\beta$  are learned parameters used across all batches
- At test time: Individual inputs, no mini-batch.
  - First, normalize inputs using training population statistics.

$$\hat{x} \leftarrow \frac{x - \mu_{\text{pop}}}{\sqrt{\sigma_{\text{pop}}^2 + \epsilon}}$$

• Then, scale and shift.

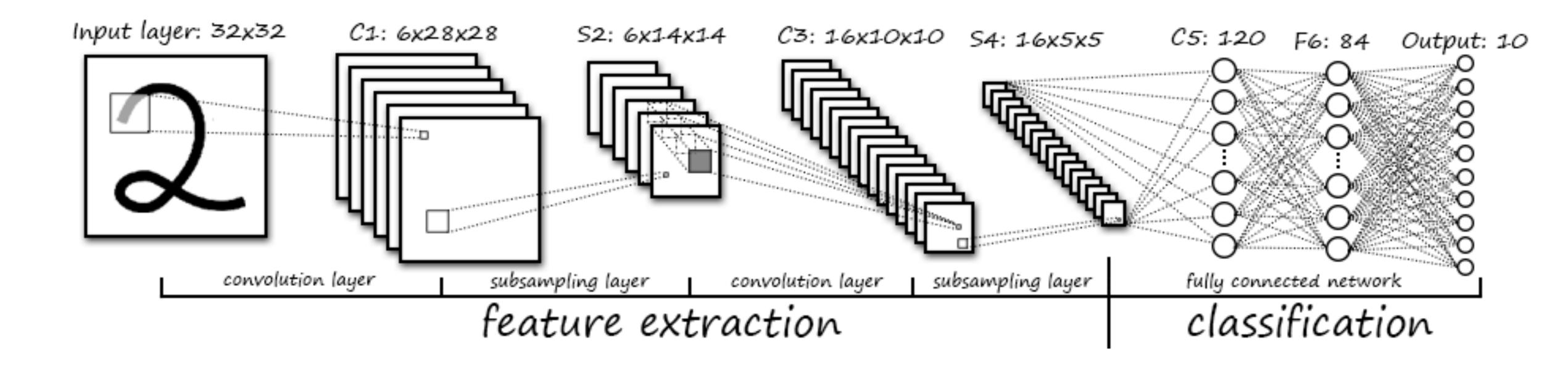
$$\hat{y} \leftarrow \gamma \hat{x} + \beta$$

#### **Convolutional Architectures**



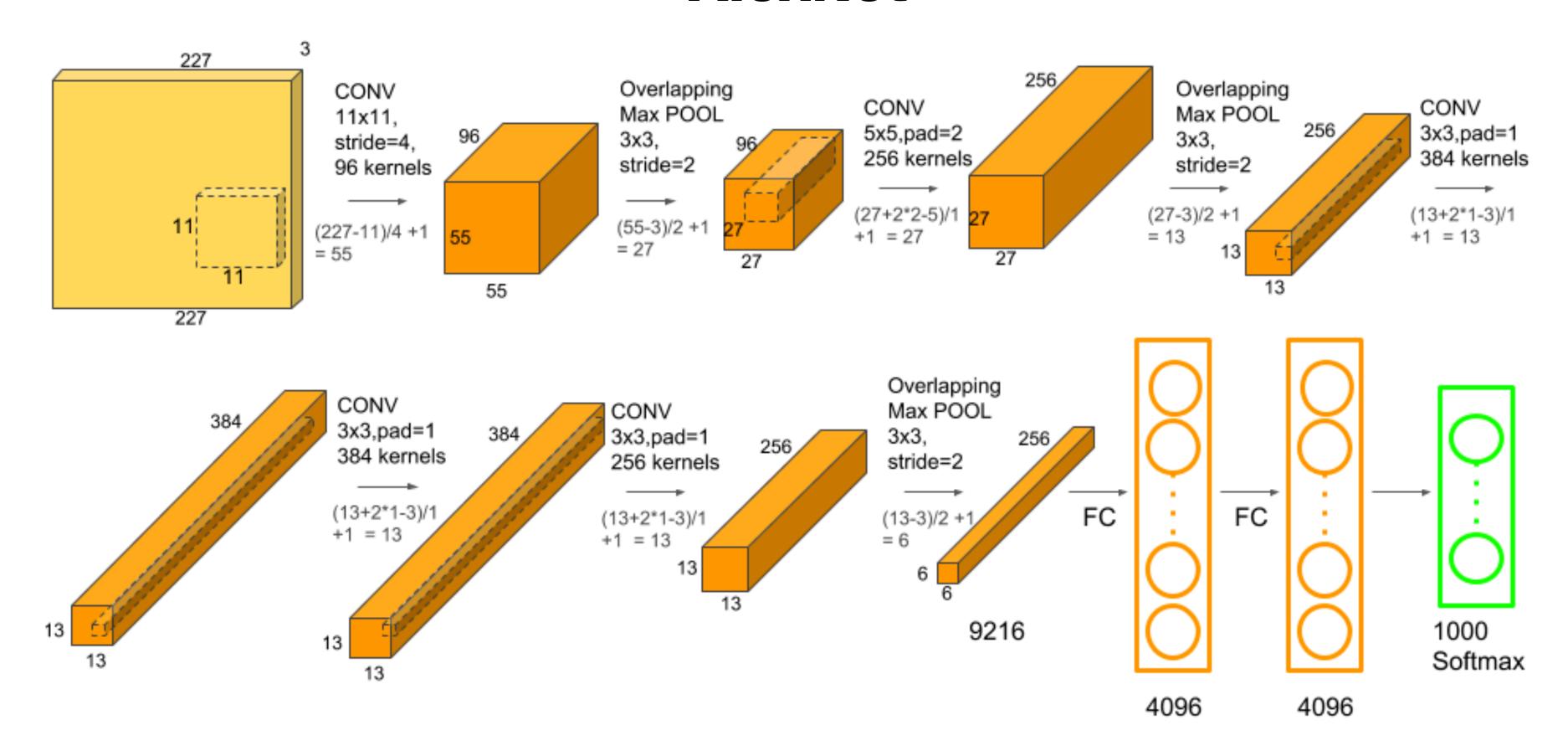
- Block that can be repeated: Convolutional layer, followed by non-linearity (e.g. ReLU) + Max pooling
- Fully connected layers before classification

#### LeNet-5



- One of the first successful CNN architectures
- Used to classify images of hand-written digits

#### **AlexNet**



- Winner (by a large margin) of the ImageNet challenge in 2012.
- Much larger than previous architectures.