DeepRob

Lecture 7
Convolutional Neural Networks
University of Michigan and University of Minnesota

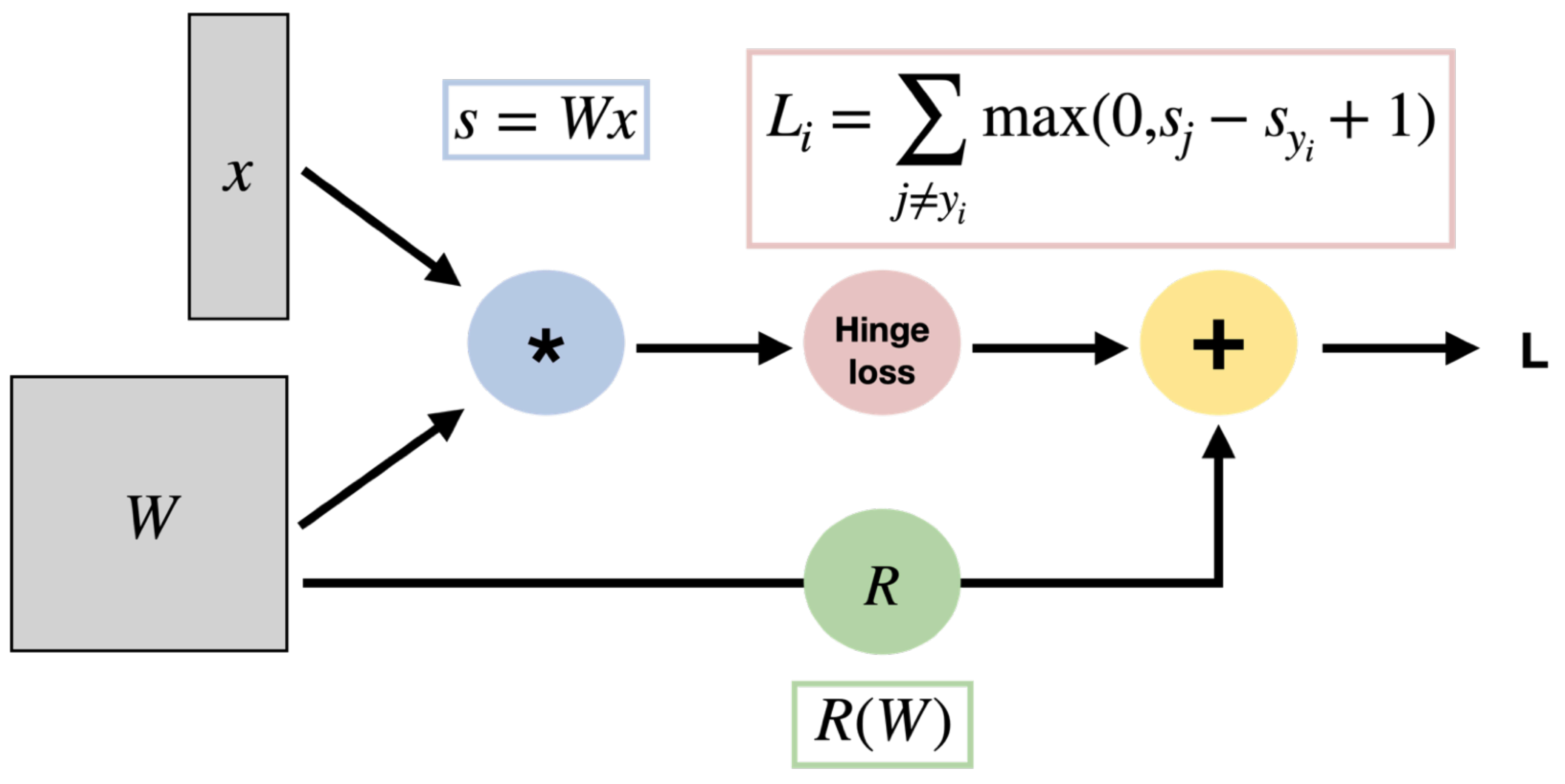
Slides adapted from Justin Johnson's Deep Learning for Computer Vision course

Project 1—Reminder

- Instructions and code available on the website
  - Here: deeprob.org/projects/project1/
- Uses Python, PyTorch and Google Colab
- Implement KNN, linear SVM, and linear softmax classifiers
- **Autograder is online and updated**
- **Due Thursday, January 26th 11:59 PM EST**

Recap from Previous Lecture

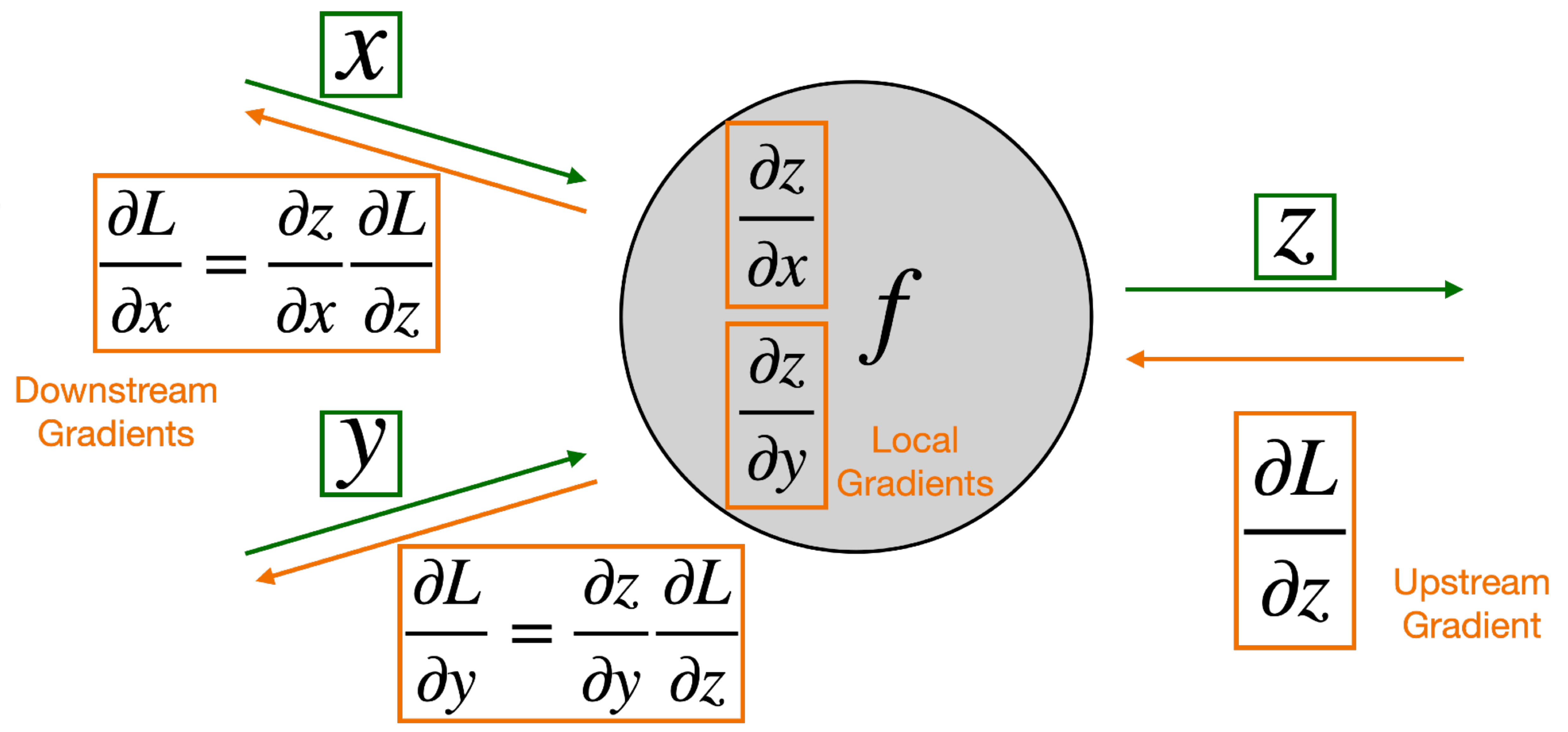
Represent complex expressions as **computational graphs**



1. **Forward pass**: Compute outputs

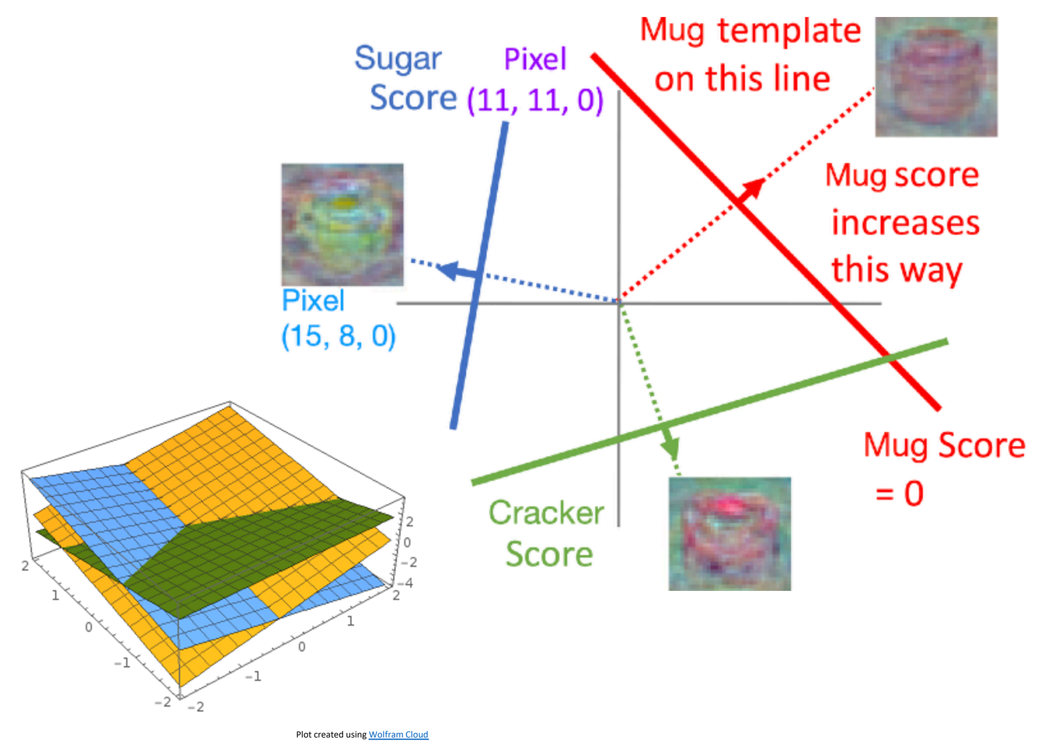
2. **Backward pass**: Compute gradients

During the backward pass, each node in the graph receives **upstream gradients** and multiplies them by **local gradients** to compute **downstream gradients**

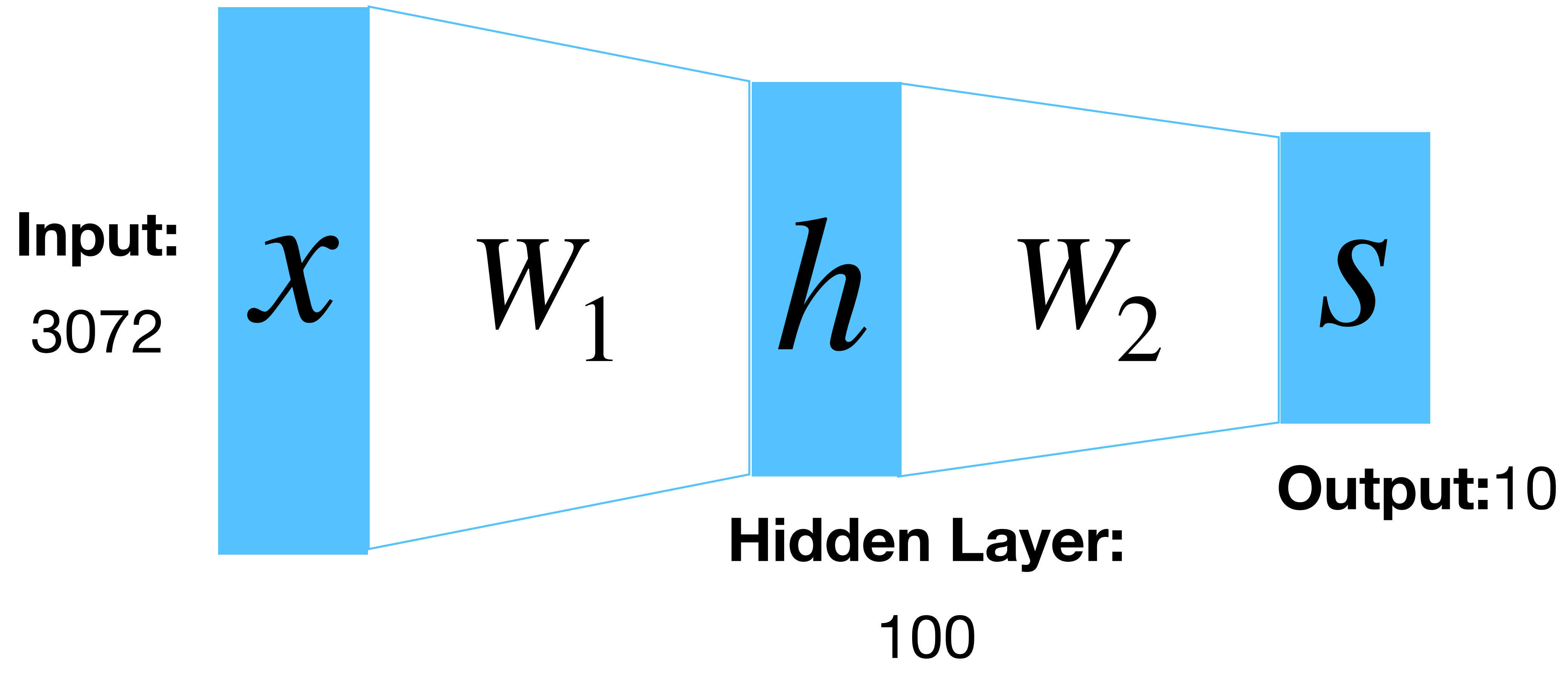


x
y
z
f
$\frac{\partial z}{\partial x}$
$\frac{\partial z}{\partial y}$
Local Gradients
$\frac{\partial L}{\partial x} = \frac{\partial z}{\partial x} \frac{\partial L}{\partial z}$
$\frac{\partial L}{\partial y} = \frac{\partial z}{\partial y} \frac{\partial L}{\partial z}$
Downstream Gradients
$\frac{\partial L}{\partial z}$
Upstream Gradient

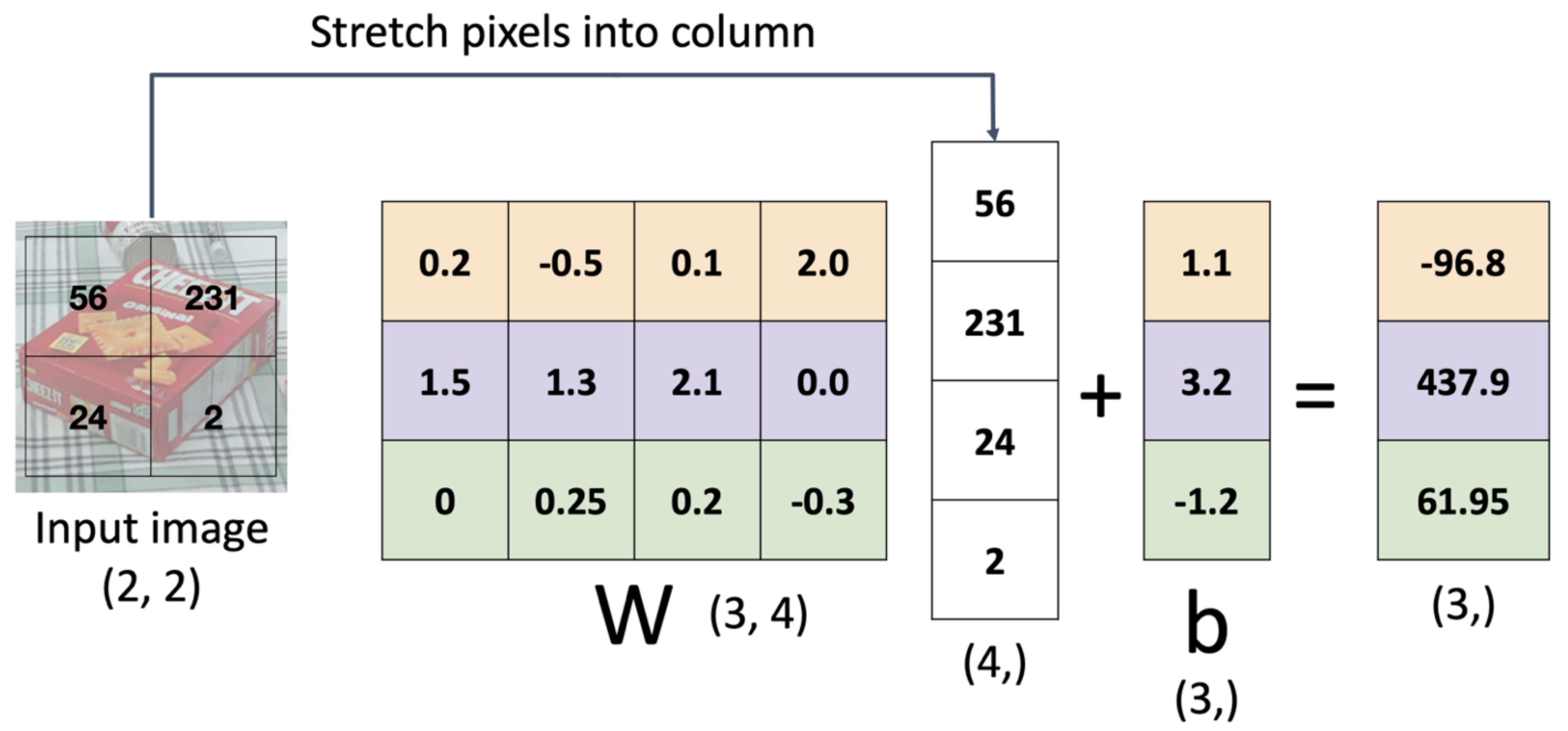
Recap from Previous Lecture



$$f(x) = W_2 \max(0, W_1 x + b_1) + b_2$$

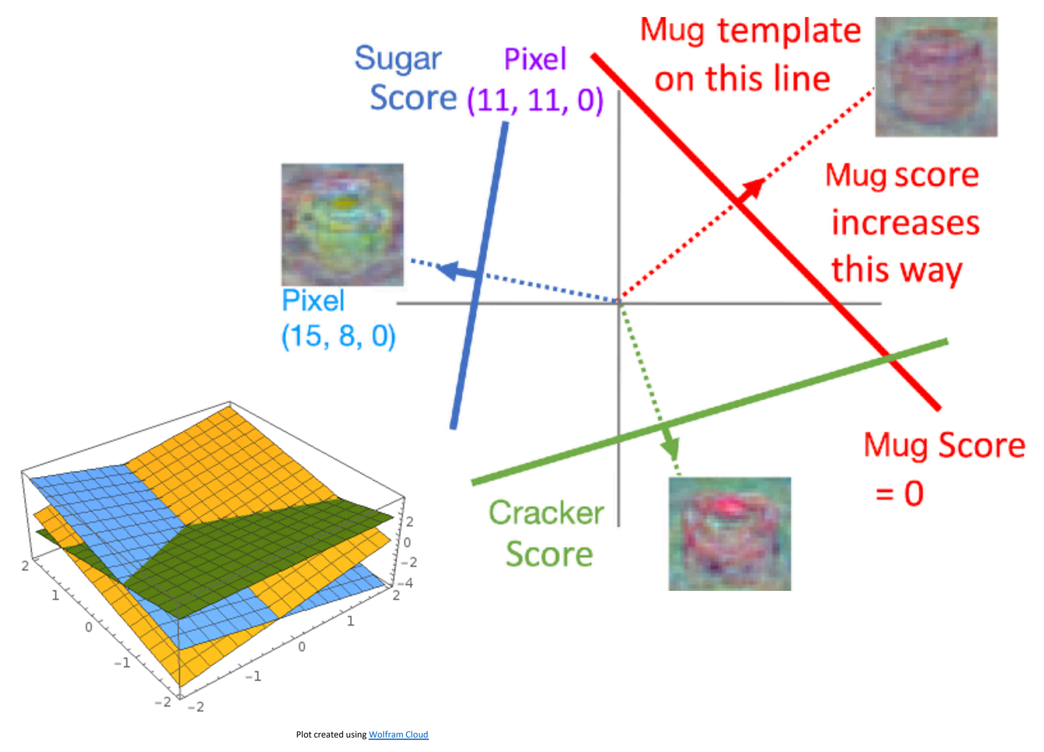


Problem: So far our classifiers don't respect the spatial structure of images!



0.2	-0.5	0.1	2.0	56		1.1		-96.8
1.5	1.3	2.1	0.0	231	+	3.2	=	437.9
0	0.25	0.2	-0.3	24		-1.2		61.95
				2				

Recap from Previous Lecture



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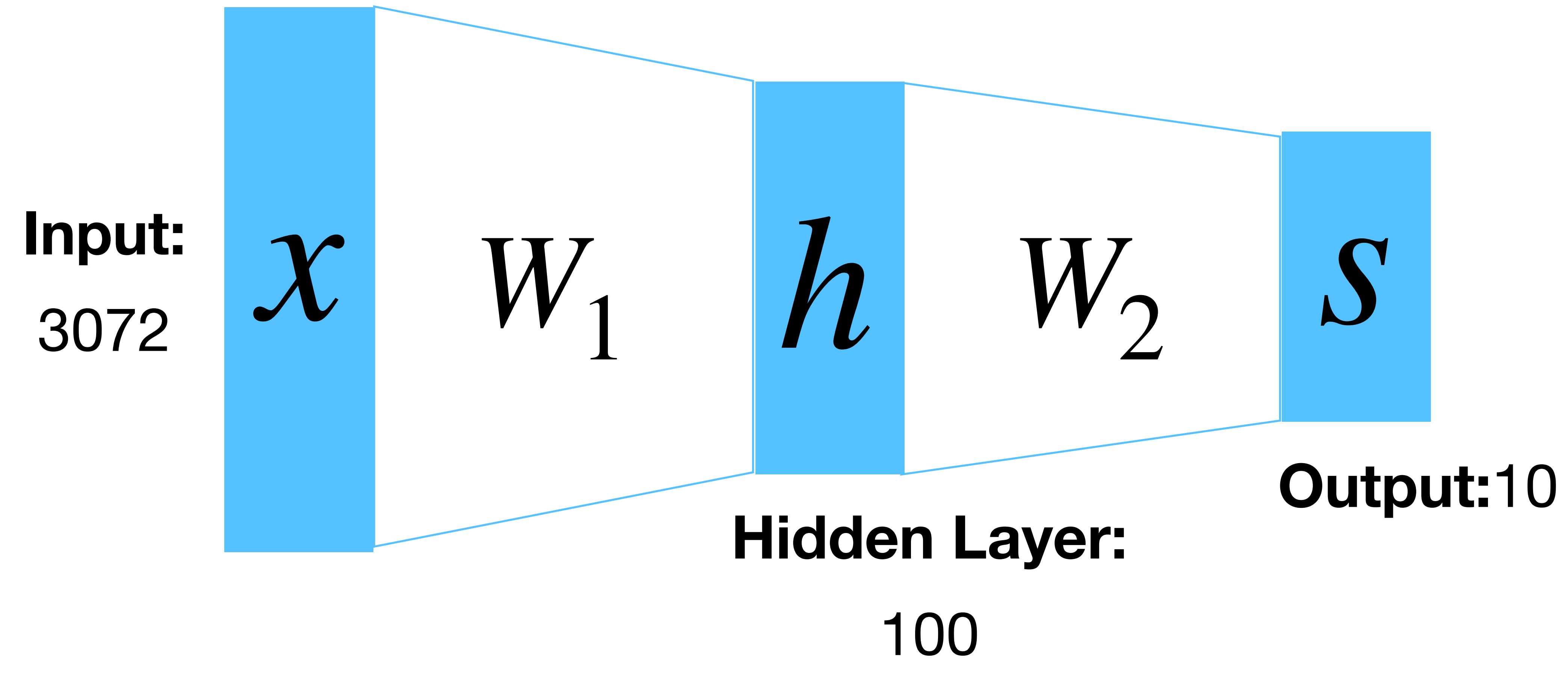
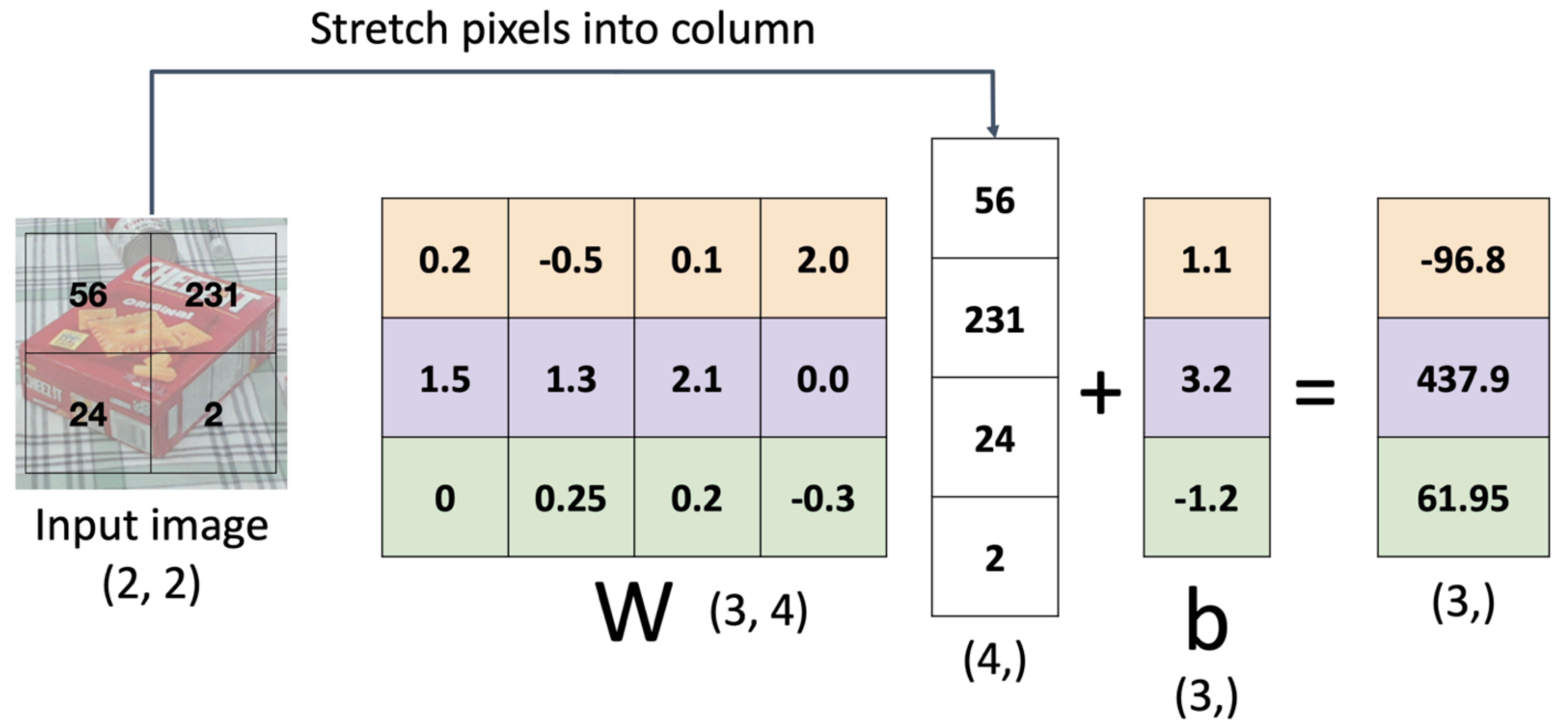


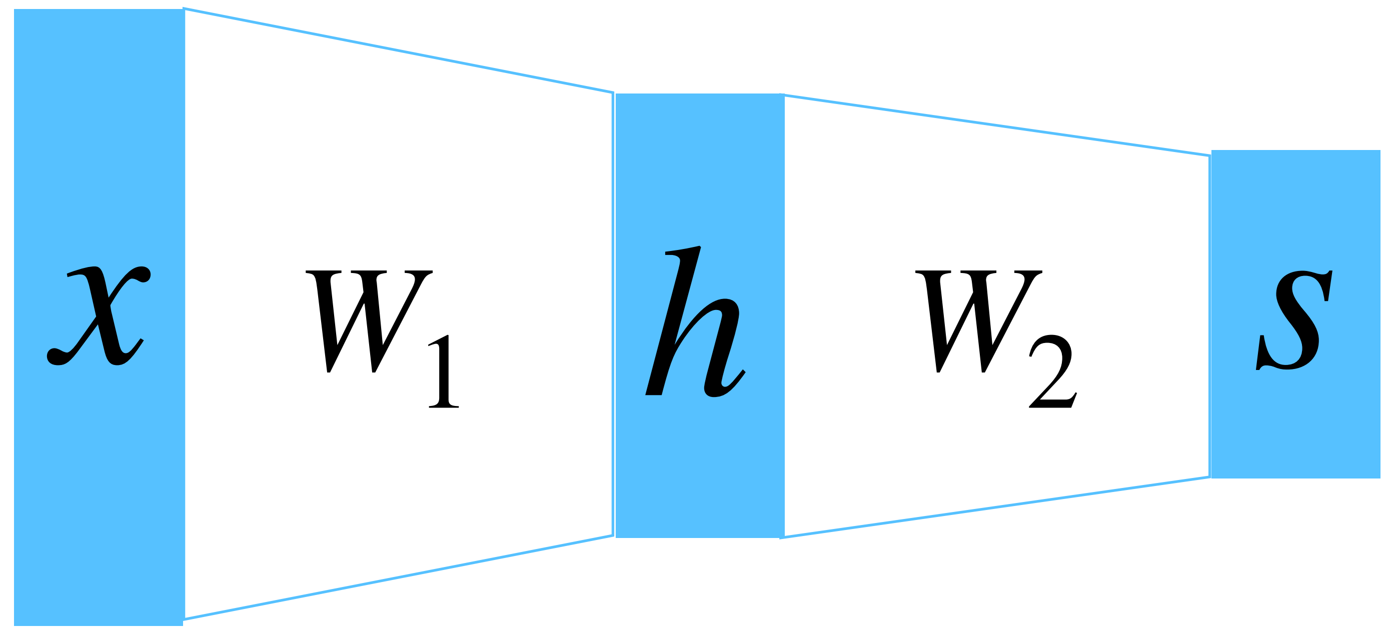
Problem: So far our classifiers don't respect the spatial structure of images!

Solution: Define new computational nodes that operate on images!

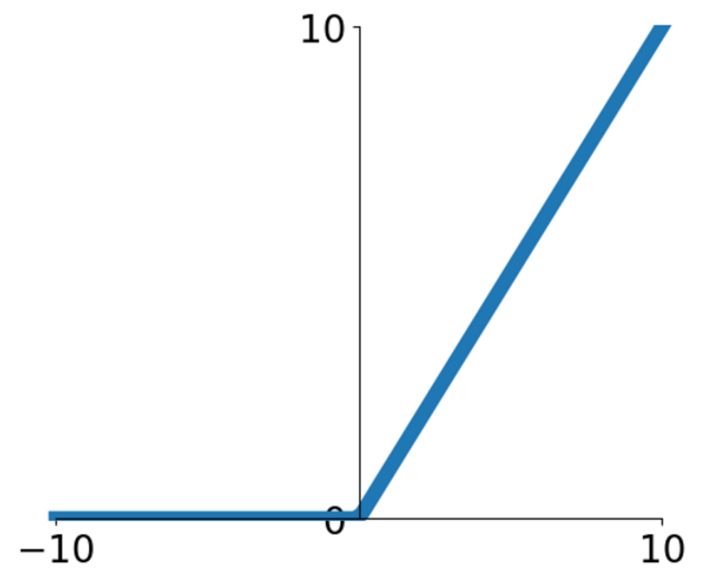


Components of Fully-Connected Networks

Fully-Connected Layers

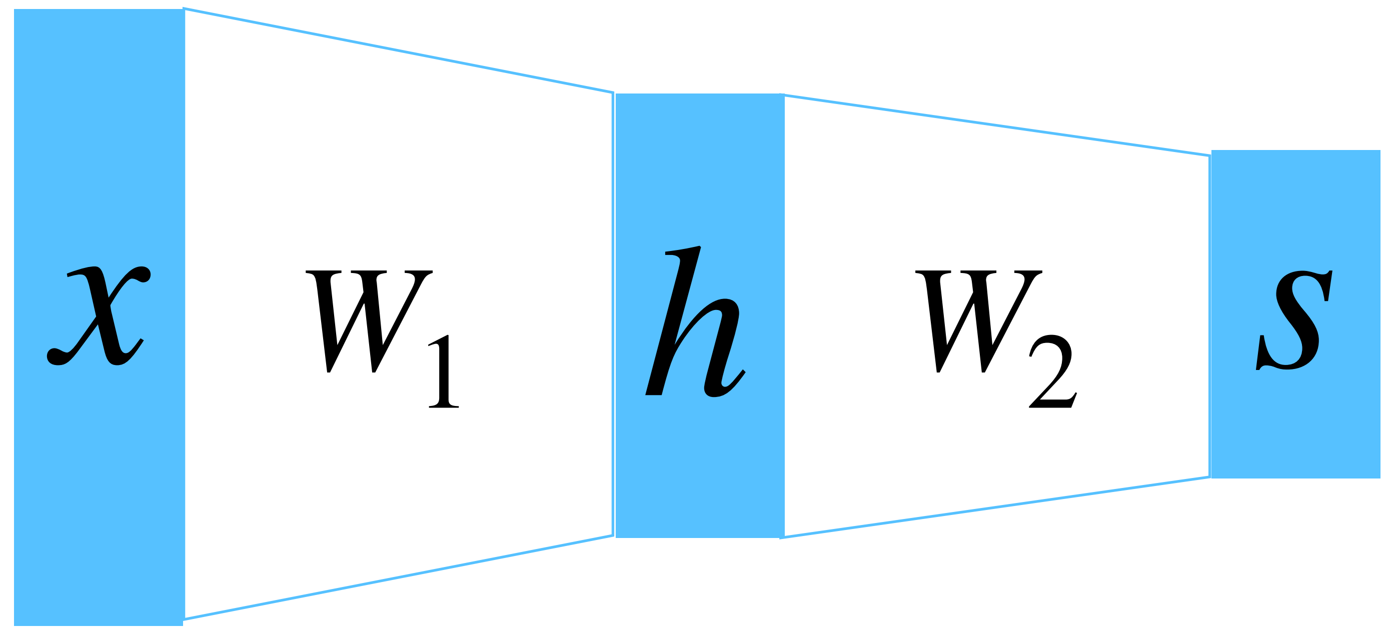


Activation Functions

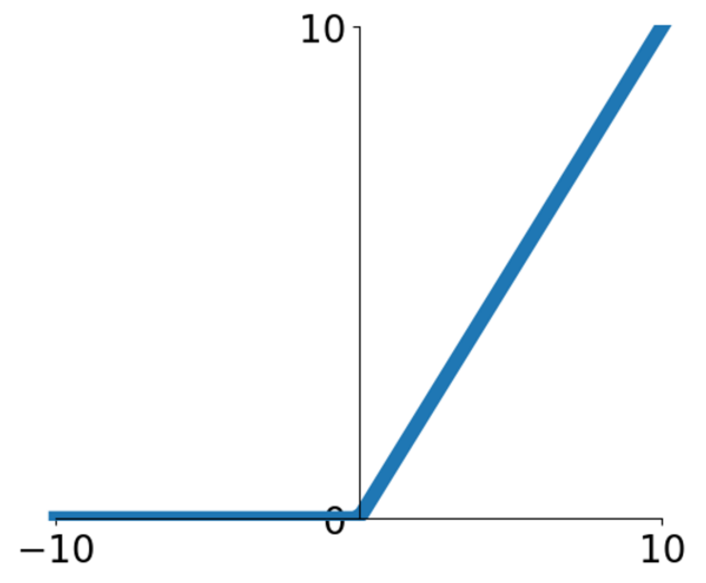


Components of Convolutional Neural Networks

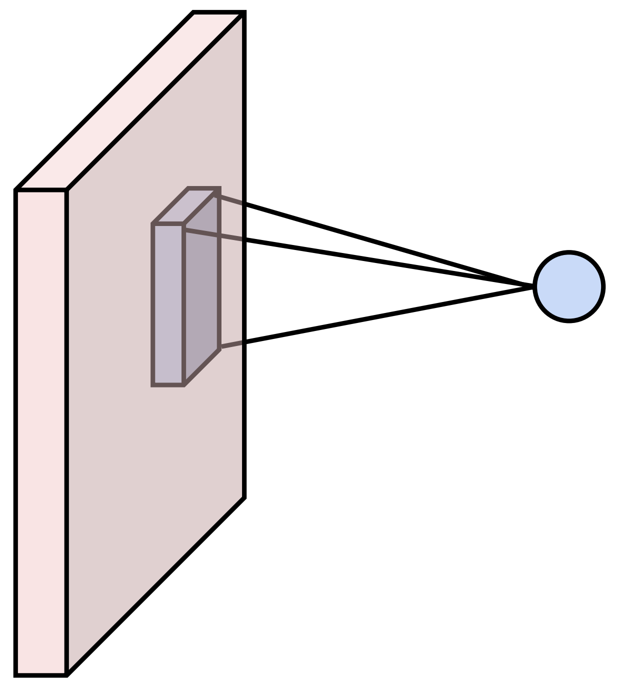
Fully-Connected Layers



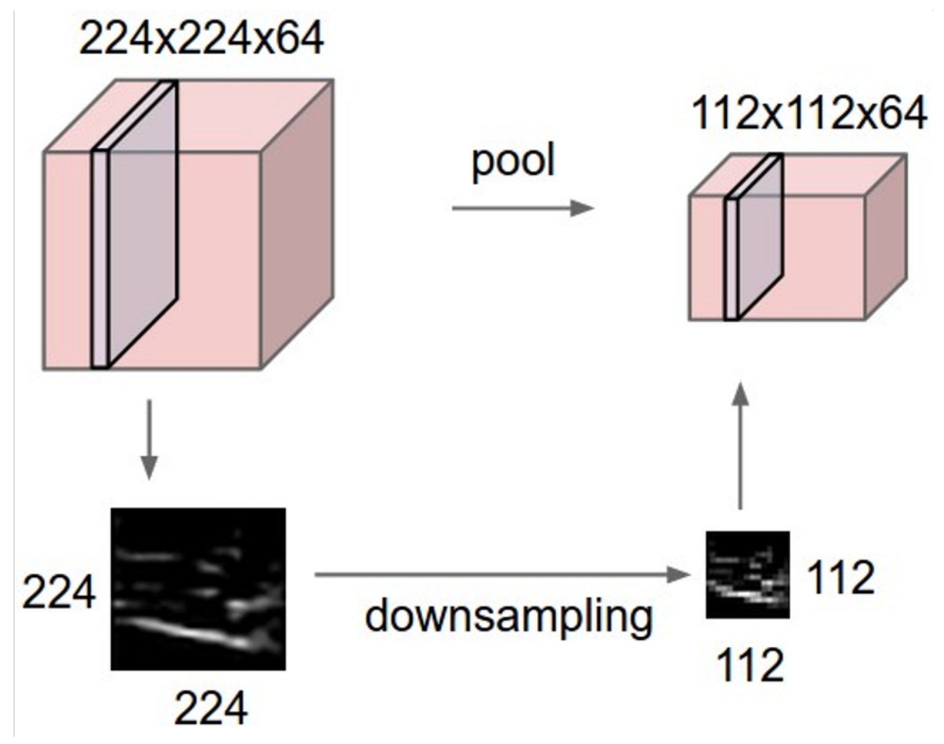
Activation Functions



Convolution Layers



Pooling Layers

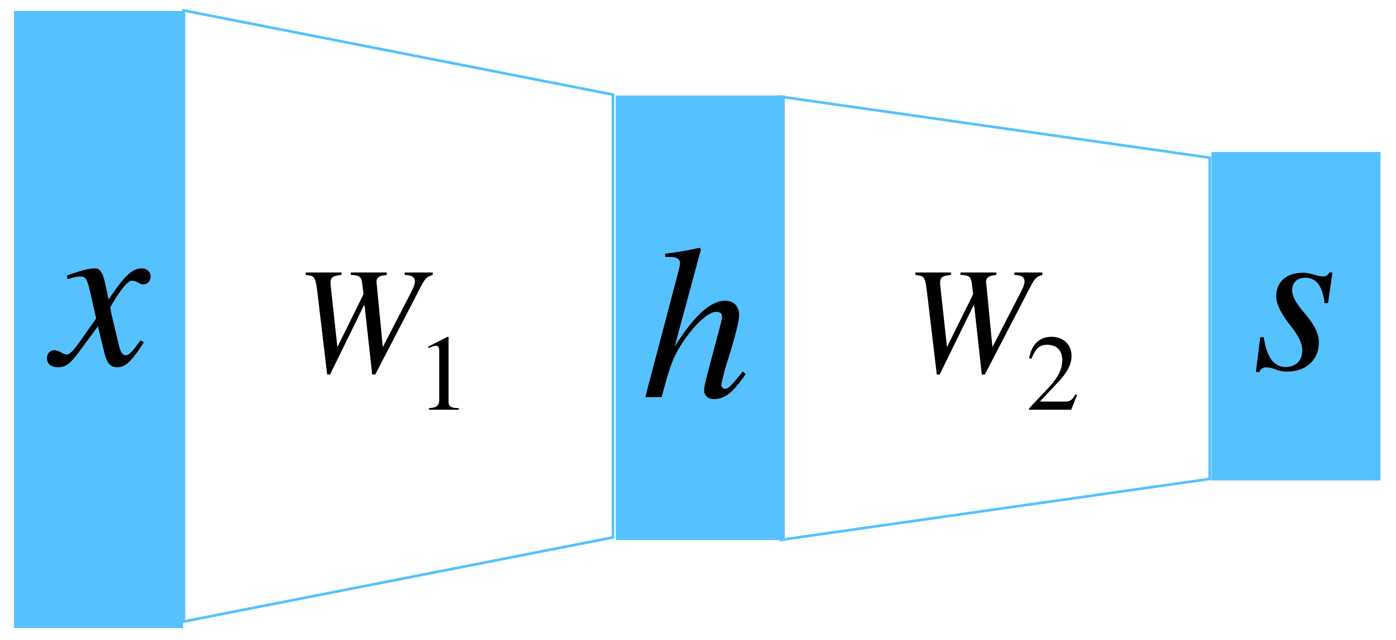


Normalization

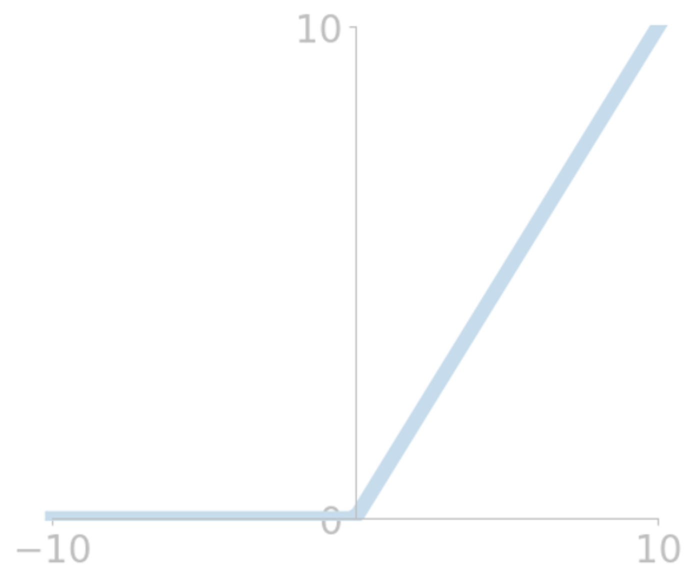
$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Components of Convolutional Neural Networks

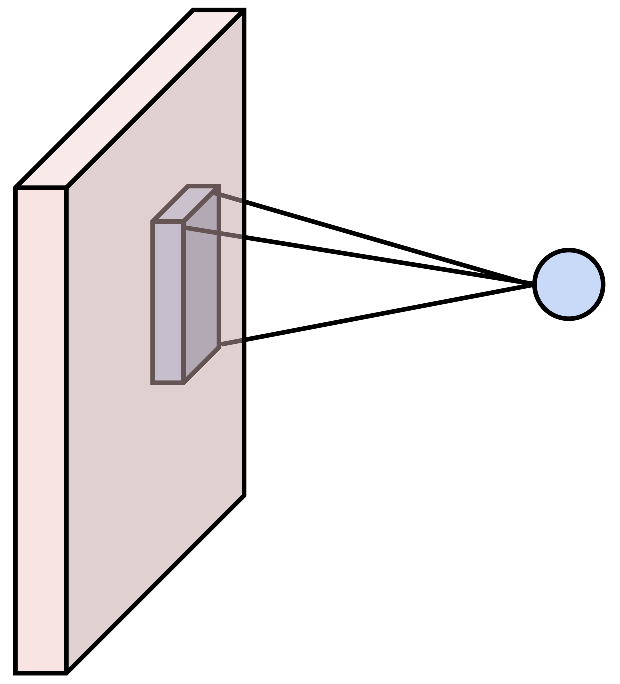
Fully-Connected Layers



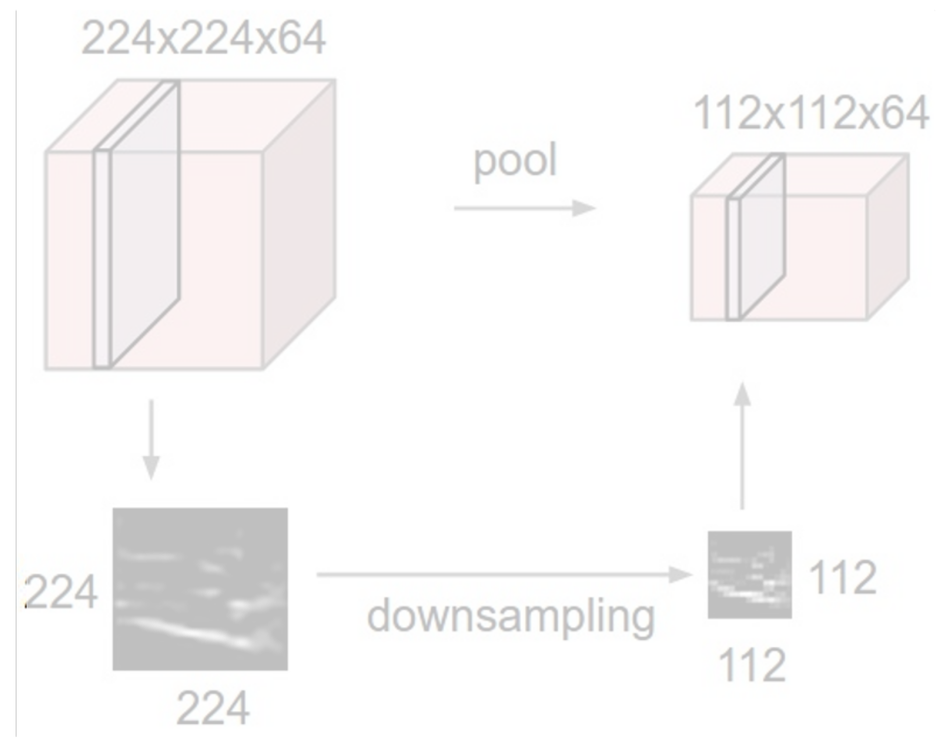
Activation Functions



Convolution Layers



Pooling Layers

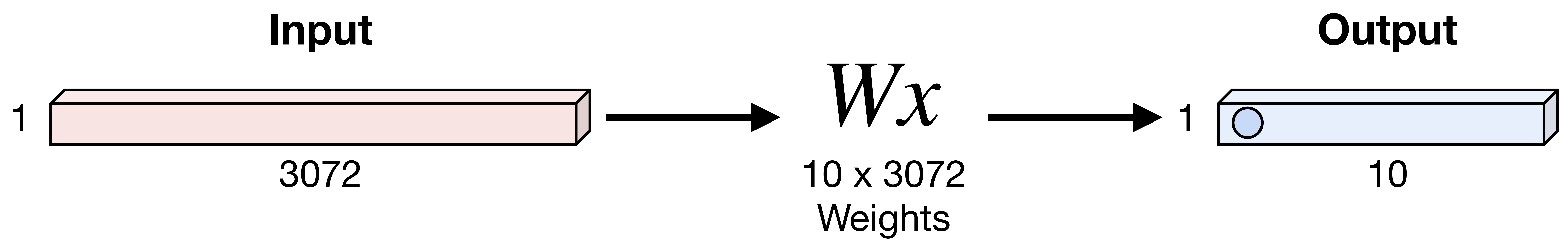


Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

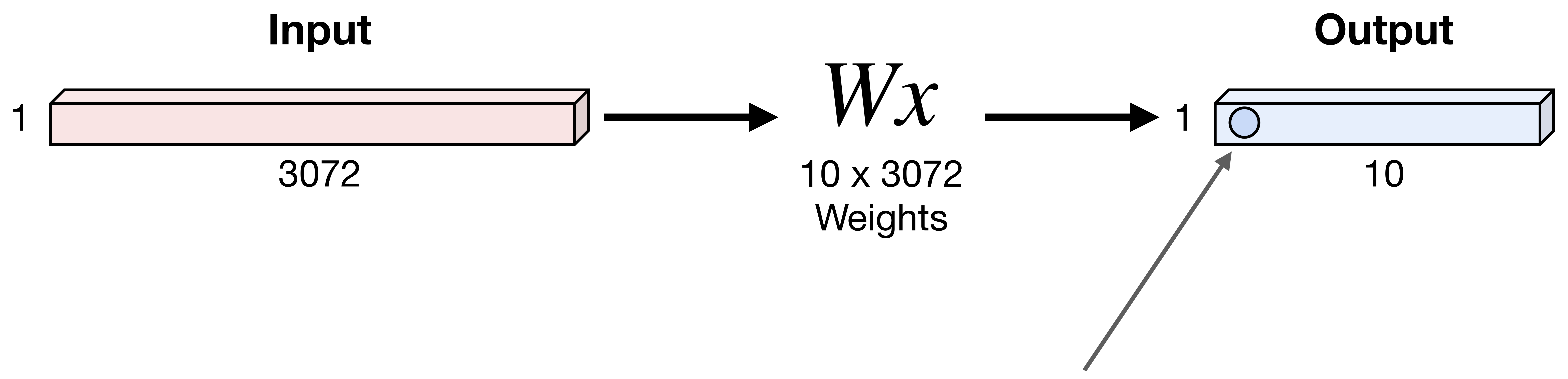
Fully-Connected Layer

3x32x32 image $\longrightarrow$ stretch to 3072x1



Fully-Connected Layer

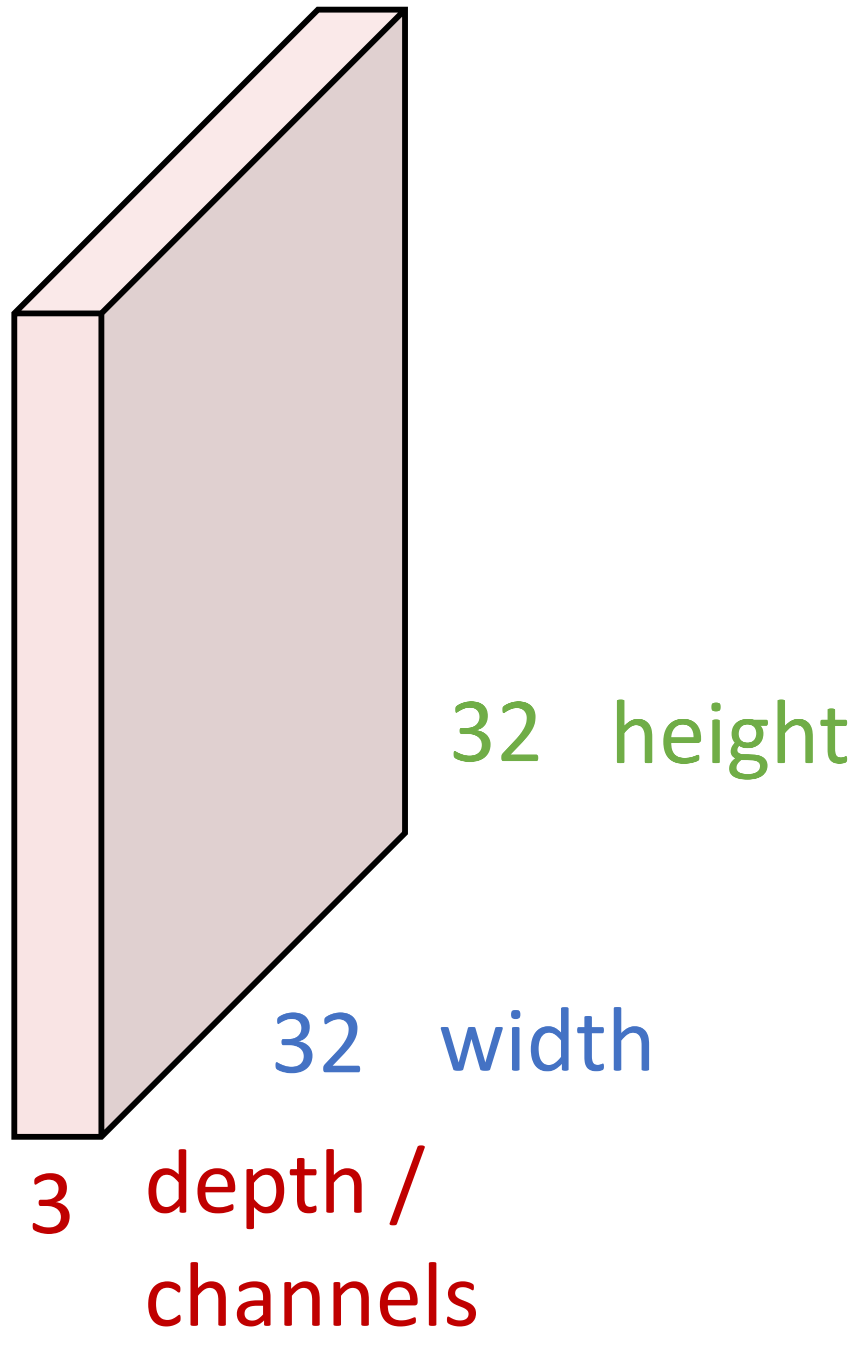
3x32x32 image ⟶ stretch to 3072x1



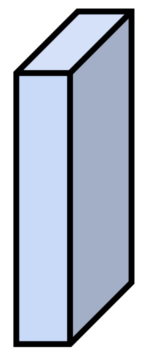
1 number:
The result of taking a dot product between a row of W and the input

Convolution Layer

3x32x32 image: preserve spatial structure



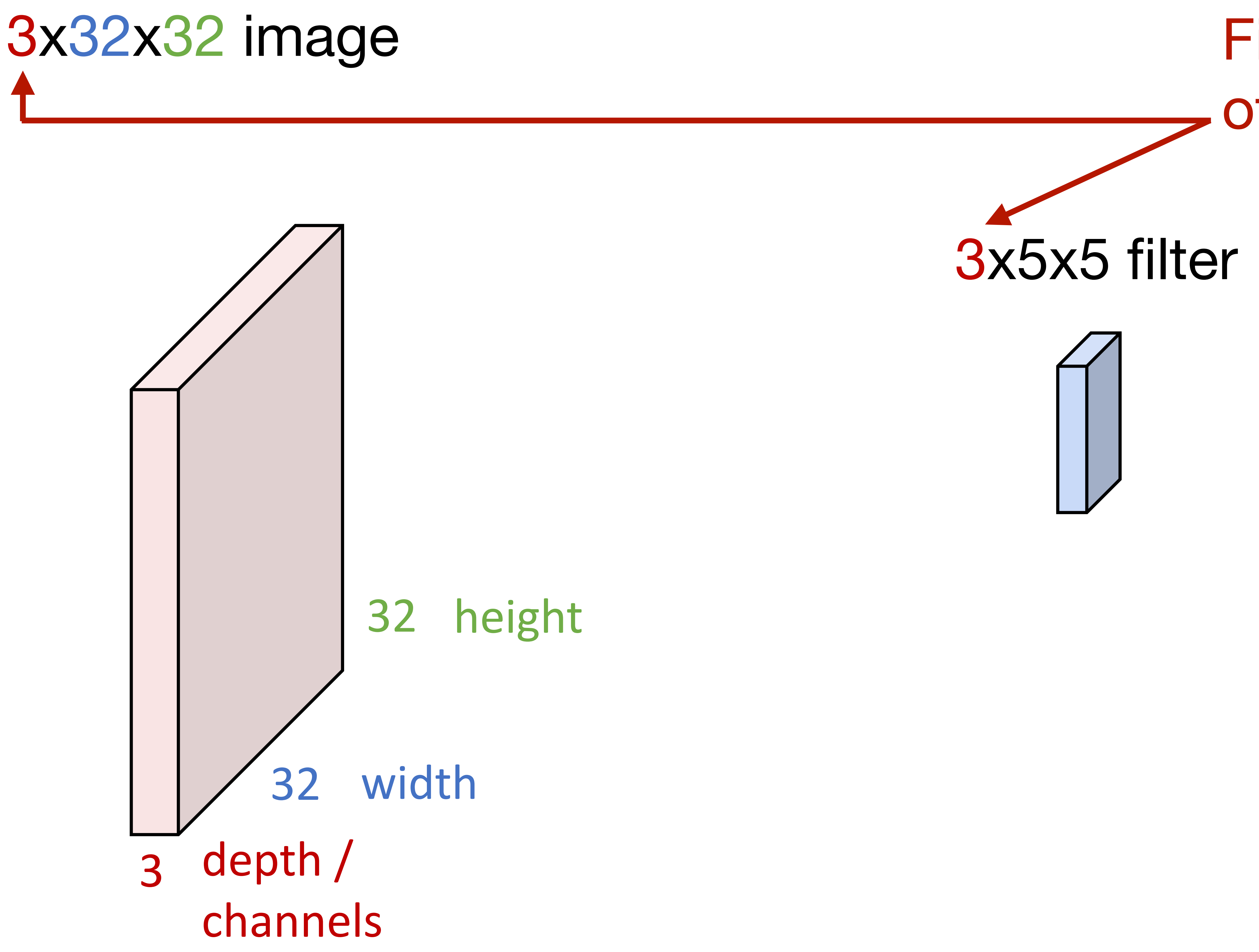
3x5x5 filter



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

Convolution Layer

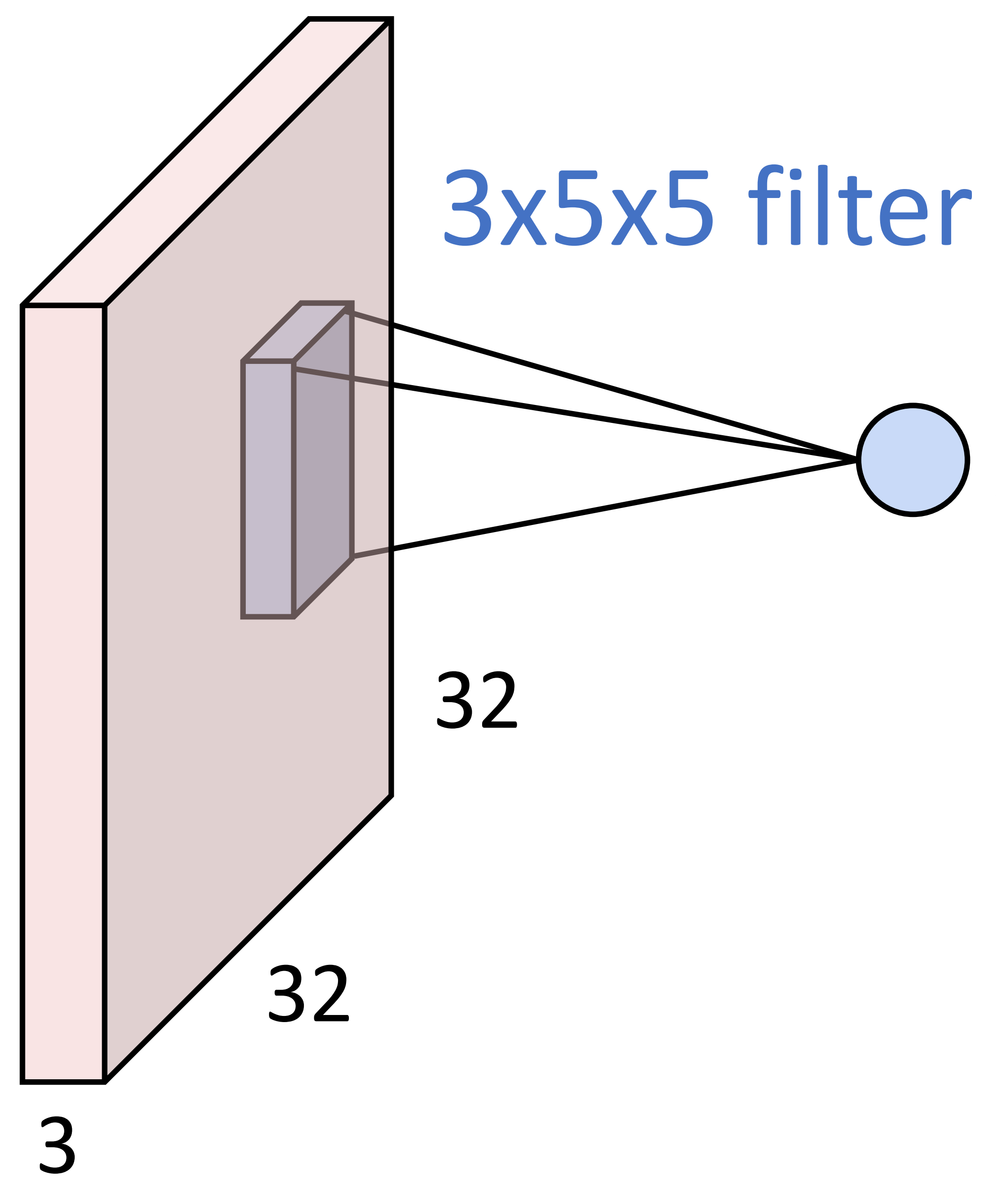
Filters always extend the full depth of the input volume



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

Convolution Layer

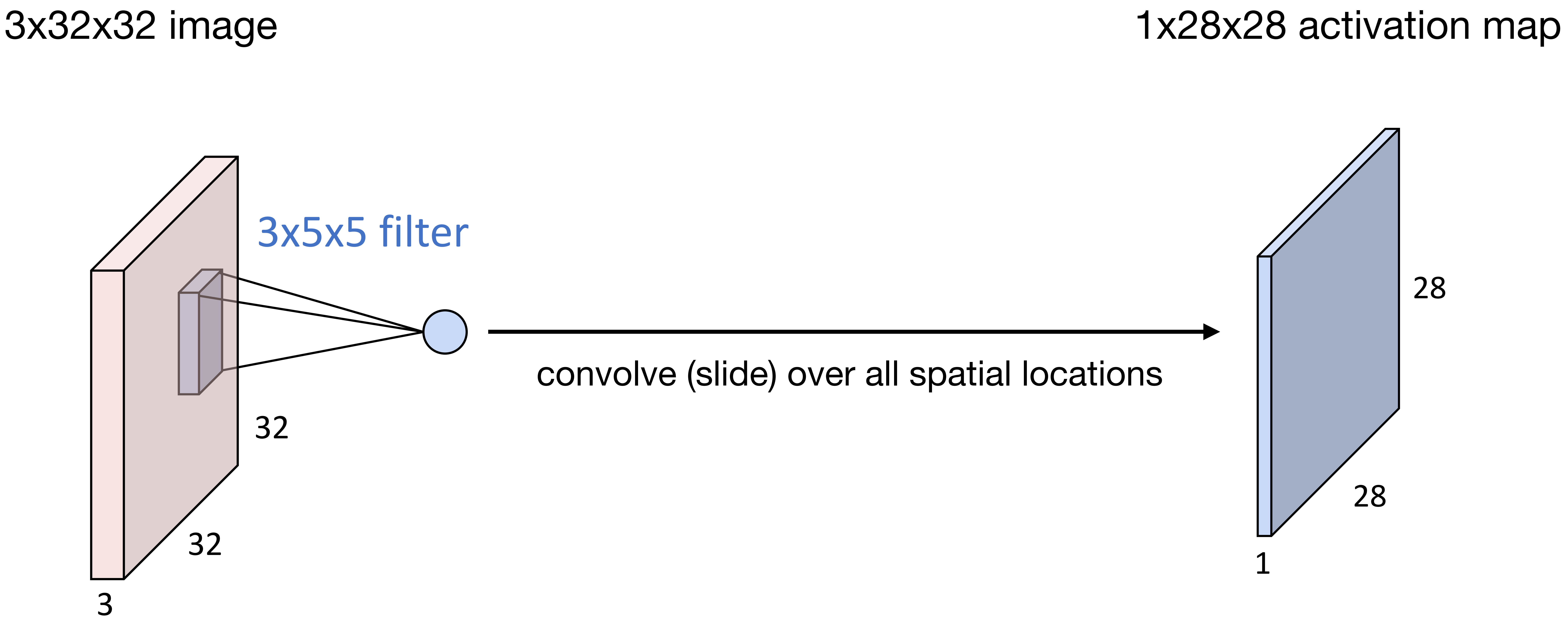
3x32x32 image



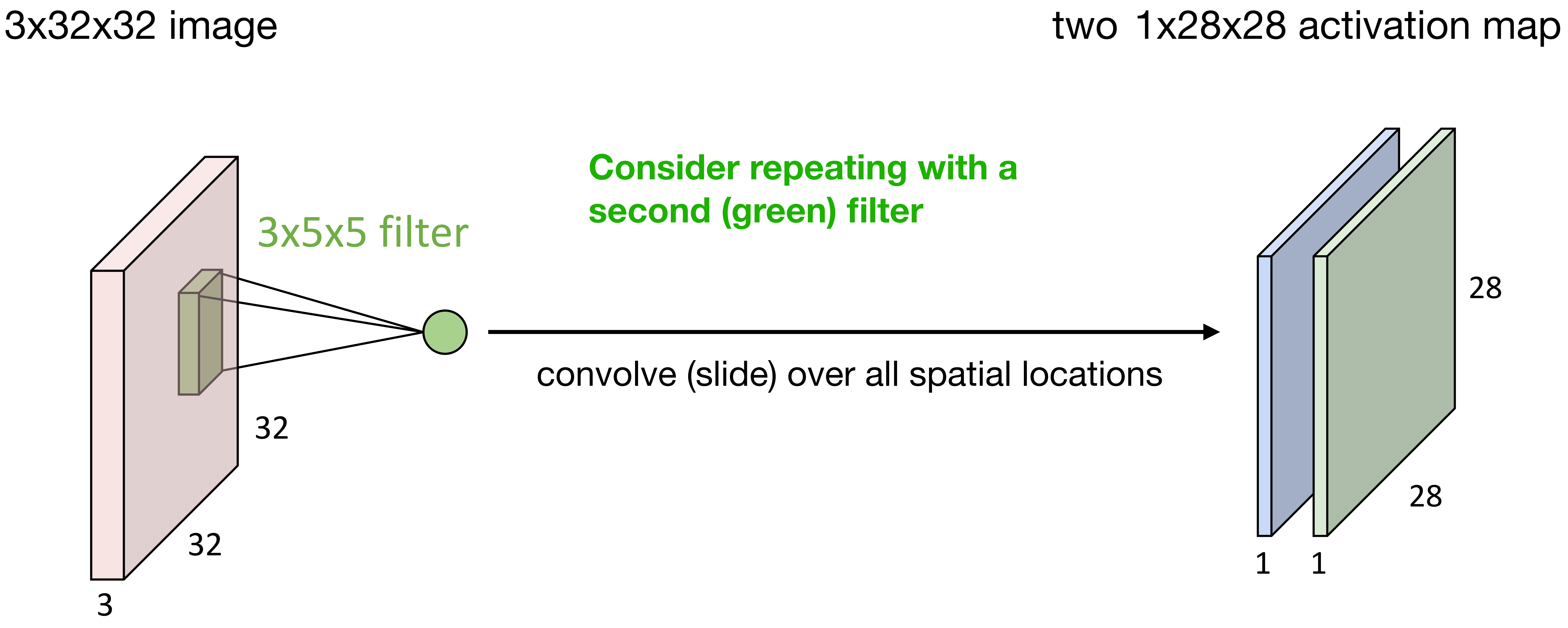
1 number:
The result of taking a dot product between the filter and a small 3x5x5 portion of the image
(i.e. 3*5*5=75-dimensional dot product + bias)

$$w^T x + b$$

Convolution Layer



Convolution Layer

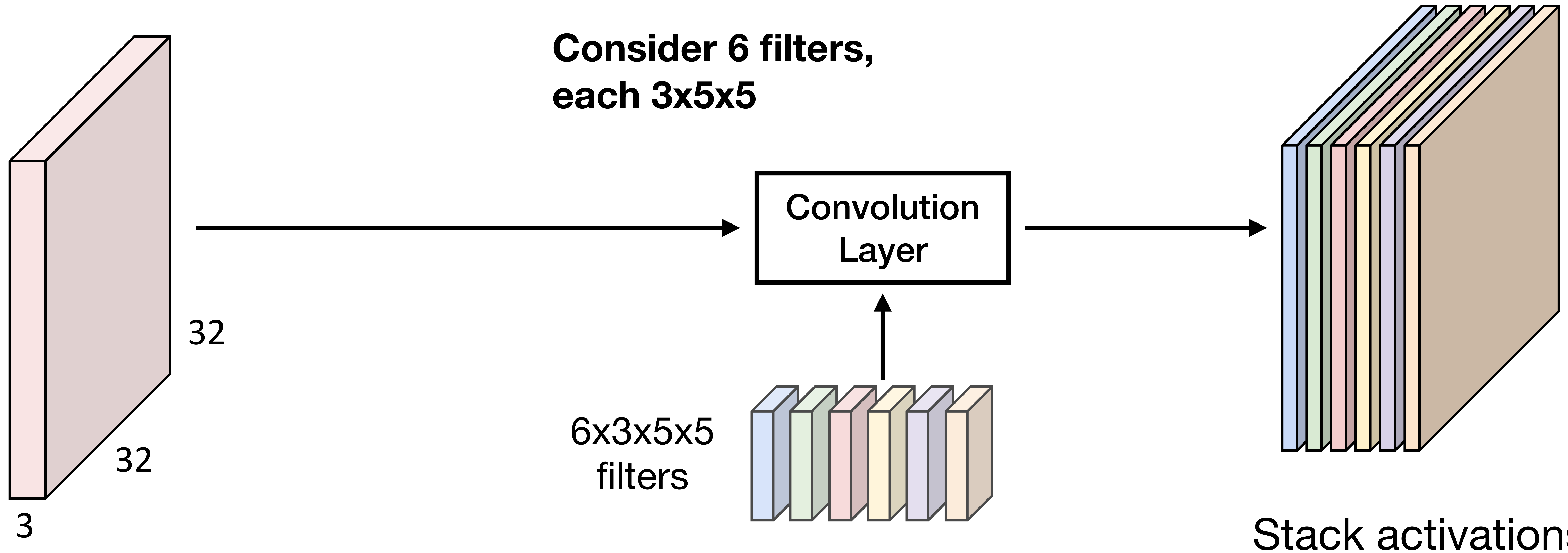

3x32x32 image
3x5x5 filter
32
32
3
Consider repeating with a second (green) filter
convolve (slide) over all spatial locations
two 1x28x28 activation map
28
28
1
1

Convolution Layer

3x32x32 image

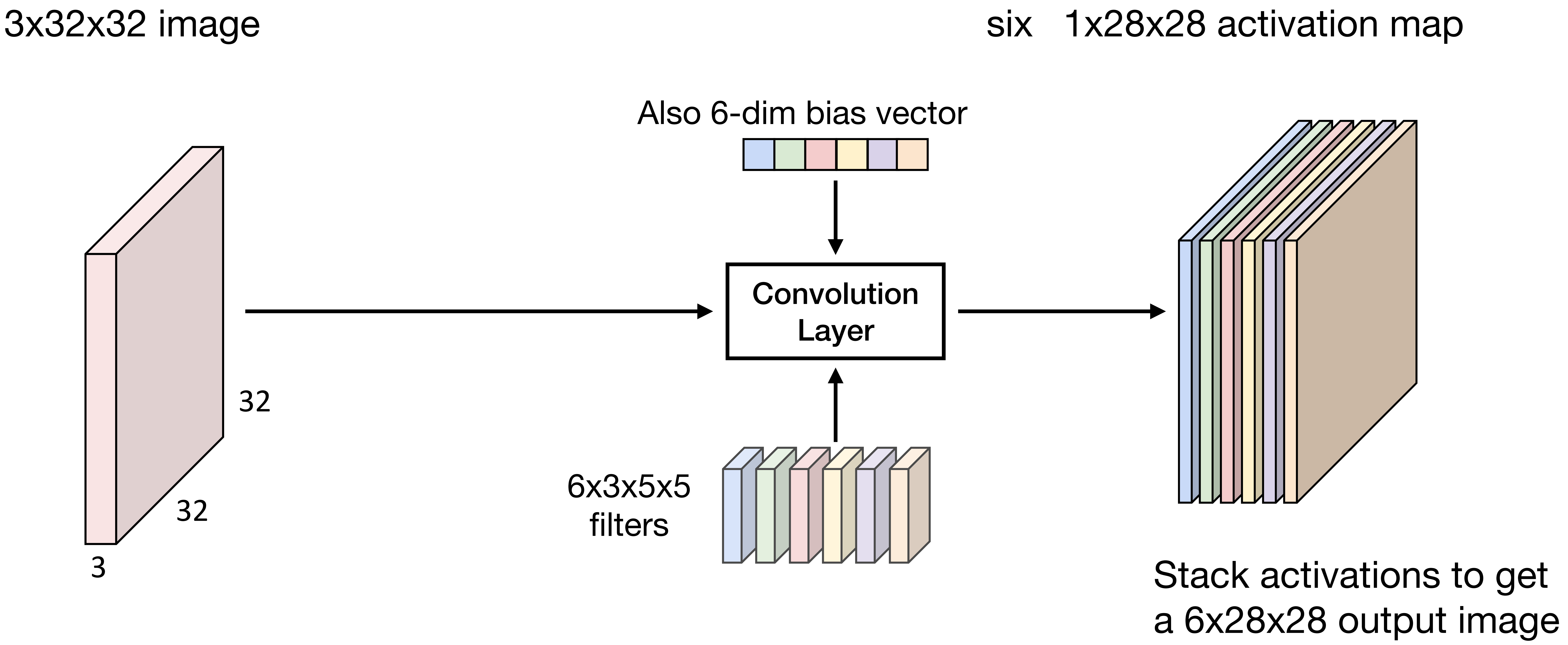
six 1x28x28 activation map

Consider 6 filters, each 3x5x5



Stack activations to get a 6x28x28 output image

Convolution Layer



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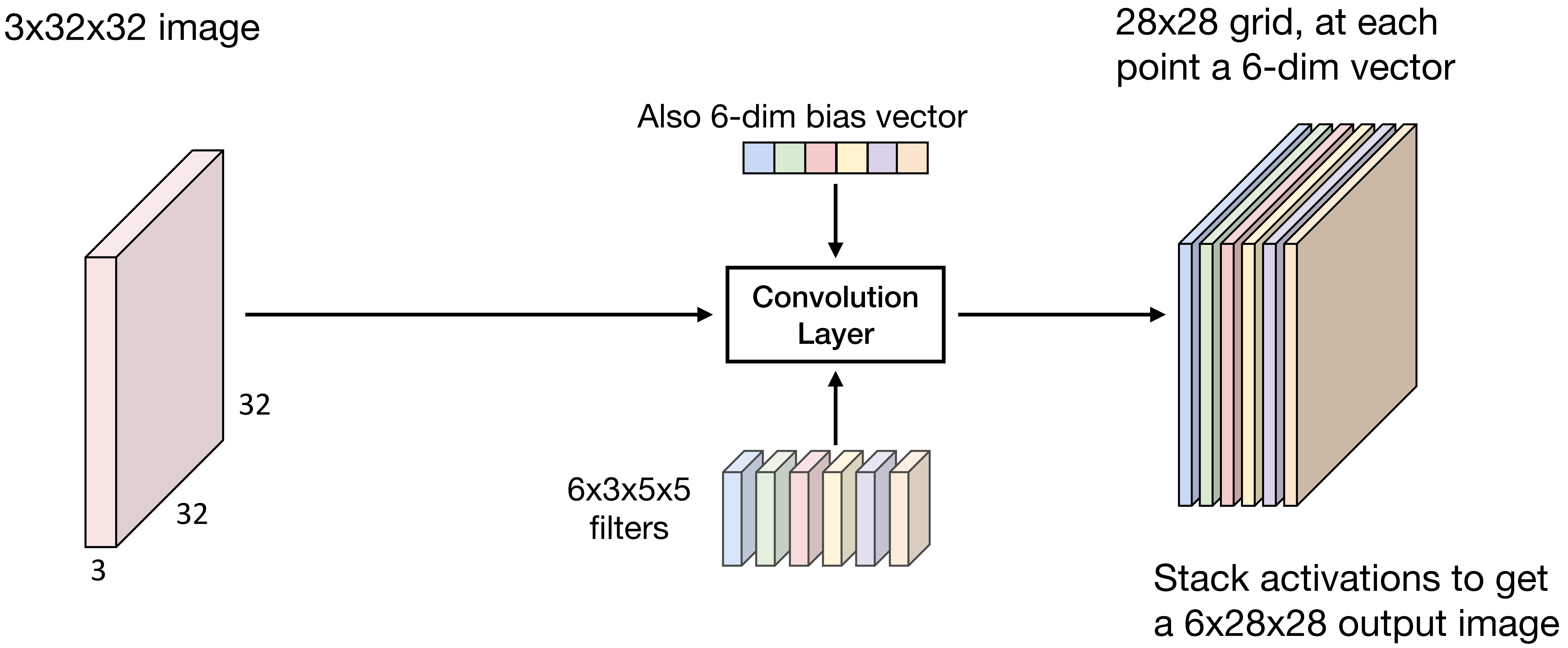
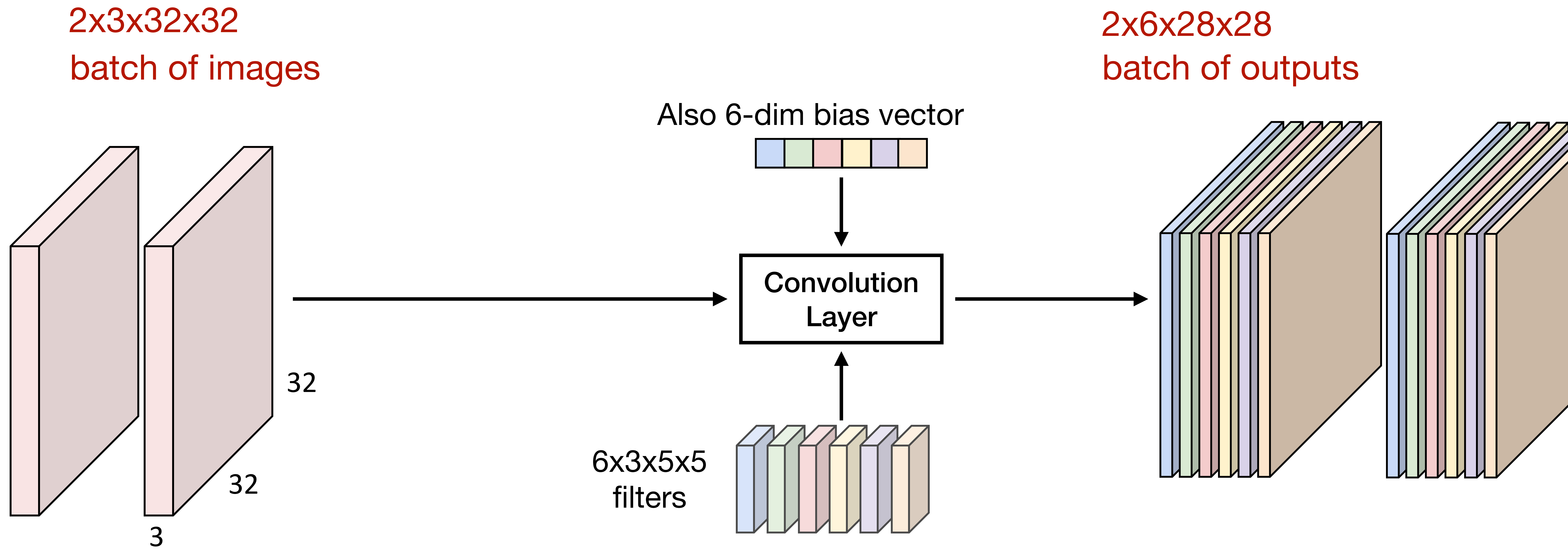
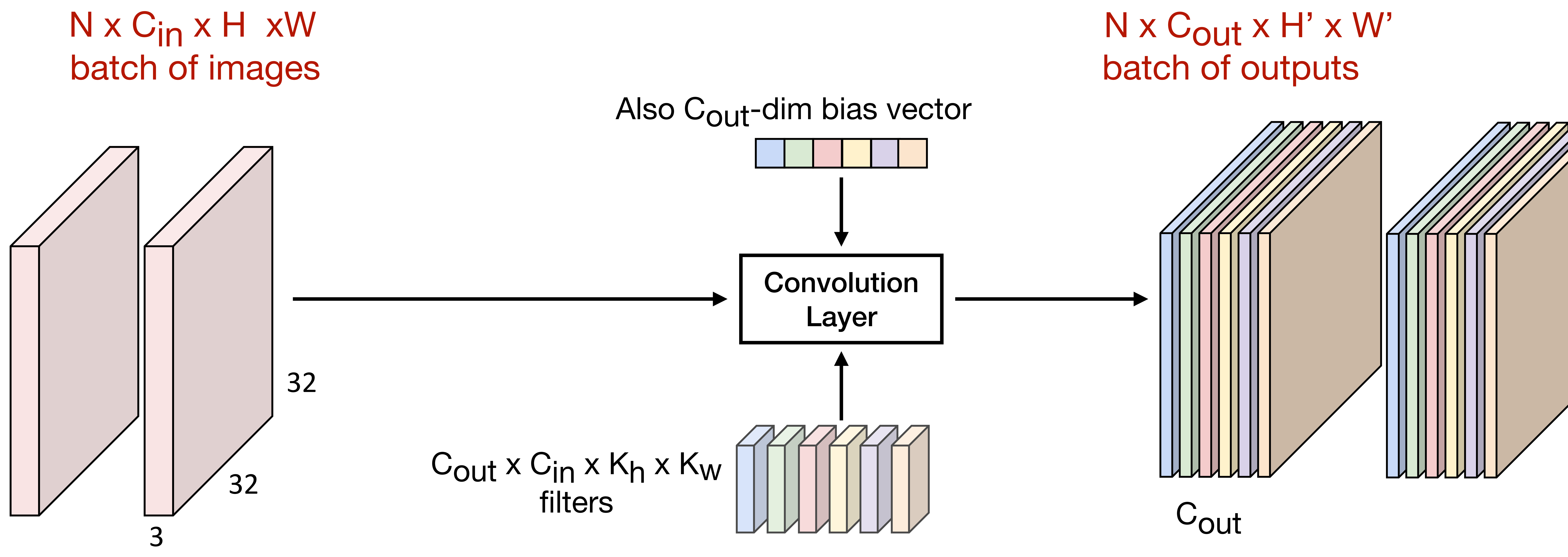
Convolution Layer


3x32x32 image
32
32
3
Also 6-dim bias vector
Convolution Layer
6x3x5x5 filters
28x28 grid, at each point a 6-dim vector
Stack activations to get a 6x28x28 output image

Convolution Layer

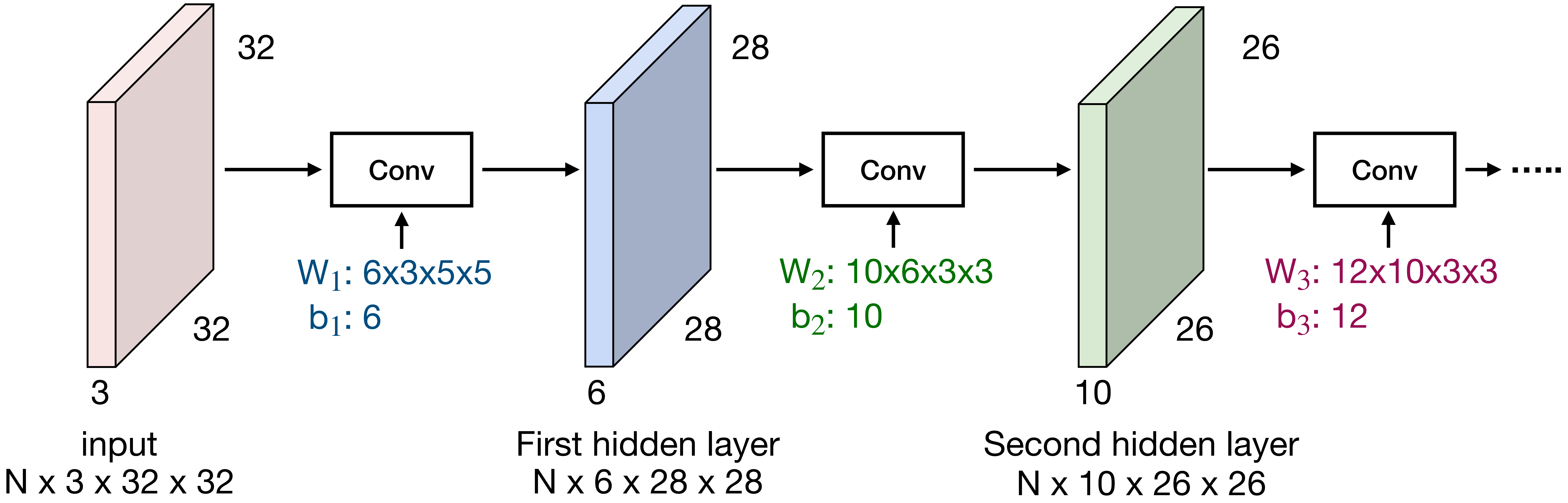


Convolution Layer



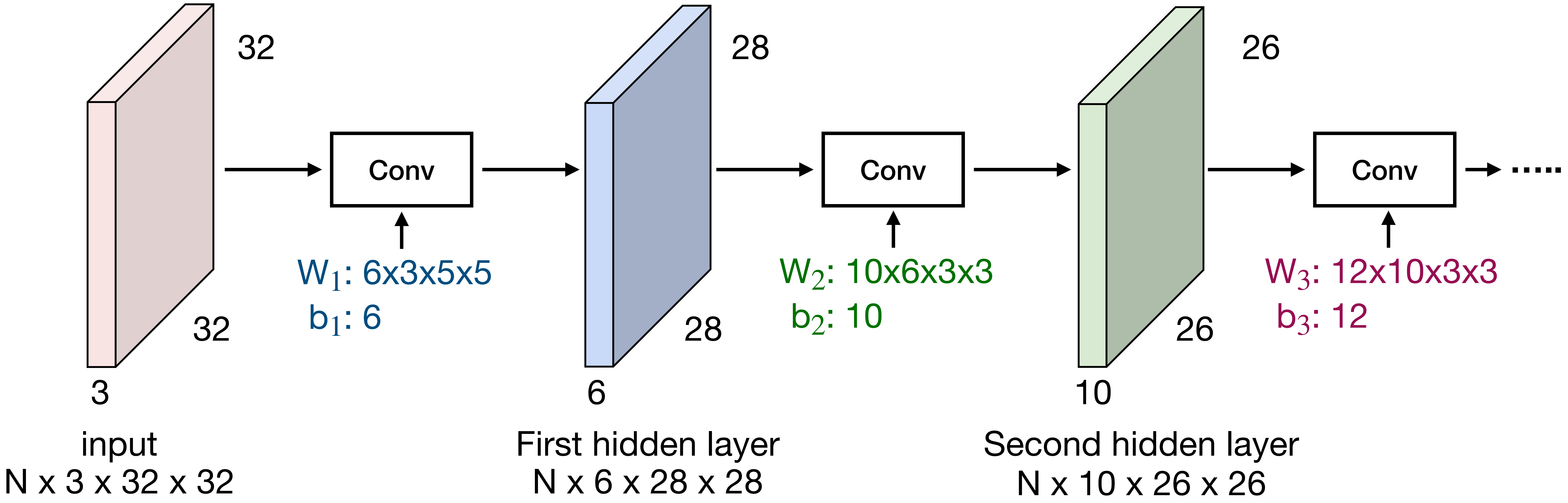
$N \times C_{in} \times H \times W$
batch of images
32
32
3
Also C_{out}-dim bias vector
Convolution Layer
$C_{out} \times C_{in} \times K_h \times K_w$
filters
$N \times C_{out} \times H' \times W'$
batch of outputs
C_{out}

Stacking Convolutions



Stacking Convolutions

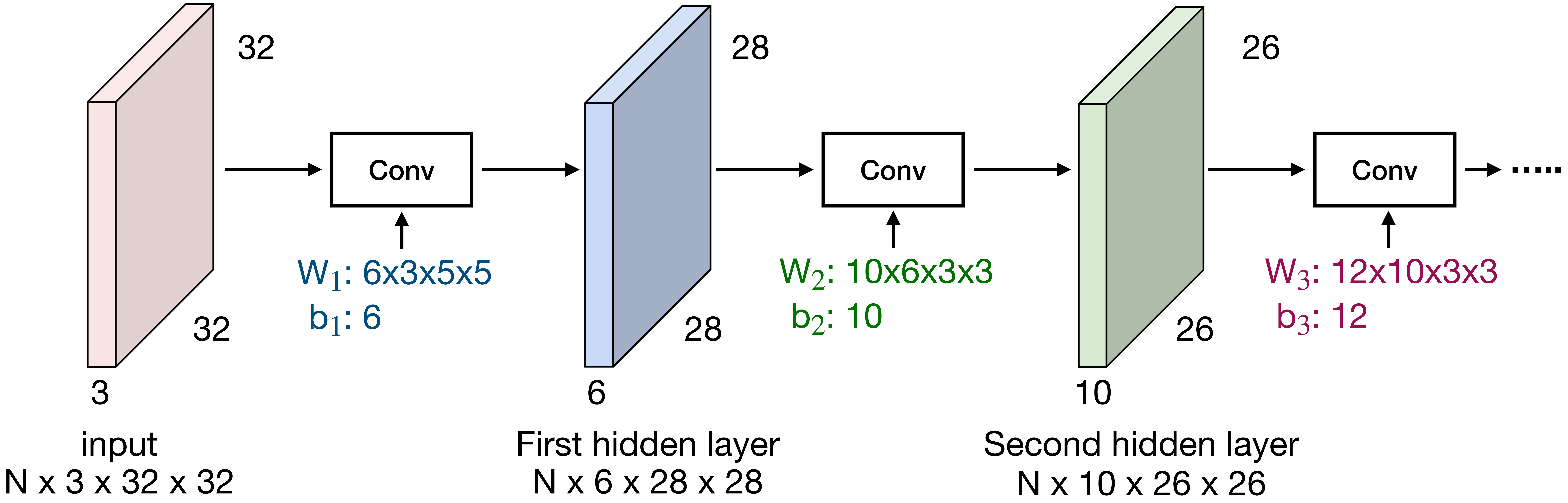
Q: What happens if we stack two convolution layers?



Stacking Convolutions

Q: What happens if we stack two convolution layers?

(Recall $y=W_2W_1x$ is a linear classifier)



Stacking Convolutions

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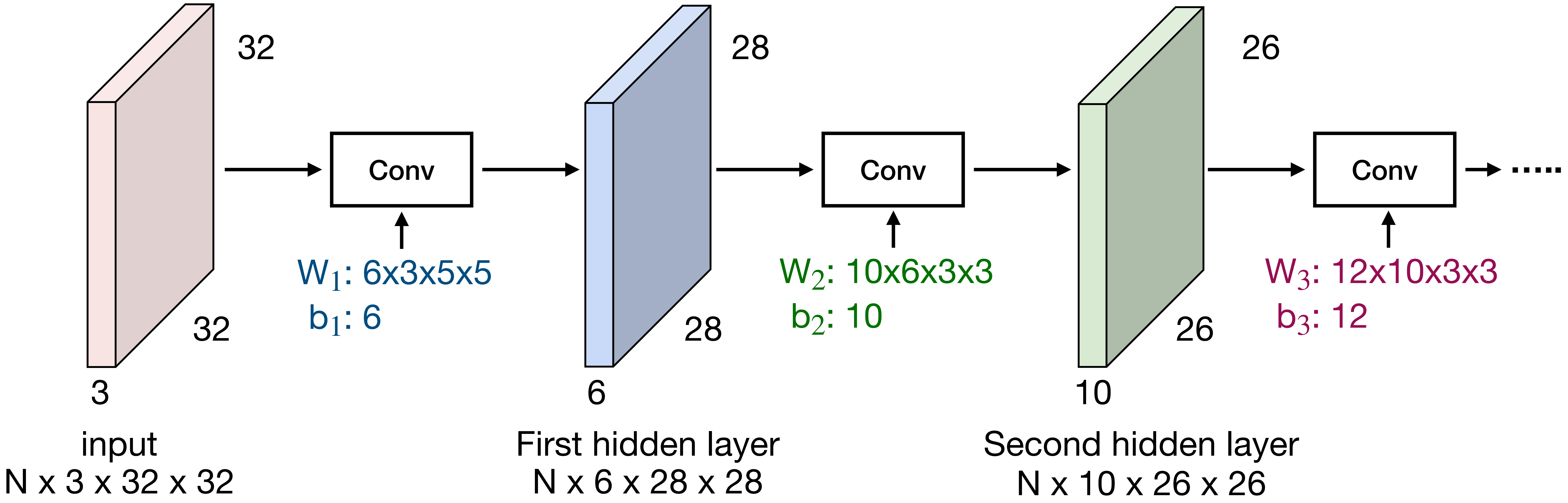
A: We get another convolution!



Stacking Convolutions

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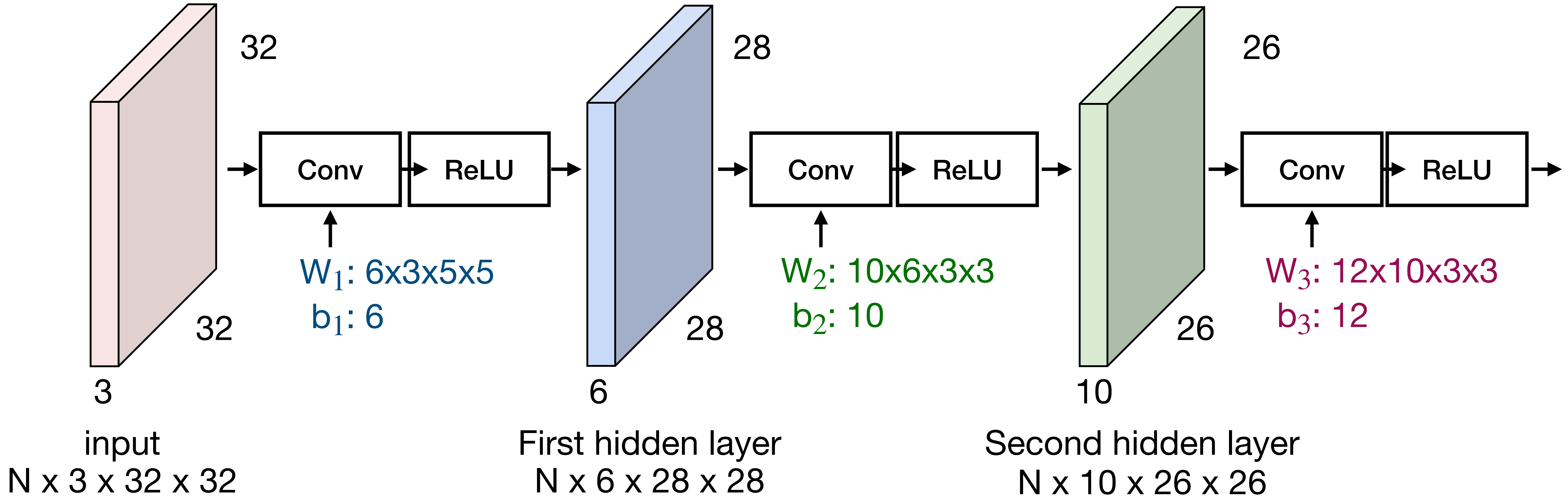
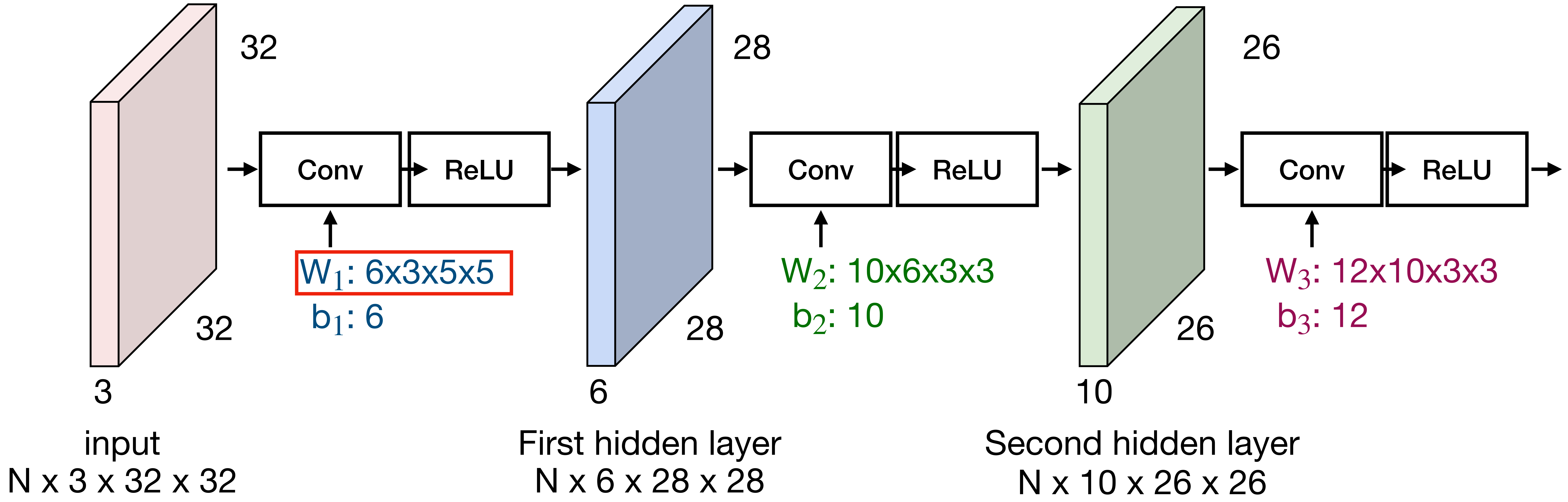


What do convolutional filters learn?



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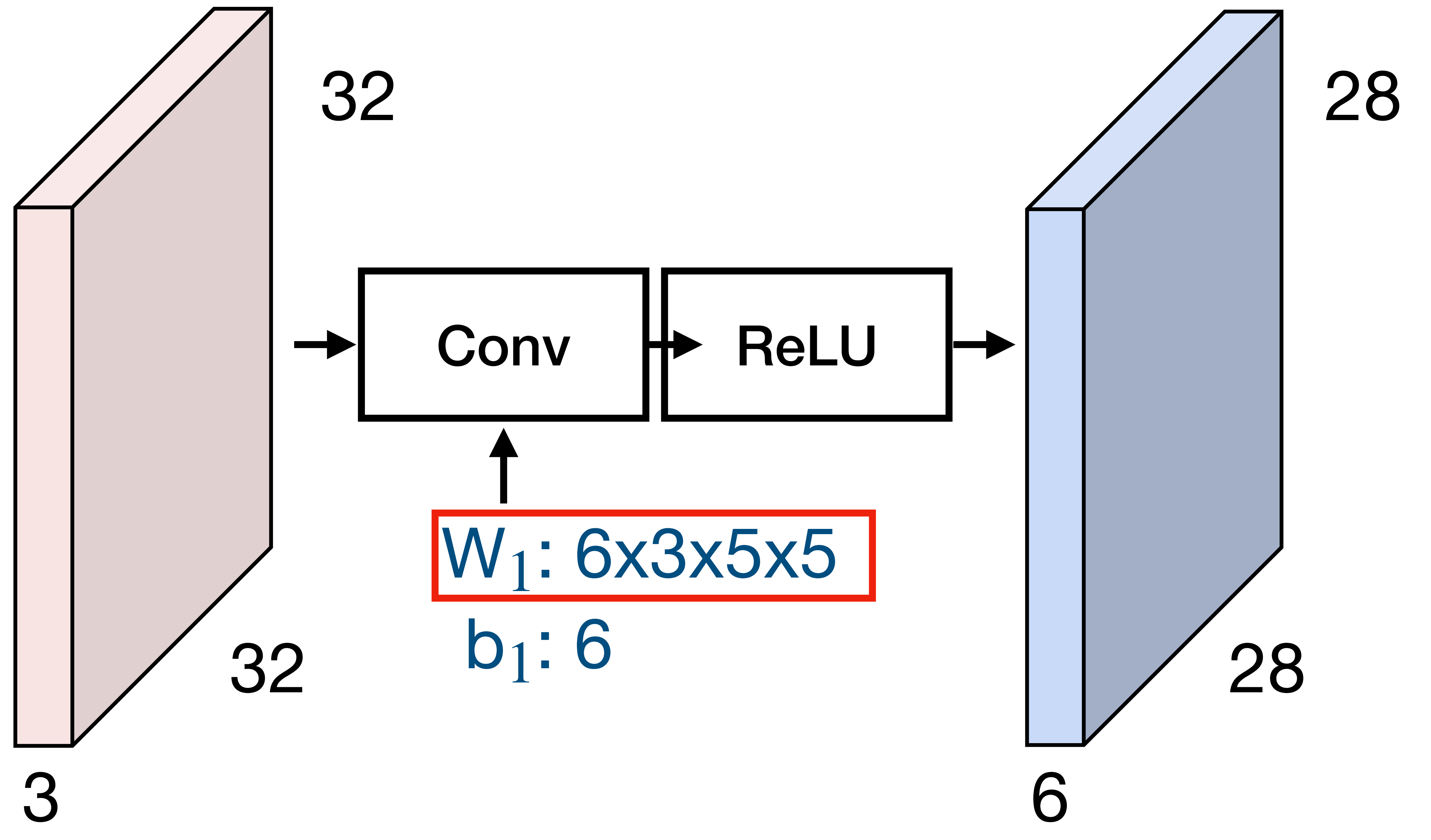
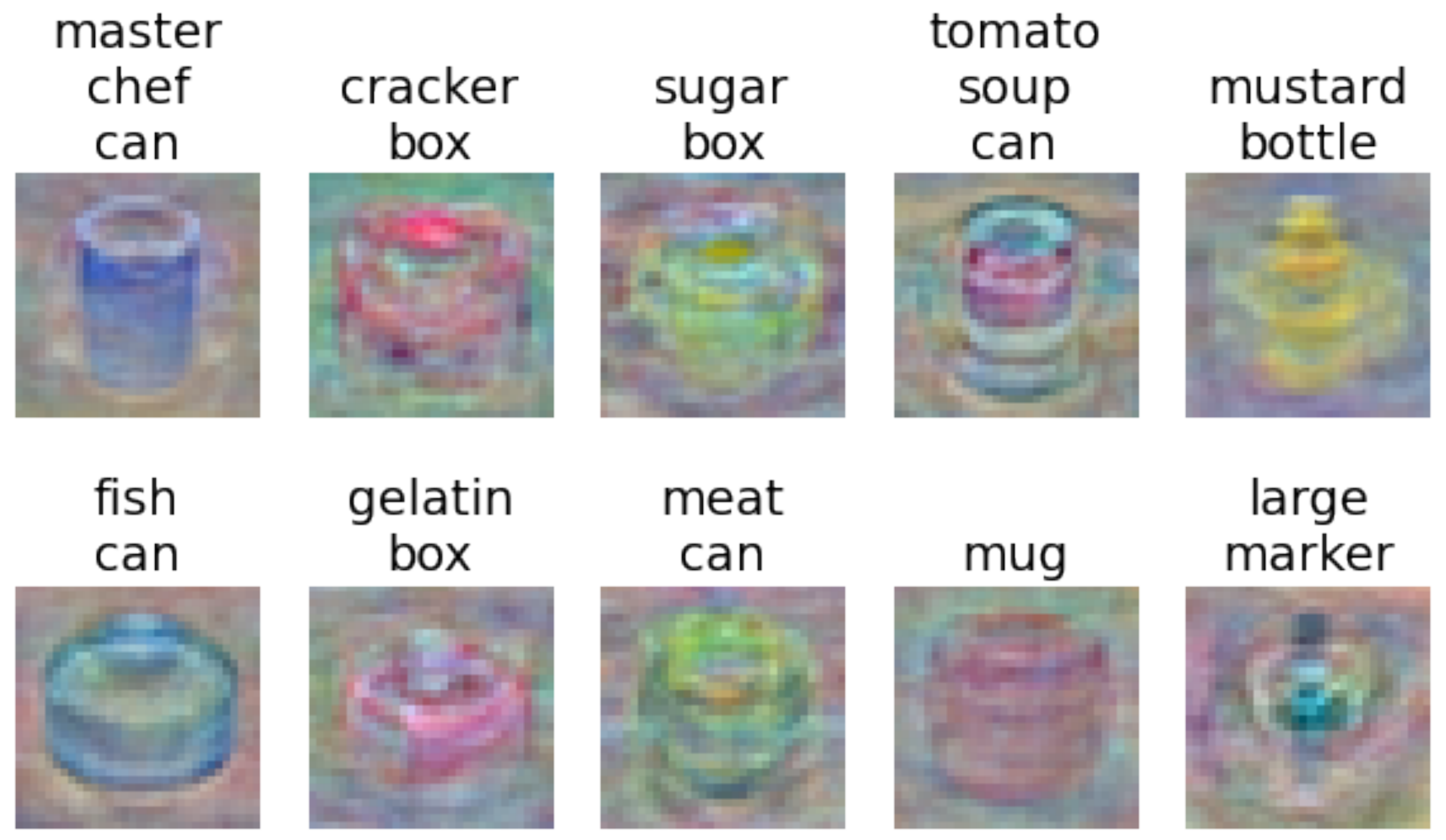


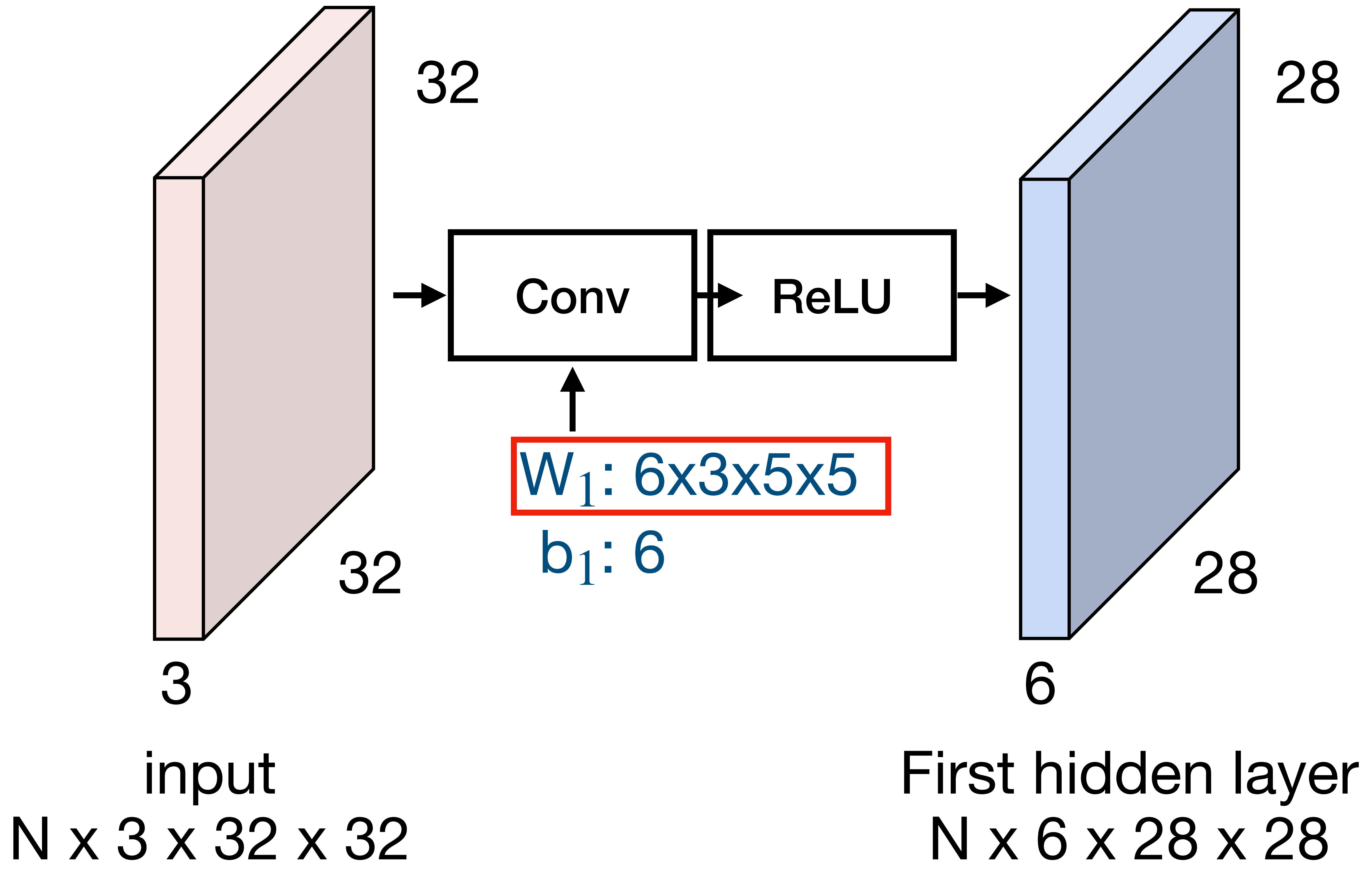
input
N x 3 x 32 x 32

First hidden layer
N x 6 x 28 x 28

Linear classifier: One template per class

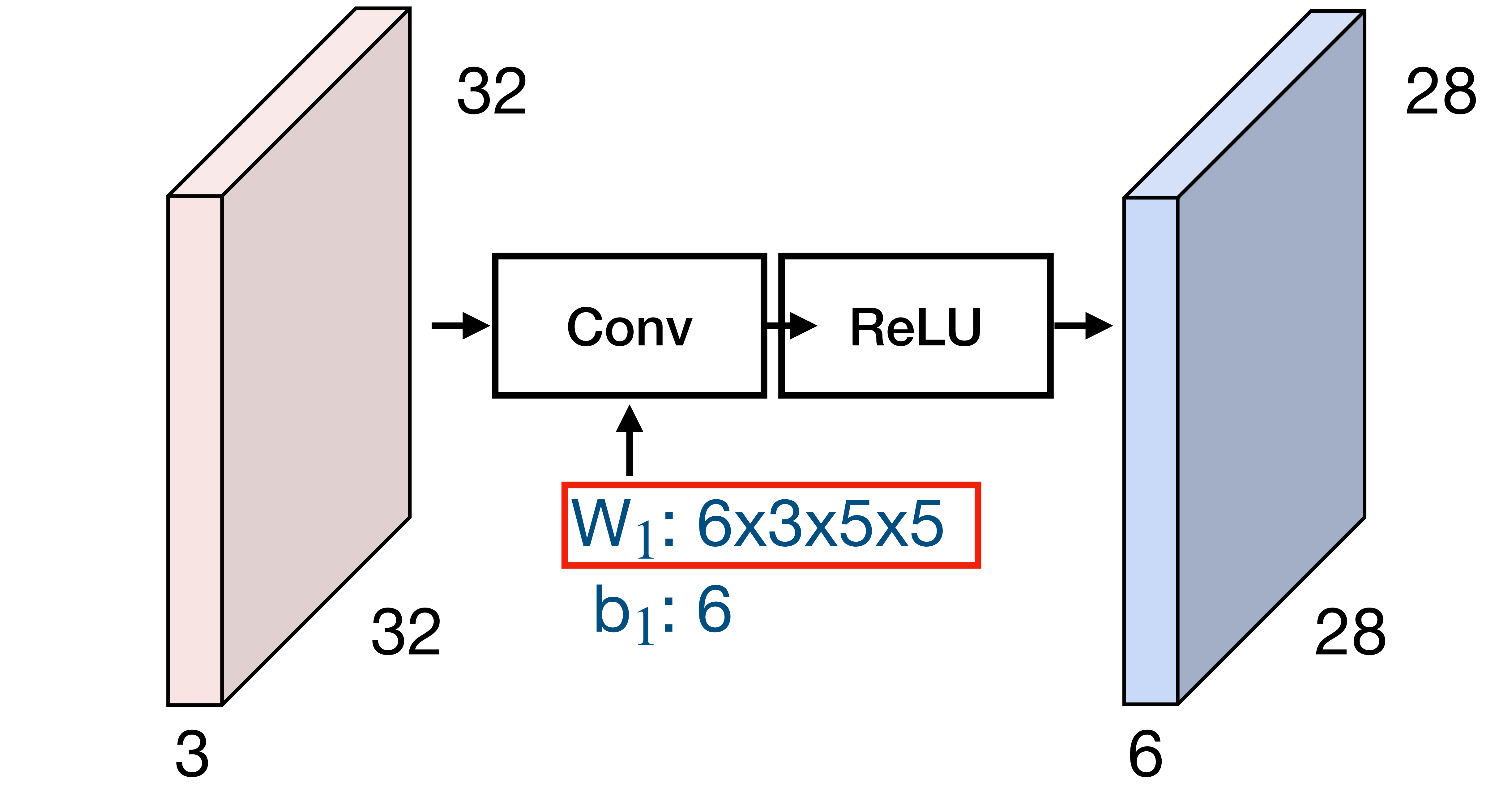


What do convolutional filters learn?



MLP: Bank of whole-image templates

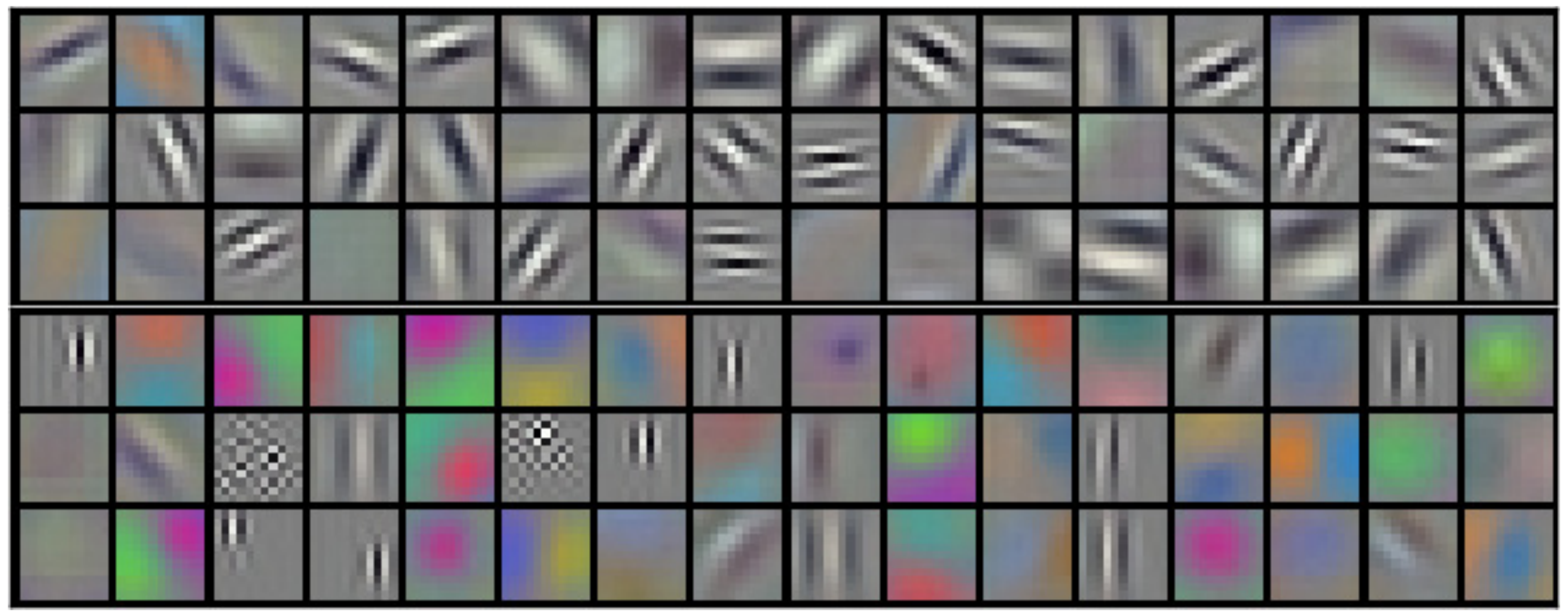
What do convolutional filters learn?



input
N x 3 x 32 x 32

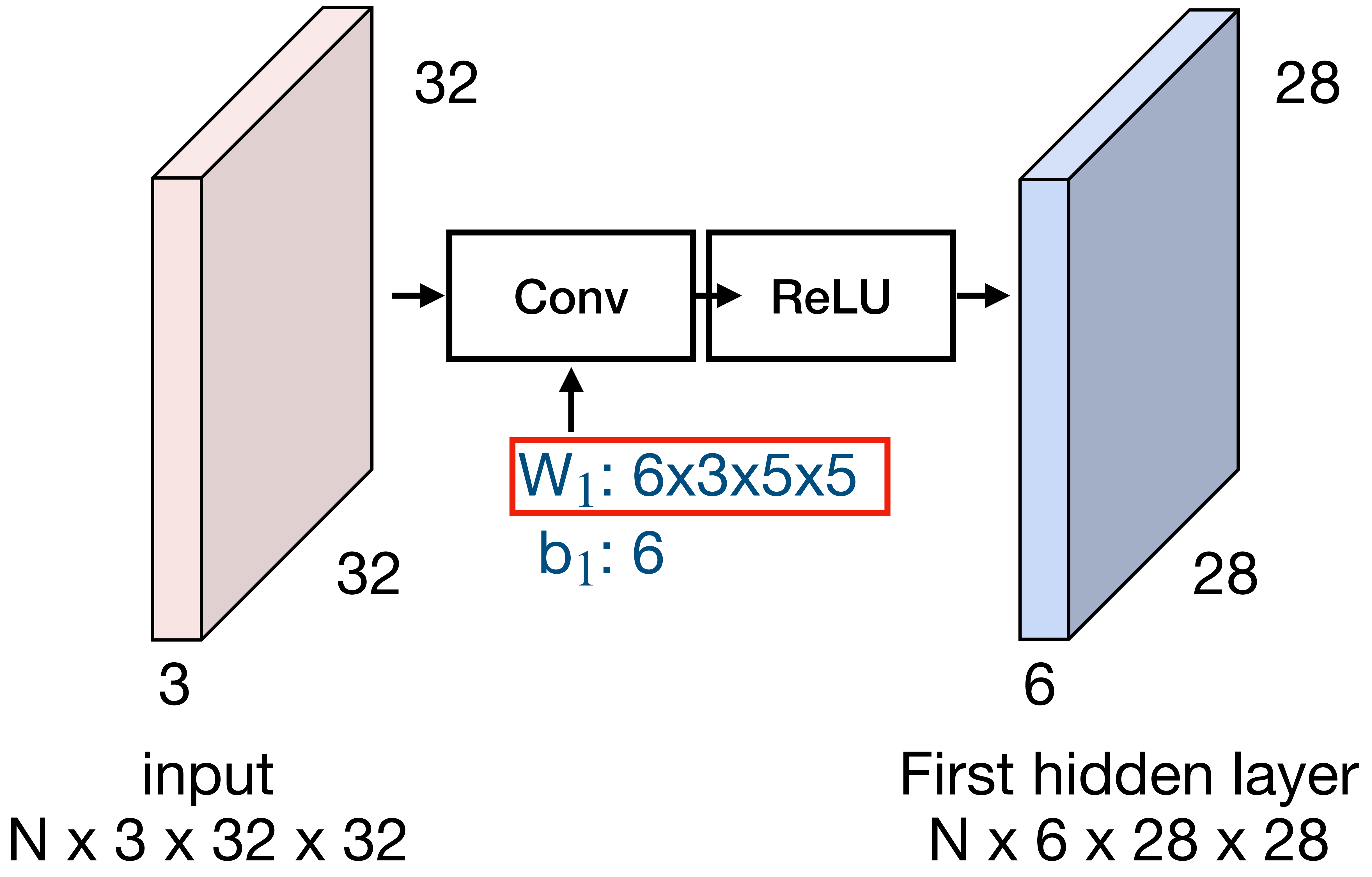
First hidden layer
N x 6 x 28 x 28

First-layer conv filters: local image templates
(often learns oriented edges, opposing colors)



AlexNet: 96 filters, each 3x11x11

A closer look at spatial dimensions



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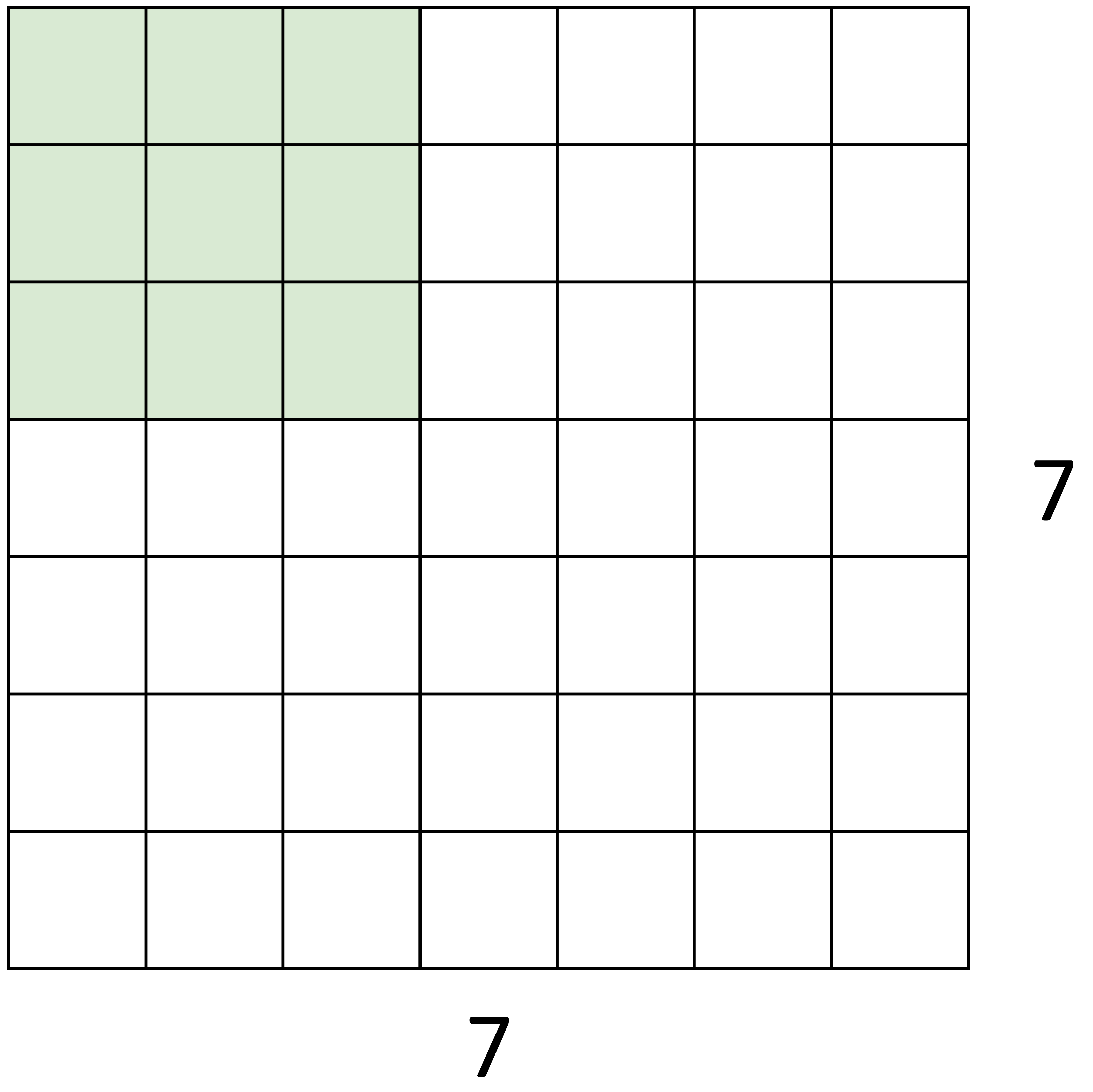
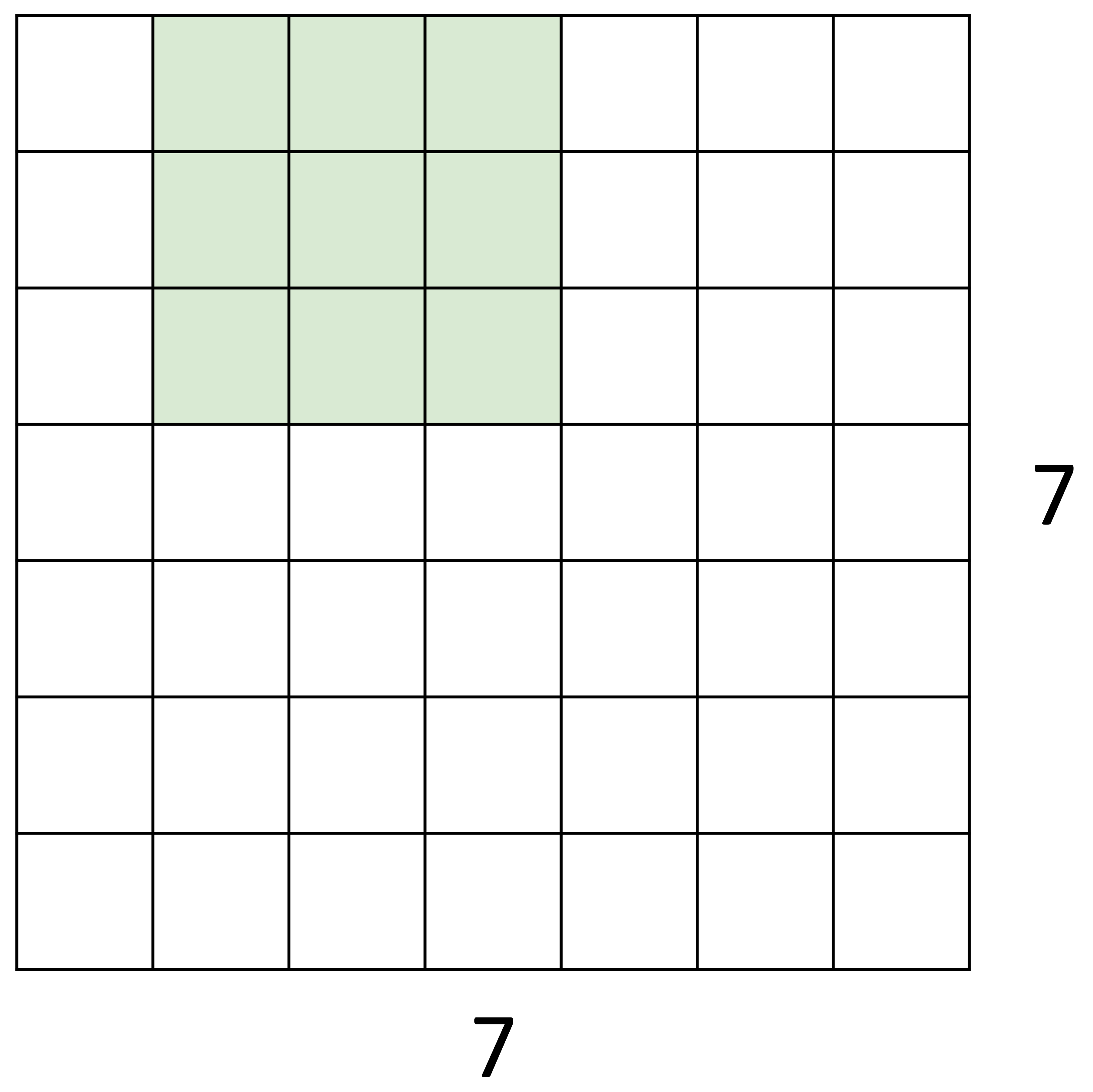


Input: 7x7

Filter: 3x3

A closer look at spatial dimensions



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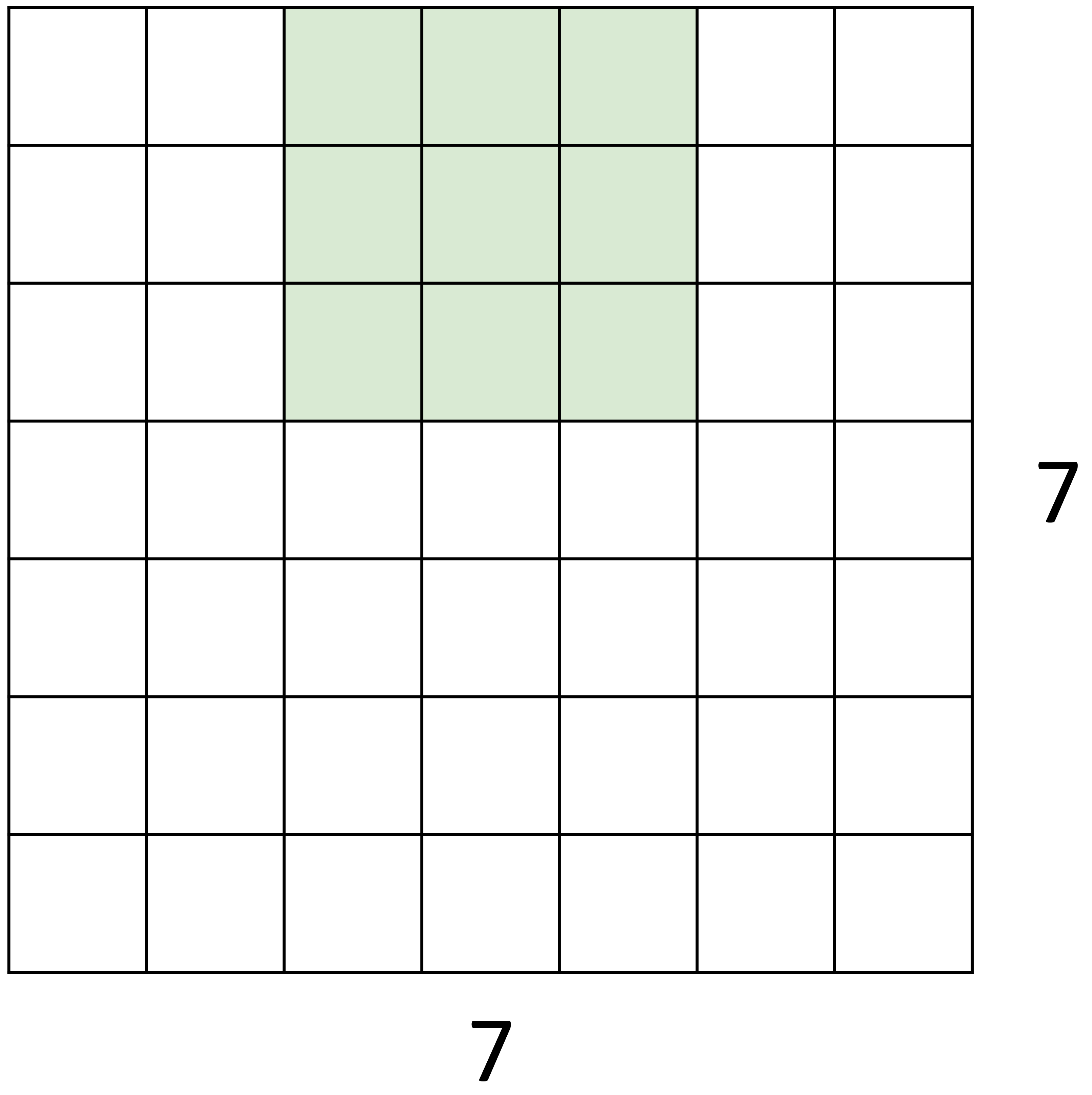

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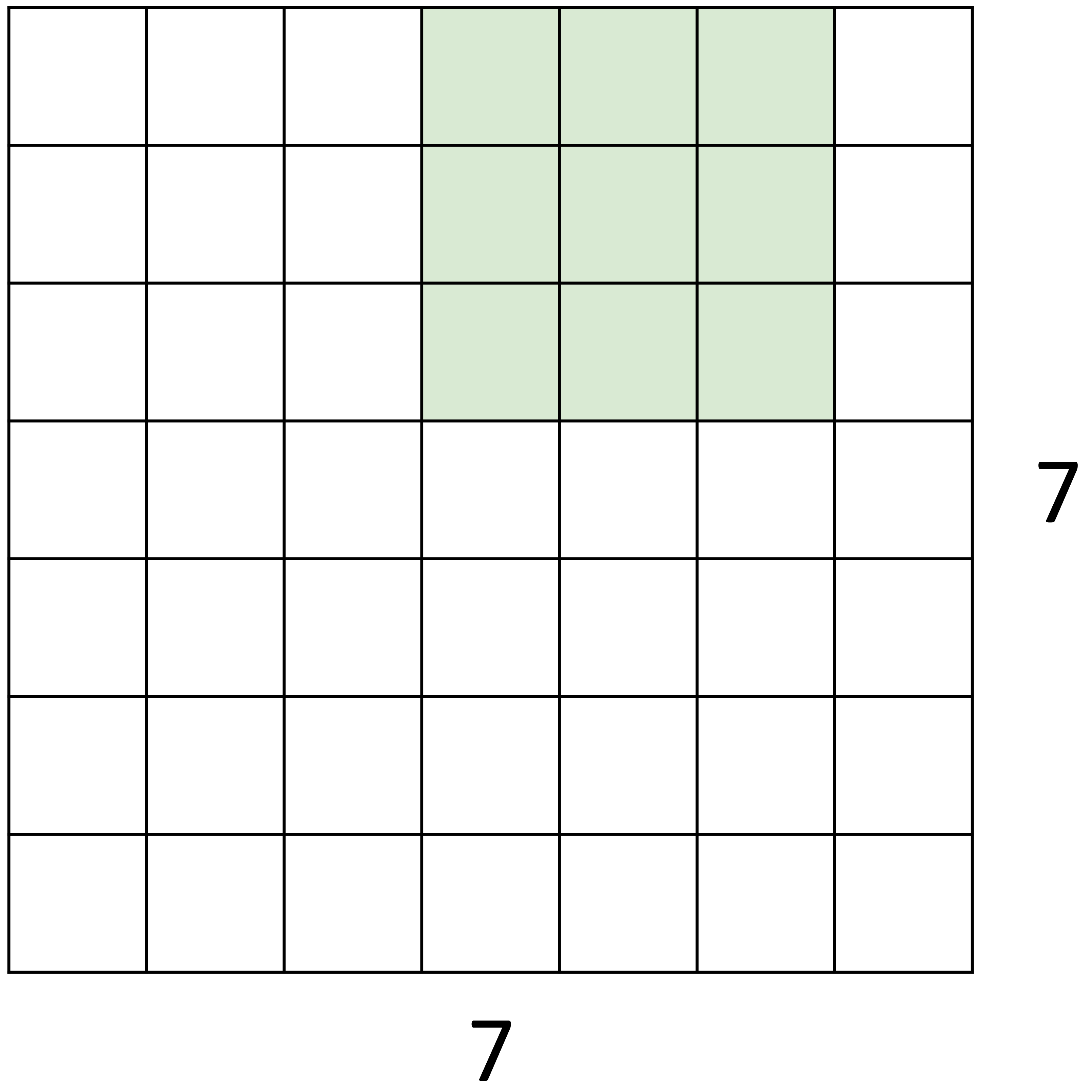

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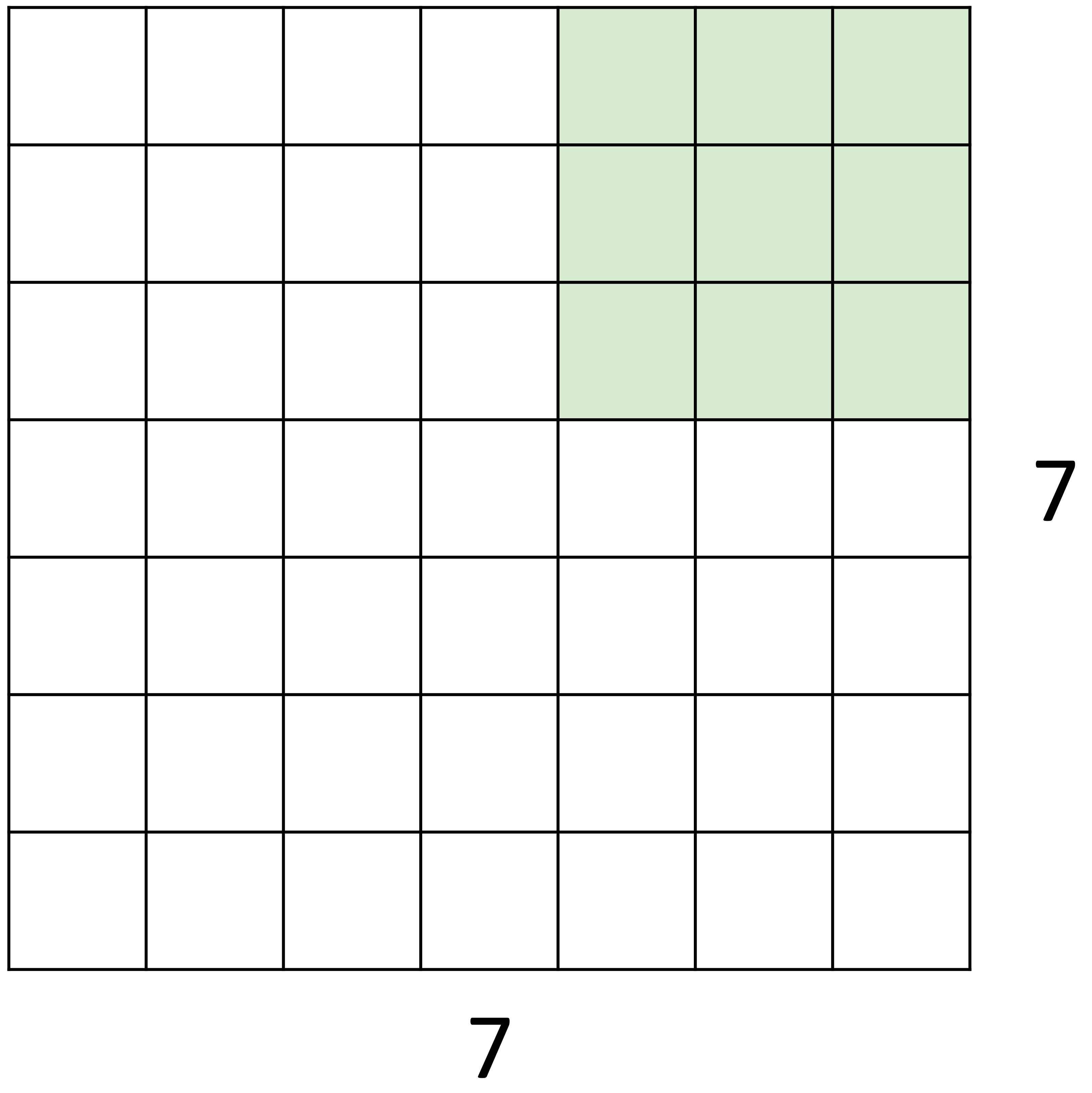
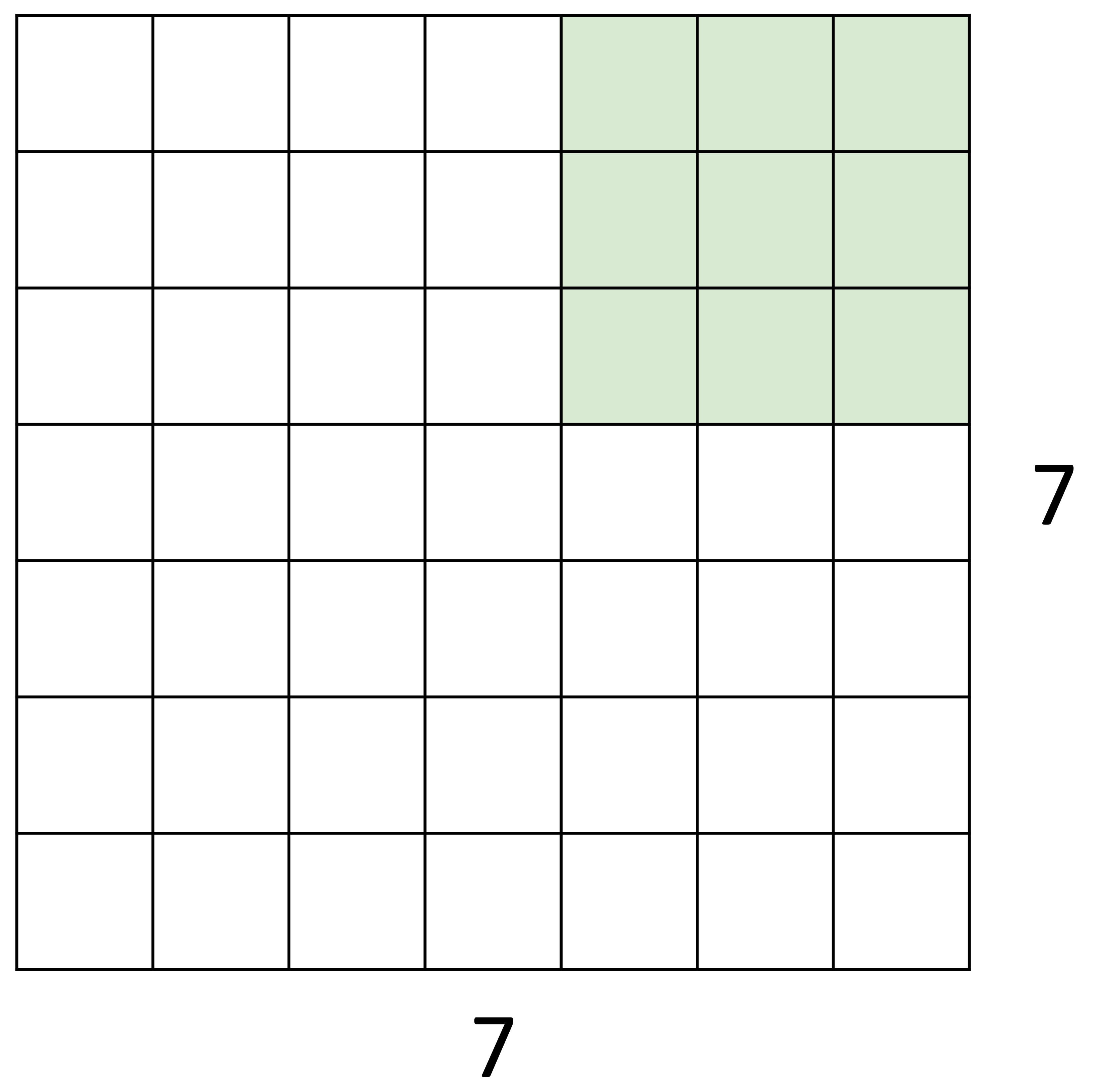


Input: 7x7

Filter: 3x3

Output: 5x5

A closer look at spatial dimensions



Input: 7x7

Filter: 3x3

Output: 5x5

In general:

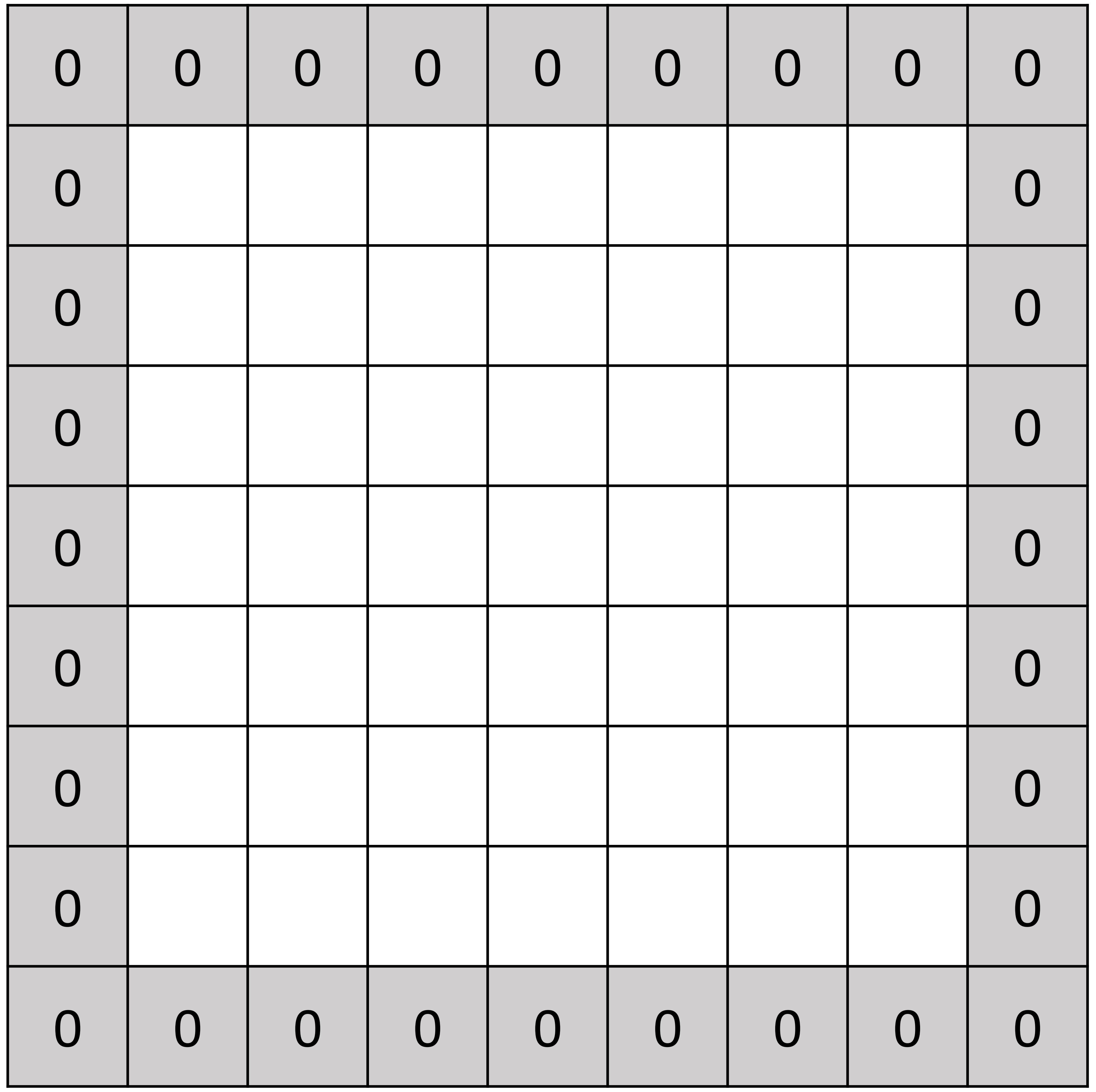
Input: W

Filter: K

Output: W – K + 1

Problem: Feature maps "shrink" with each layer!

A closer look at spatial dimensions



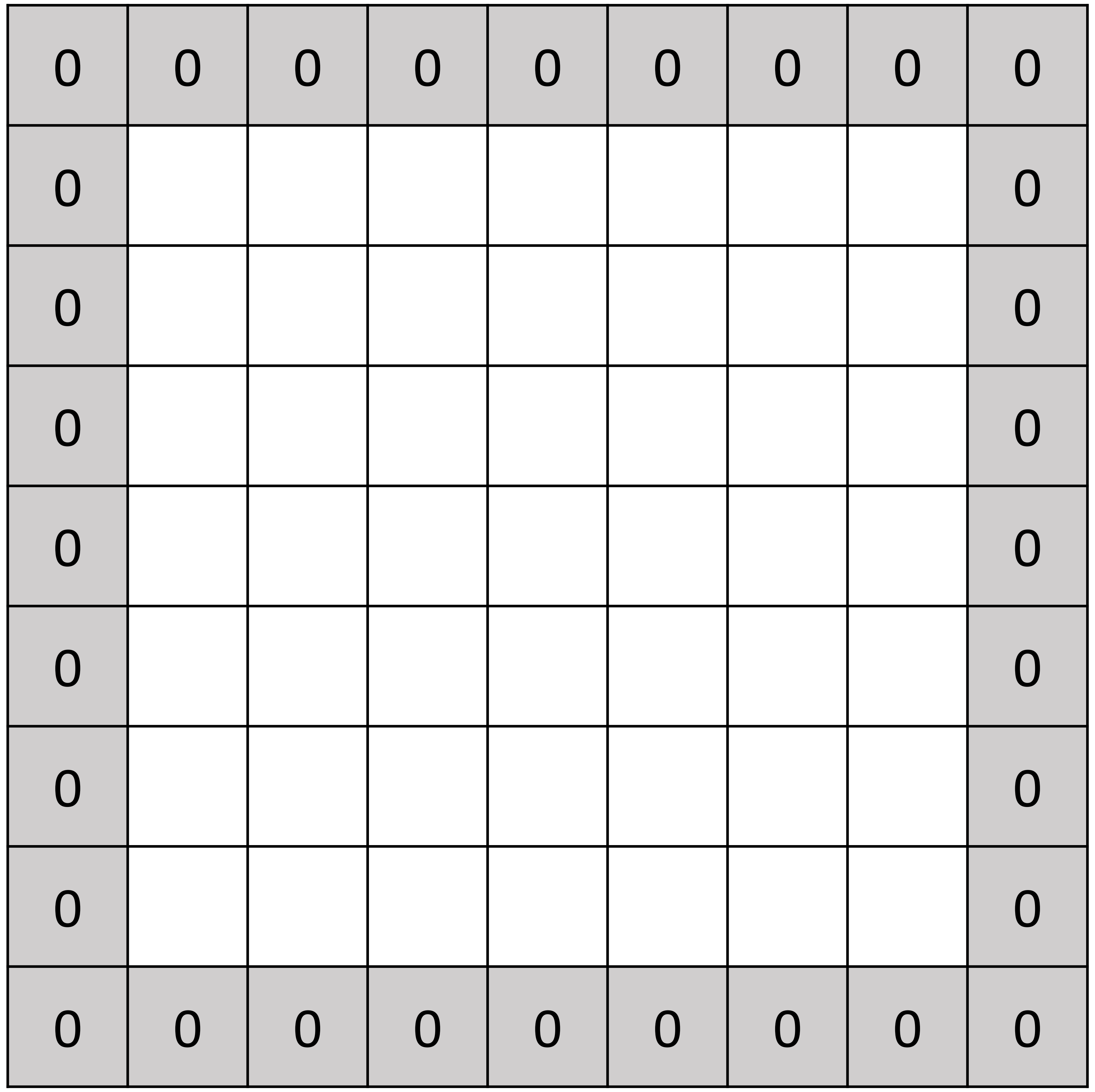
Input: 7x7
Filter: 3x3
Output: 5x5

In general:
Input: W
Filter: K
Output: W – K + 1

Problem: Feature maps "shrink" with each layer!

Solution: **padding**
Add zeros around the input

A closer look at spatial dimensions



Input: 7x7

Filter: 3x3

Output: 5x5

In general:

Input: W

Filter: K

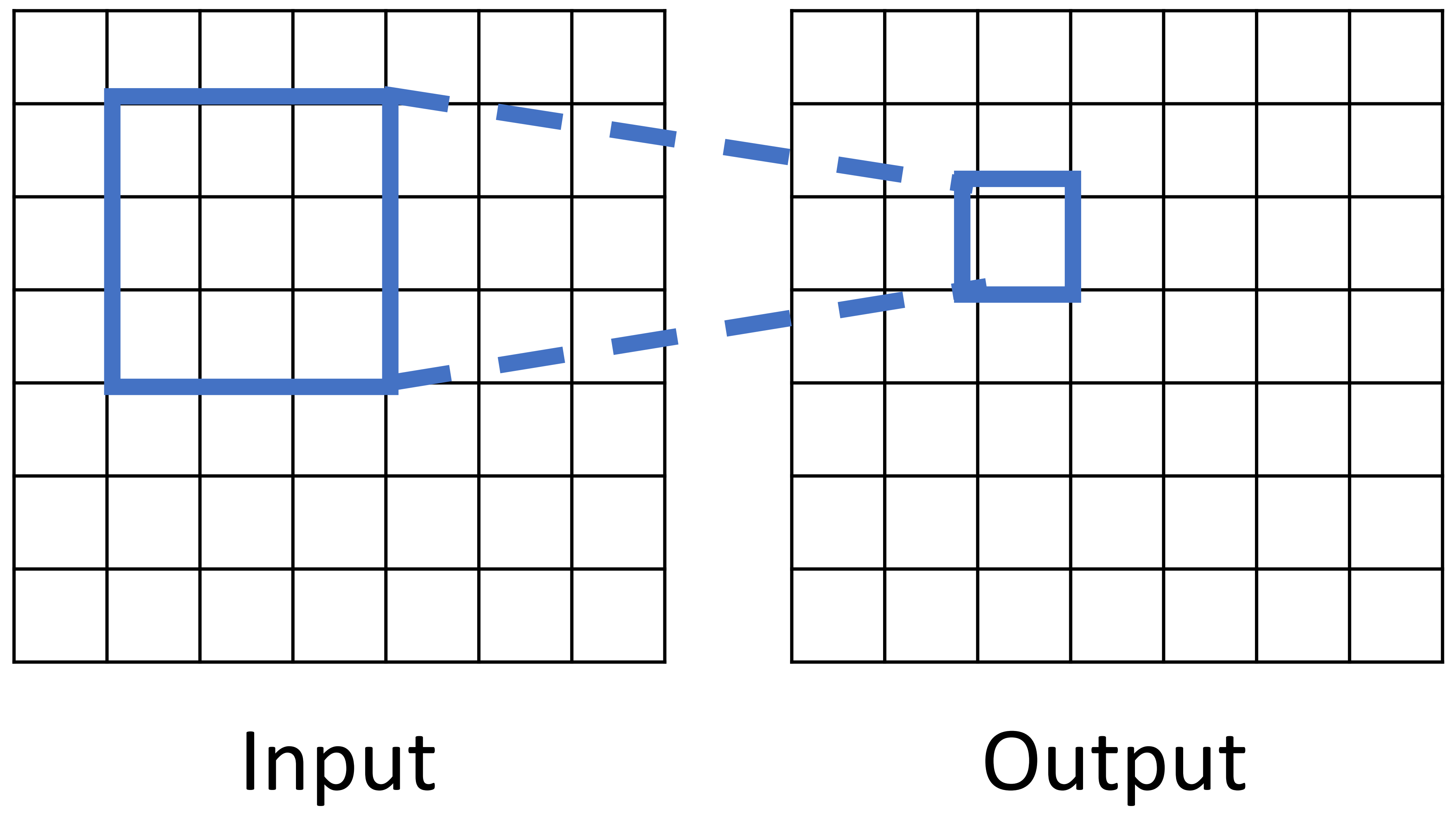
Padding: P

Output: W – K + 1 + 2P

Very common:
Set P = (K – 1) / 2 to make output have same size as input!

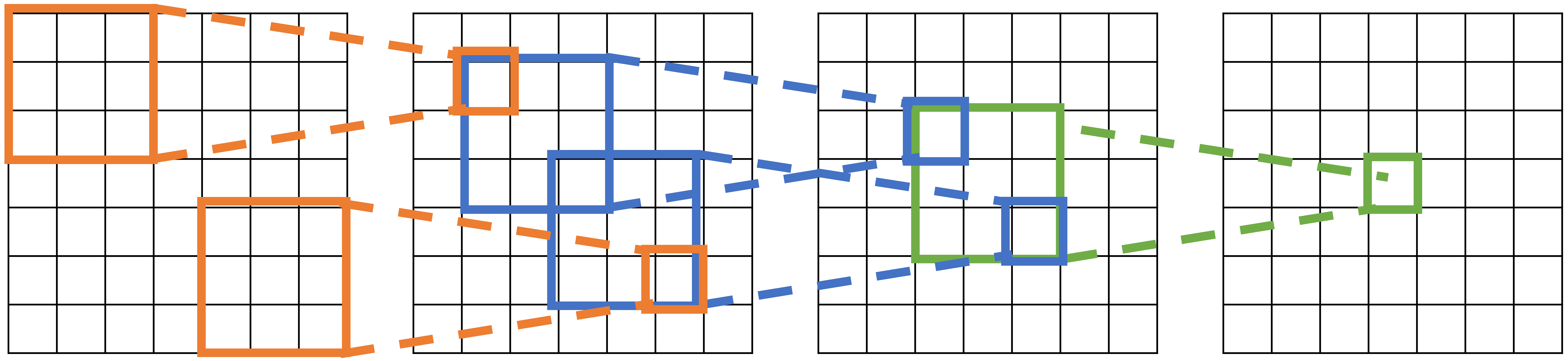
Receptive Fields

For convolution with kernel size K, each element in the output depends on a K x K **receptive field** in the input



Receptive Fields

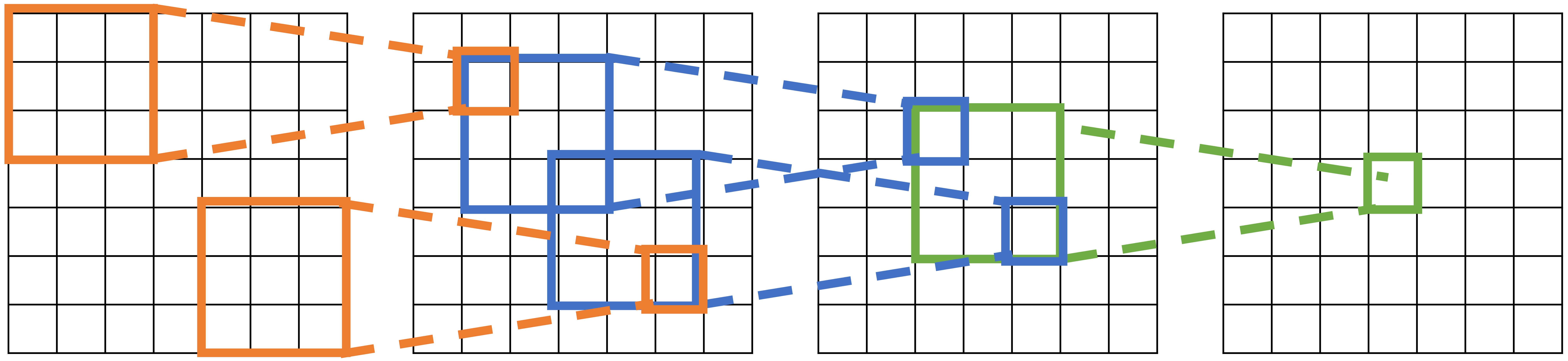
Each successive convolution adds K – 1 to the receptive field size
With L layers the receptive field size is 1 + L * (K – 1)



Be careful – ”receptive field in the input” vs “receptive field in the previous layer”
Hopefully clear from context!

Receptive Fields

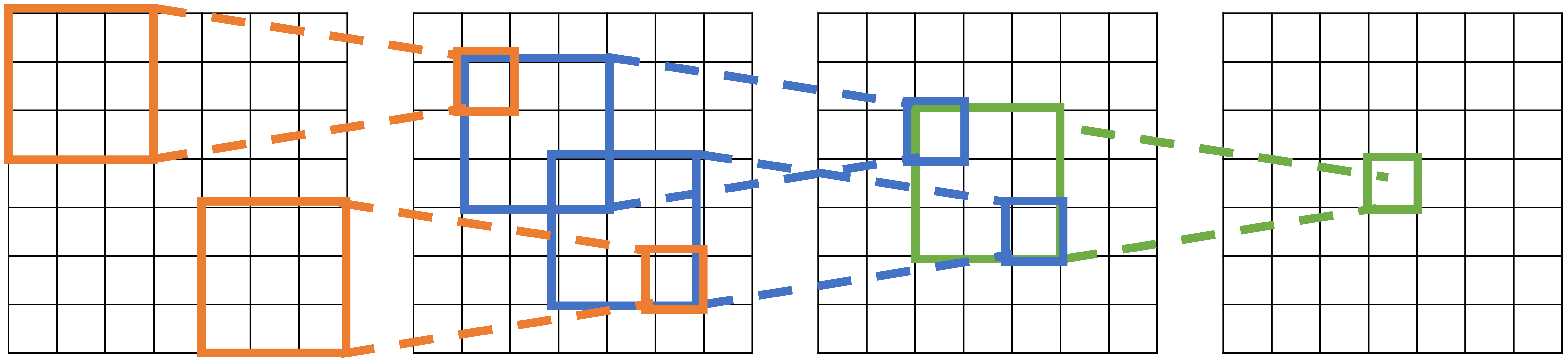
Each successive convolution adds K – 1 to the receptive field size
With L layers the receptive field size is 1 + L * (K – 1)



Problem: For large images we need many layers for each output to "see" the whole image image

Receptive Fields

Each successive convolution adds K – 1 to the receptive field size
With L layers the receptive field size is 1 + L * (K – 1)



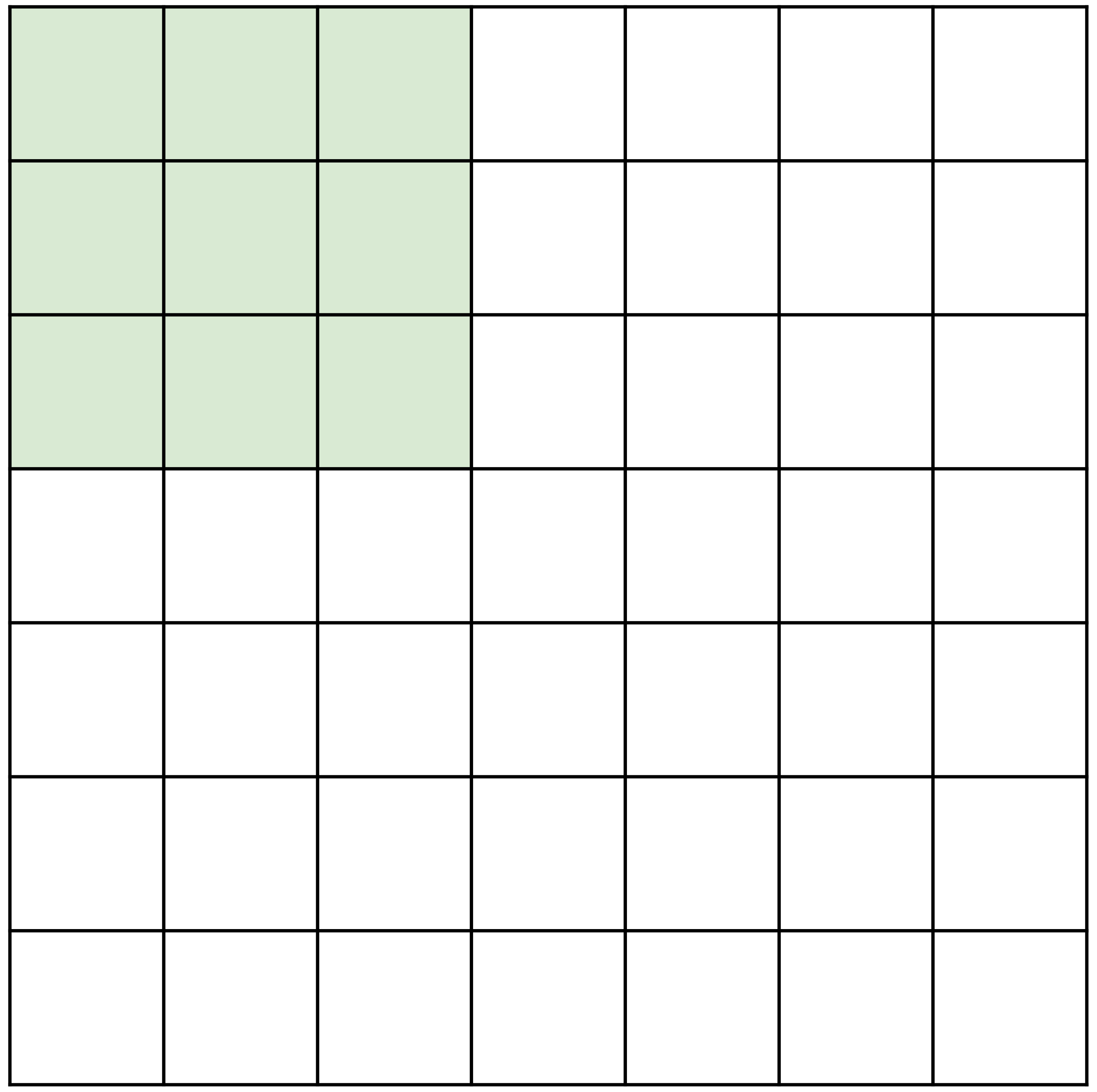
Input

Output

Problem: For large images we need many layers for each output to “see” the whole image image

Solution: Downsample inside the network

Strided Convolution

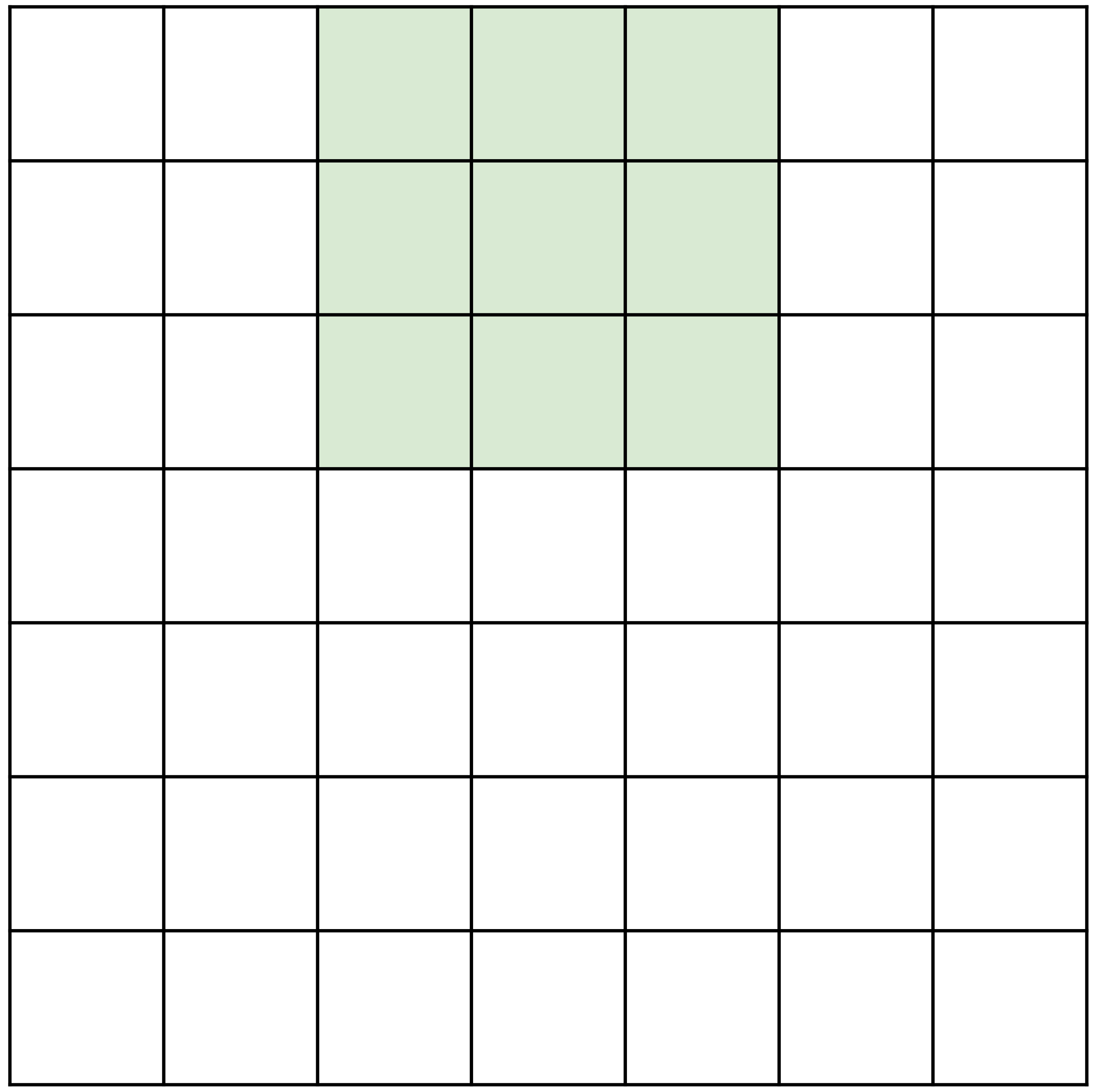


Input: 7x7

Filter: 3x3

Stride: 2

Strided Convolution

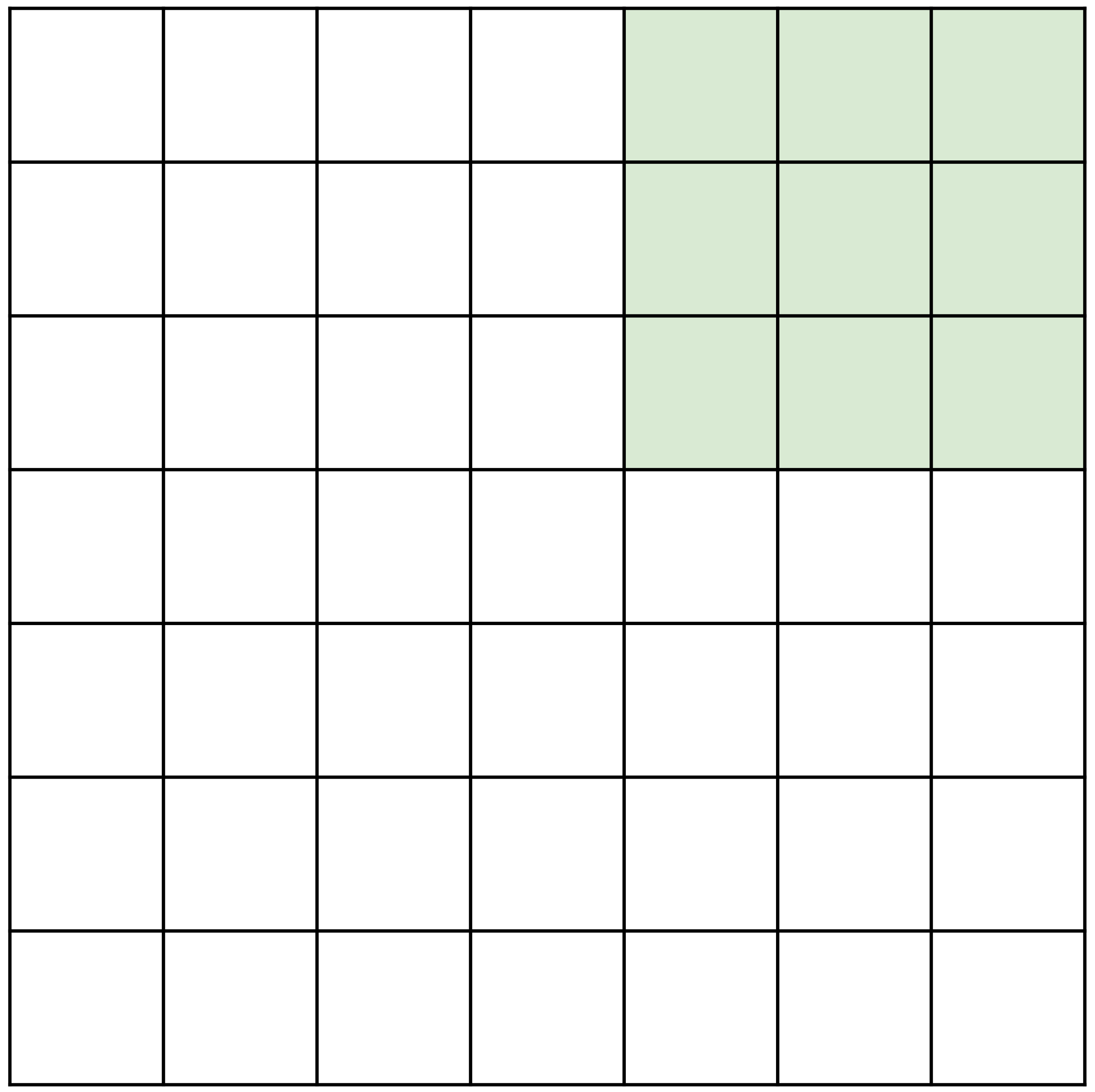


Input: 7x7

Filter: 3x3

Stride: 2

Strided Convolution



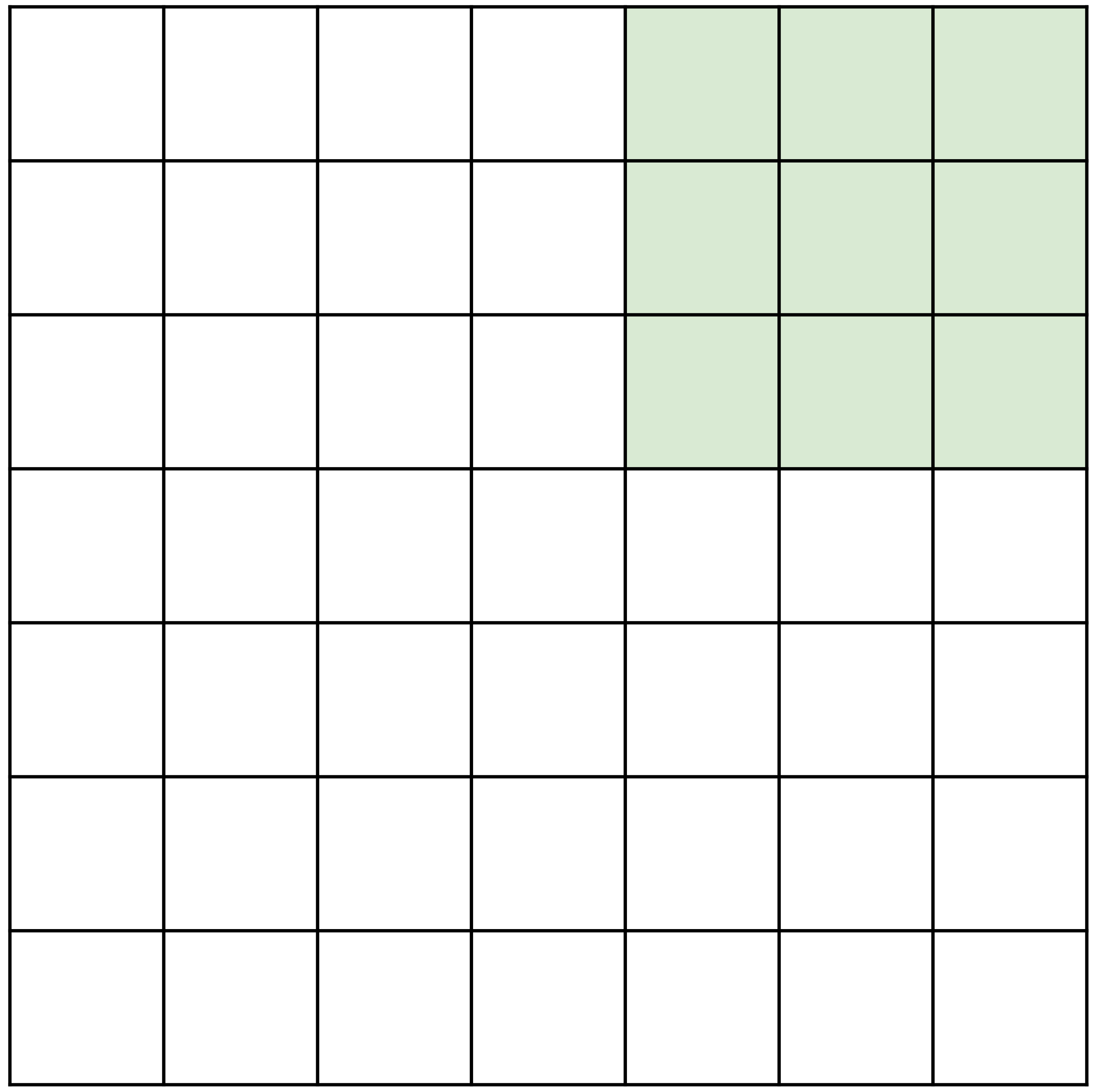
Input: 7x7

Filter: 3x3

Stride: 2

Output: 3x3

Strided Convolution



Input: 7x7

Filter: 3x3

Stride: 2

Output: 3x3

In general:

Input: W

Filter: K

Padding: P

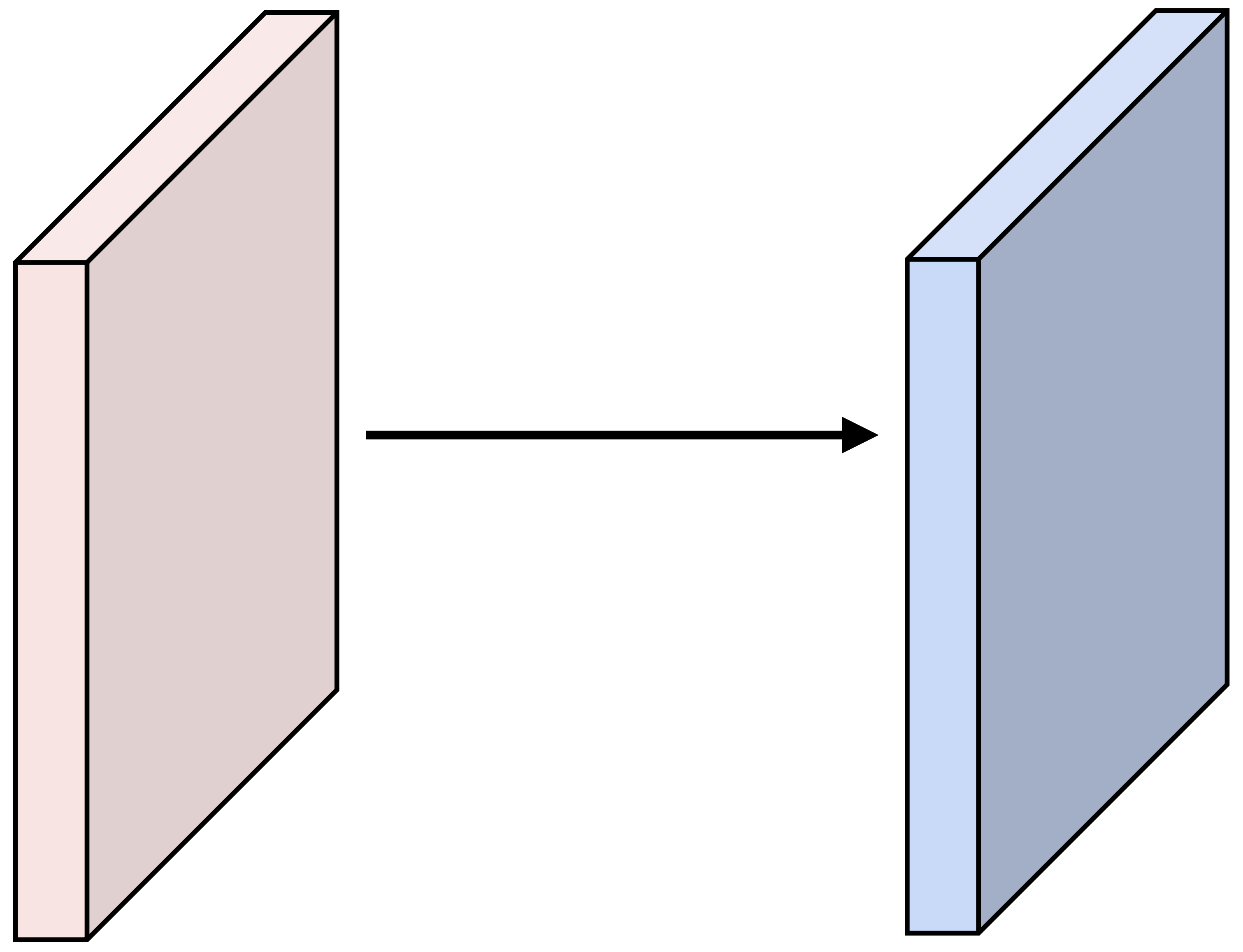
Stride: S

Output: (W – K + 2P) / S + 1

Convolution Example

Input volume: 3 x 32 x 32
10 5x5 filters with stride 1, pad 2

Q: What is the output volume size?



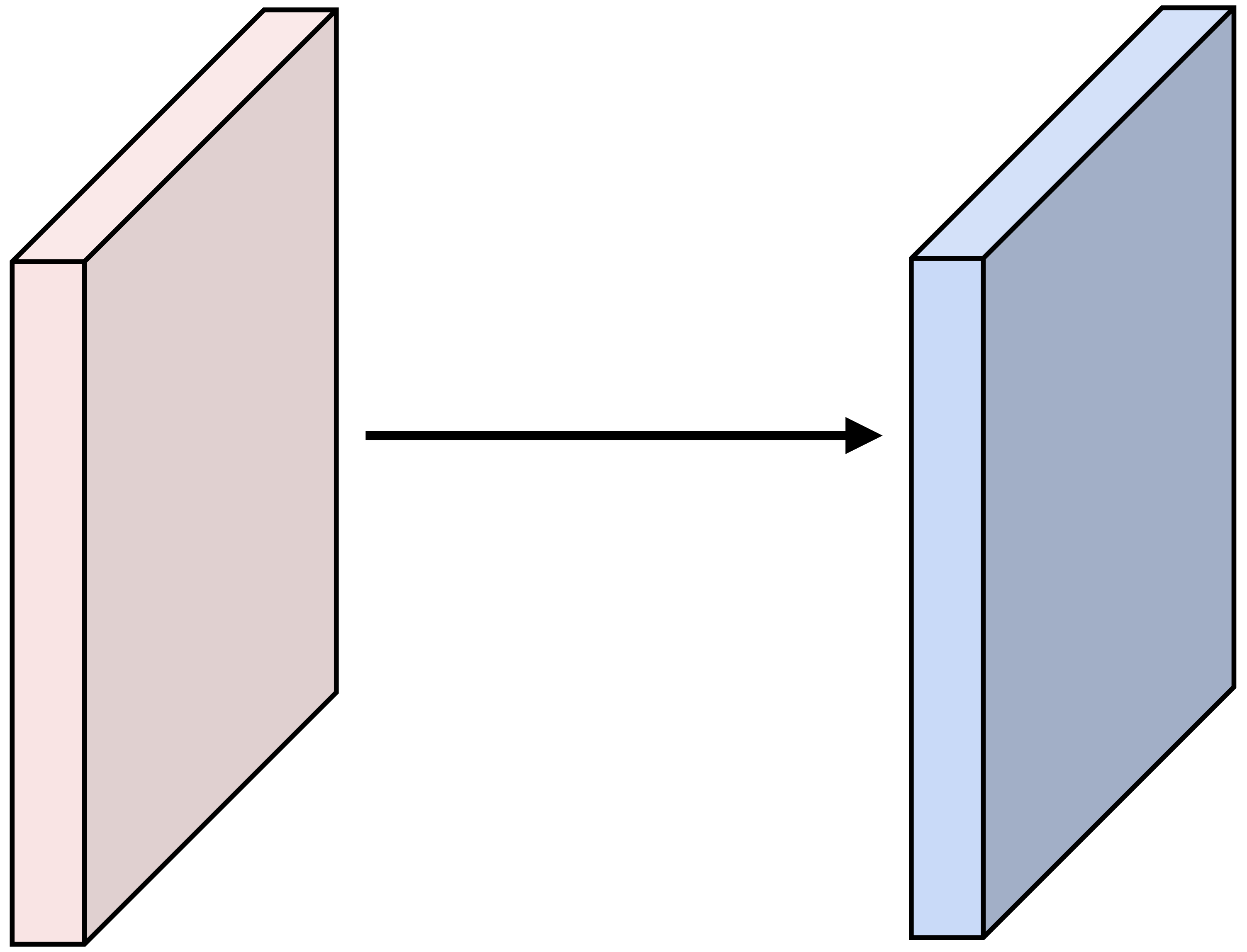
Convolution Example

Input volume: 3 x 32 x 32
10 5x5 filters with stride 1, pad 2

Q: What is the output volume size?

(32-5+2*2) / 1 + 1 = 32 spatially

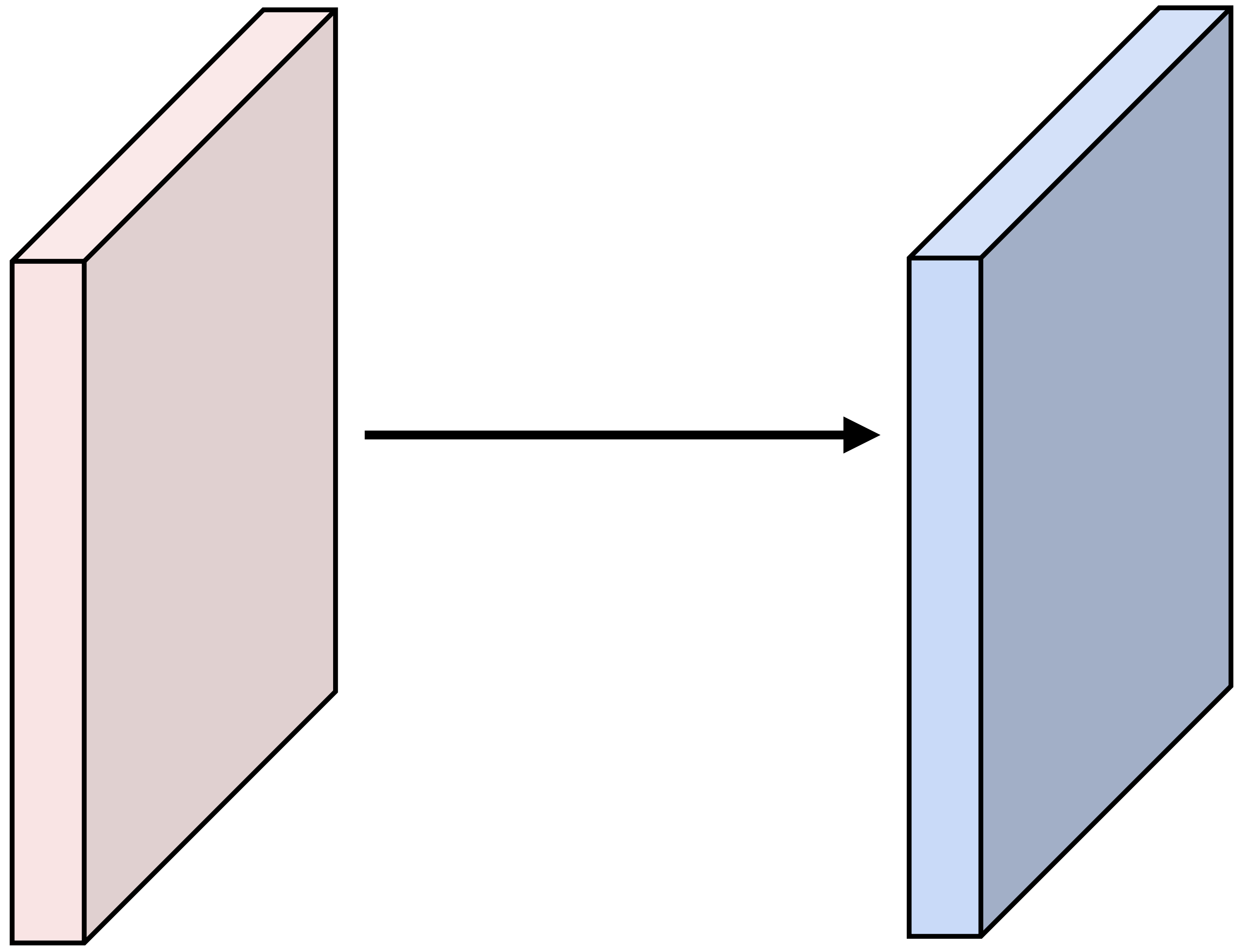
So, 10 x 32 x 32 output



Convolution Example

Input volume: 3 x 32 x 32
10 5x5 filters with stride 1, pad 2

Output volume size: 10 x 32 x 32
Q: What is the number of learnable parameters?



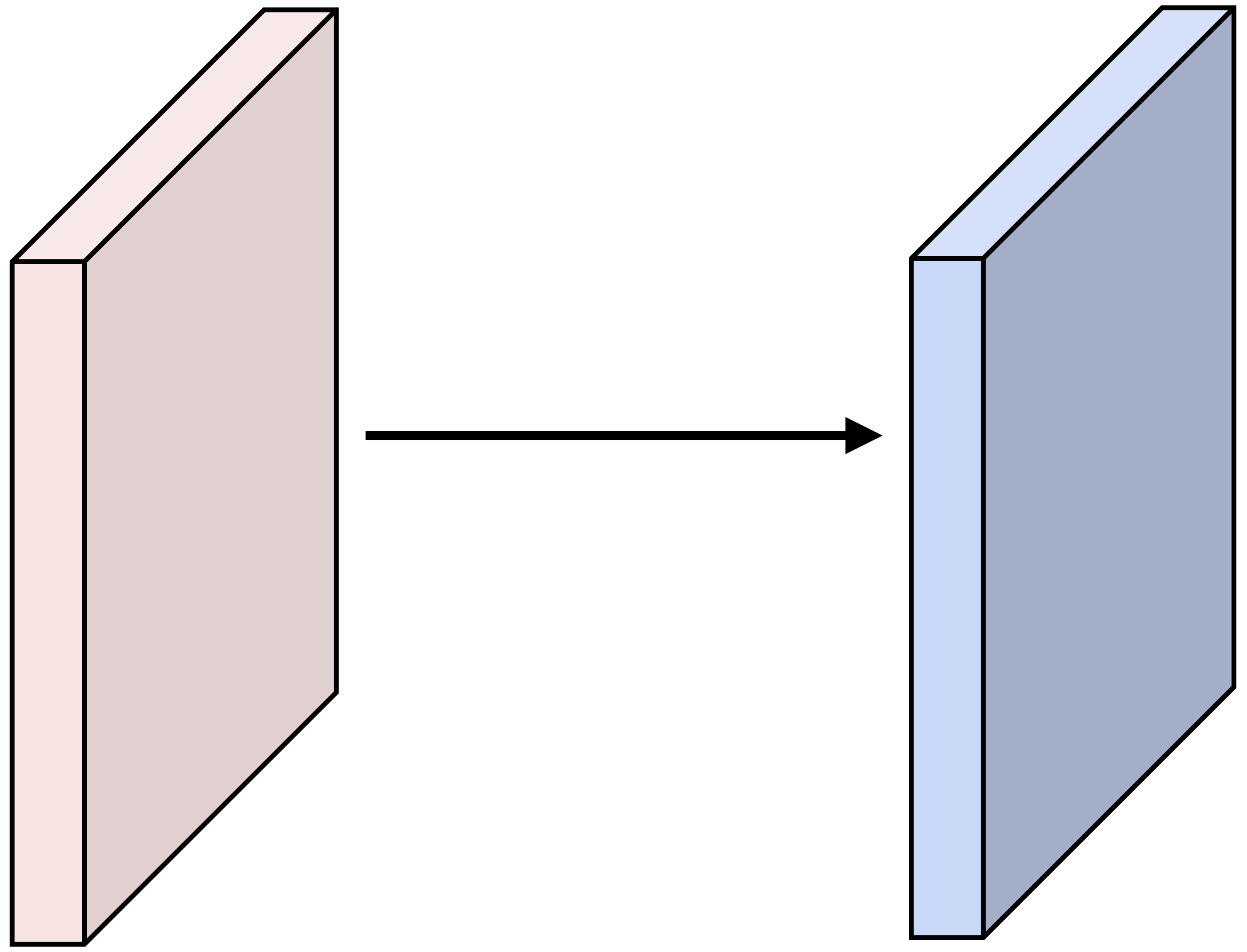
Convolution Example

Input volume: 3 x 32 x 32
10 5x5 filters with stride 1, pad 2

Output volume size: 10 x 32 x 32
Q: What is the number of learnable parameters?

Parmeters per filter: (3*5*5) + 1 = 76

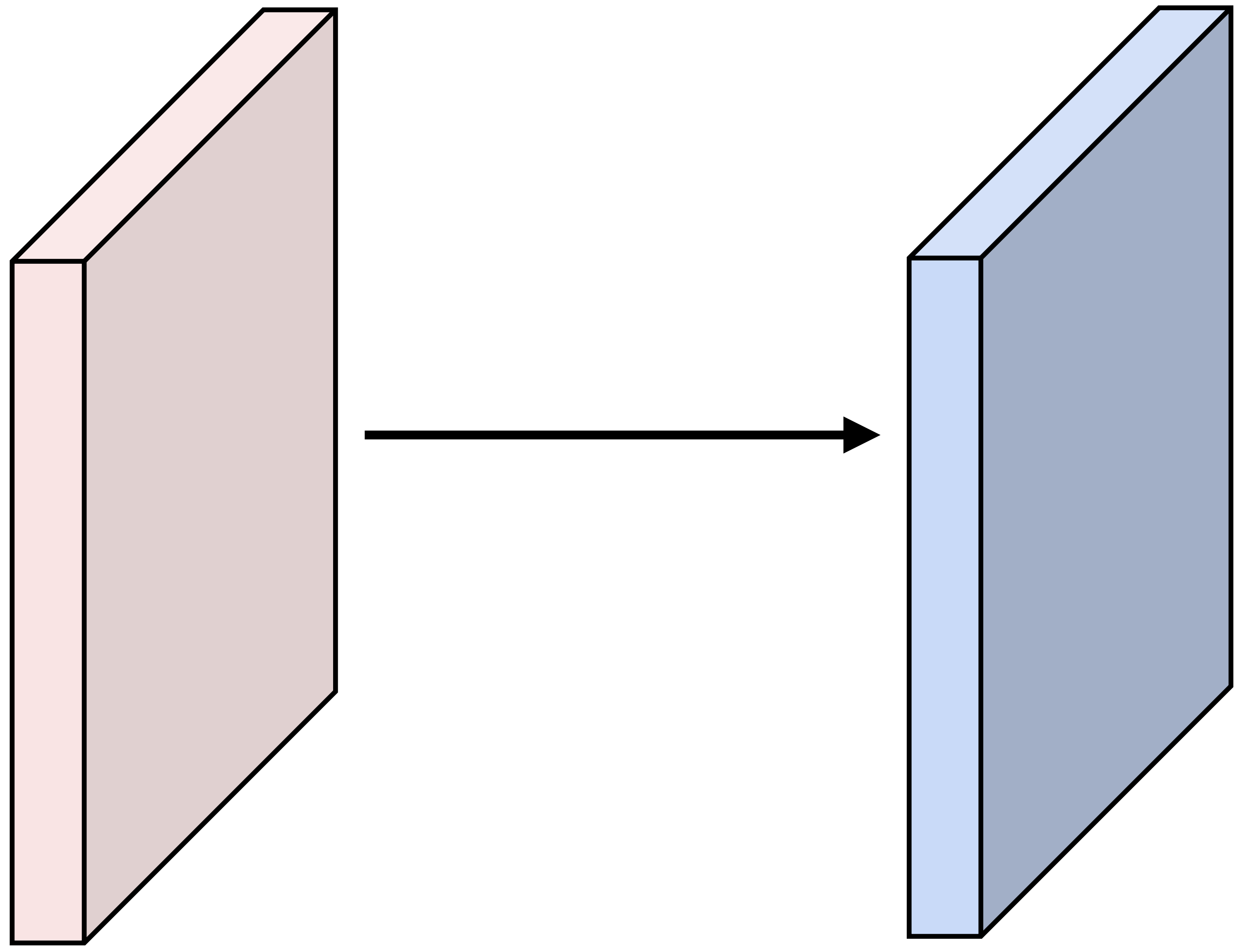
10 filters, so total is 10*76 = 760



Convolution Example

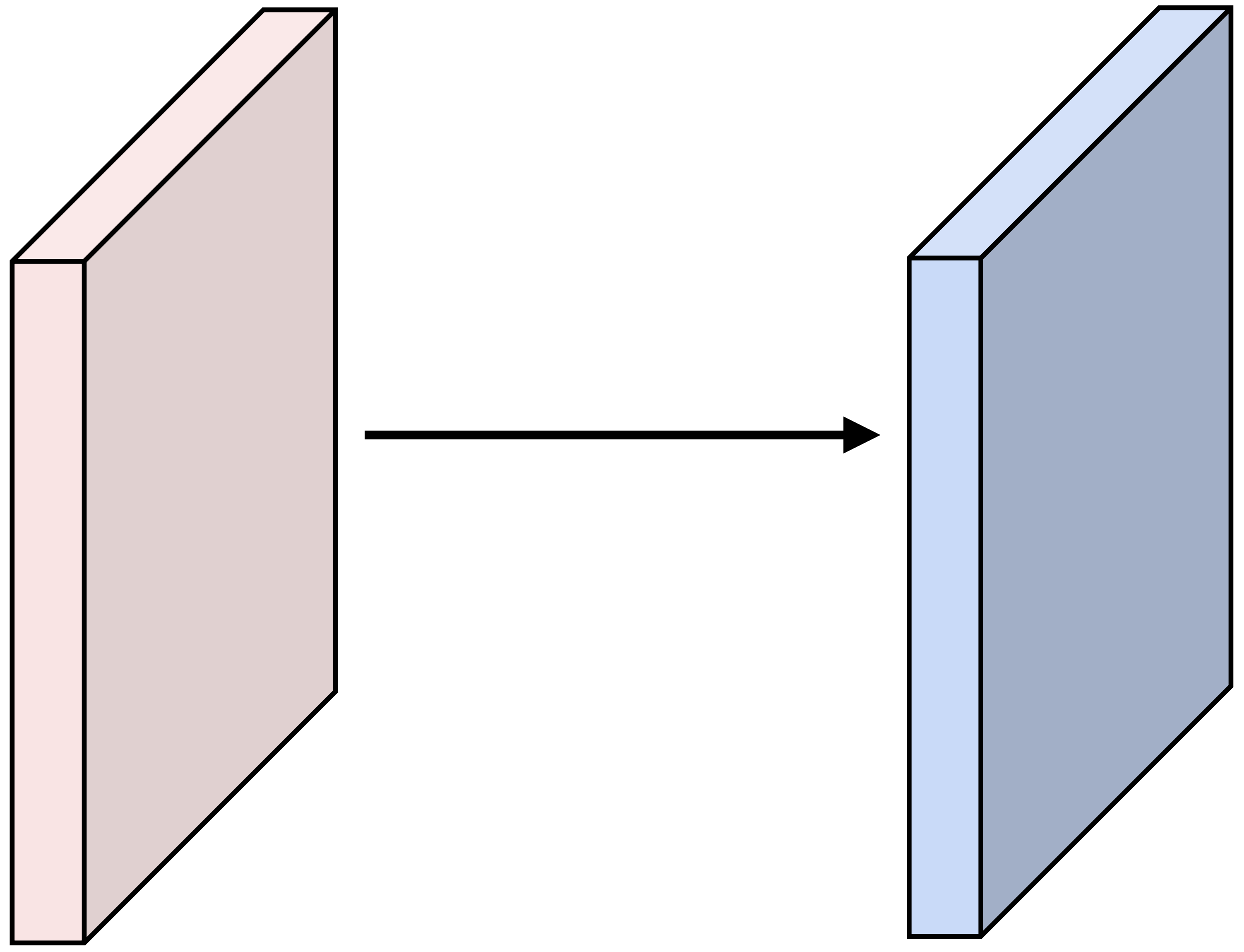
Input volume: 3 x 32 x 32
10 5x5 filters with stride 1, pad 2

Output volume size: 10 x 32 x 32
Number of learnable parameters: 760
Q: What is the number of multiply-add operations?



Convolution Example

Input volume: 3 x 32 x 32
10 5x5 filters with stride 1, pad 2

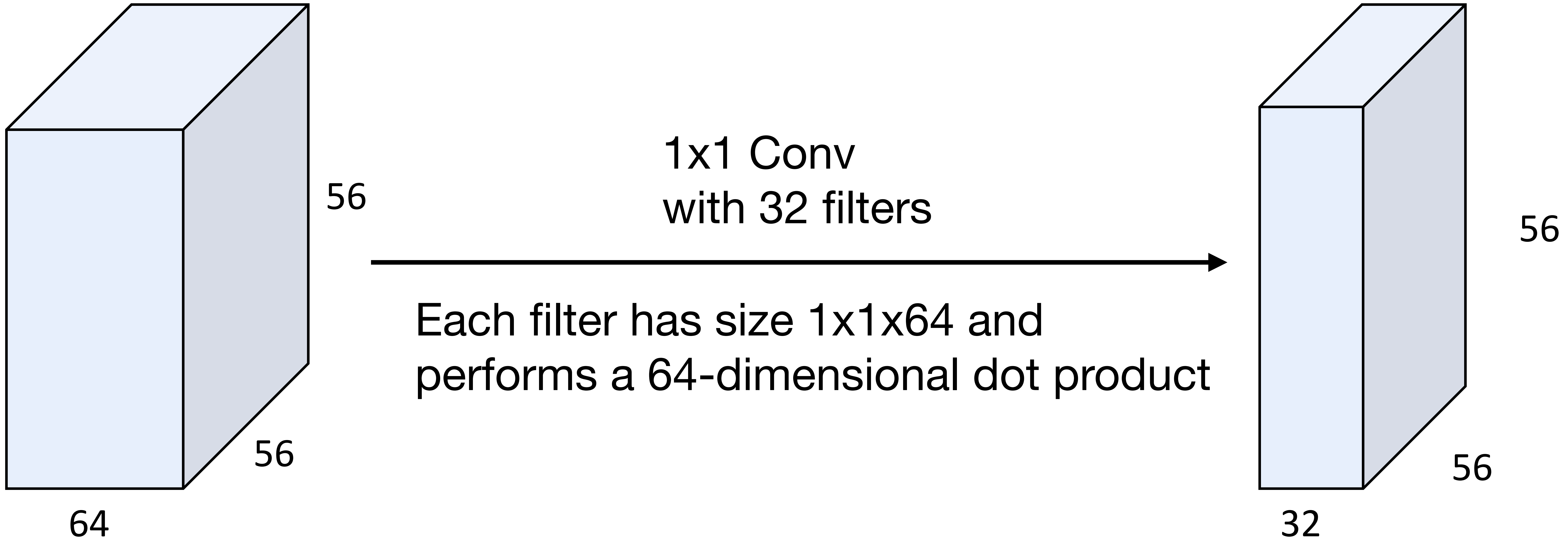


Output volume size: 10 x 32 x 32
Number of learnable parameters: 760
Q: What is the number of multiply-add operations?

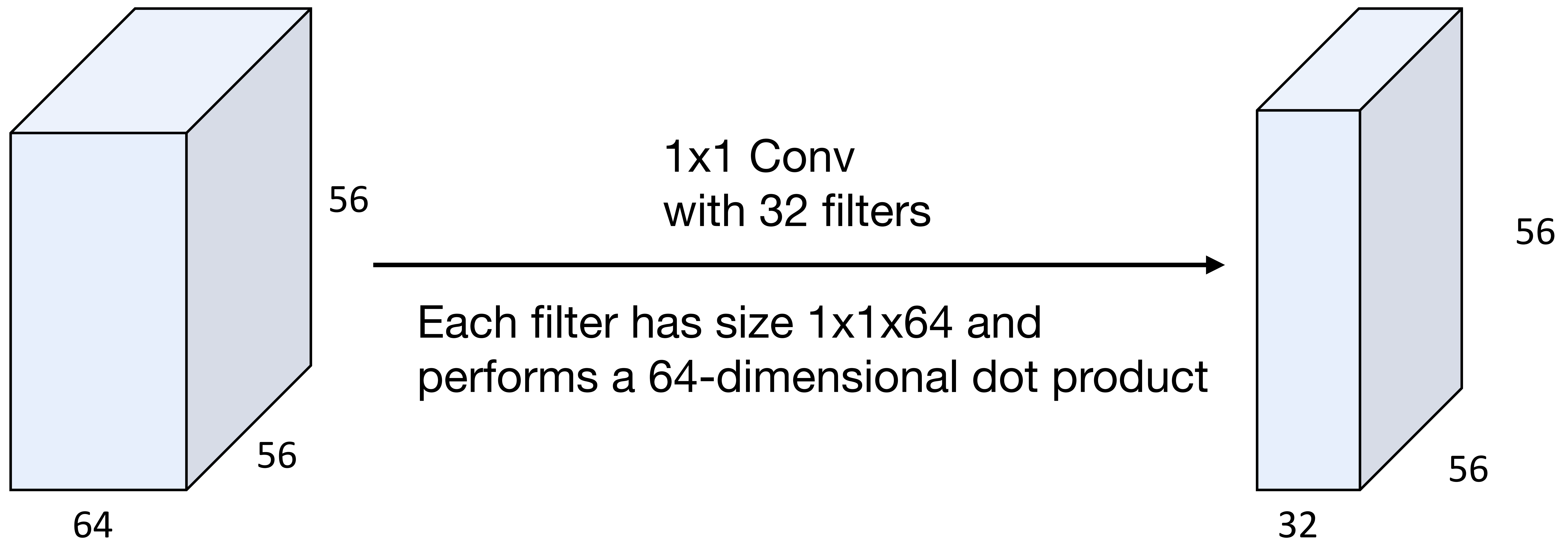
10*32*32=10,240 outputs, each from inner product

of two 3x5x5 tensors, so total = 75 * 10,240 = **768,000**

Example: 1x1 Convolution


56
56
64
1x1 Conv
with 32 filters
Each filter has size 1x1x64 and
performs a 64-dimensional dot product
56
56
32

Example: 1x1 Convolution



Each filter has size 1x1x64 and performs a 64-dimensional dot product

Stacking 1x1 conv layers gives MLP operating on each input position

Convolution Summary

Input: C_{in} x H x W

Hyperparameters:

- **Kernel size**: K_H x K_W
- **Number filters**: C_{out}
- **Padding**: P
- **Stride**: S

Weight matrix: C_{out} x C_{in} x K_H x K_W
giving C_{out} filters of size C_{in} x K_H x K_W

Bias vector: C_{out}

Output size: C_{out} x H' x W' where:

- H' = (H – K + 2P) / S + 1
- W' = (W – K + 2P) / S + 1

Convolution Summary

Input: C_{in} x H x W

Hyperparameters:

- **Kernel size**: K_H x K_W
- **Number filters**: C_{out}
- **Padding**: P
- **Stride**: S

Weight matrix: C_{out} x C_{in} x K_H x K_W
giving C_{out} filters of size C_{in} x K_H x K_W

Bias vector: C_{out}

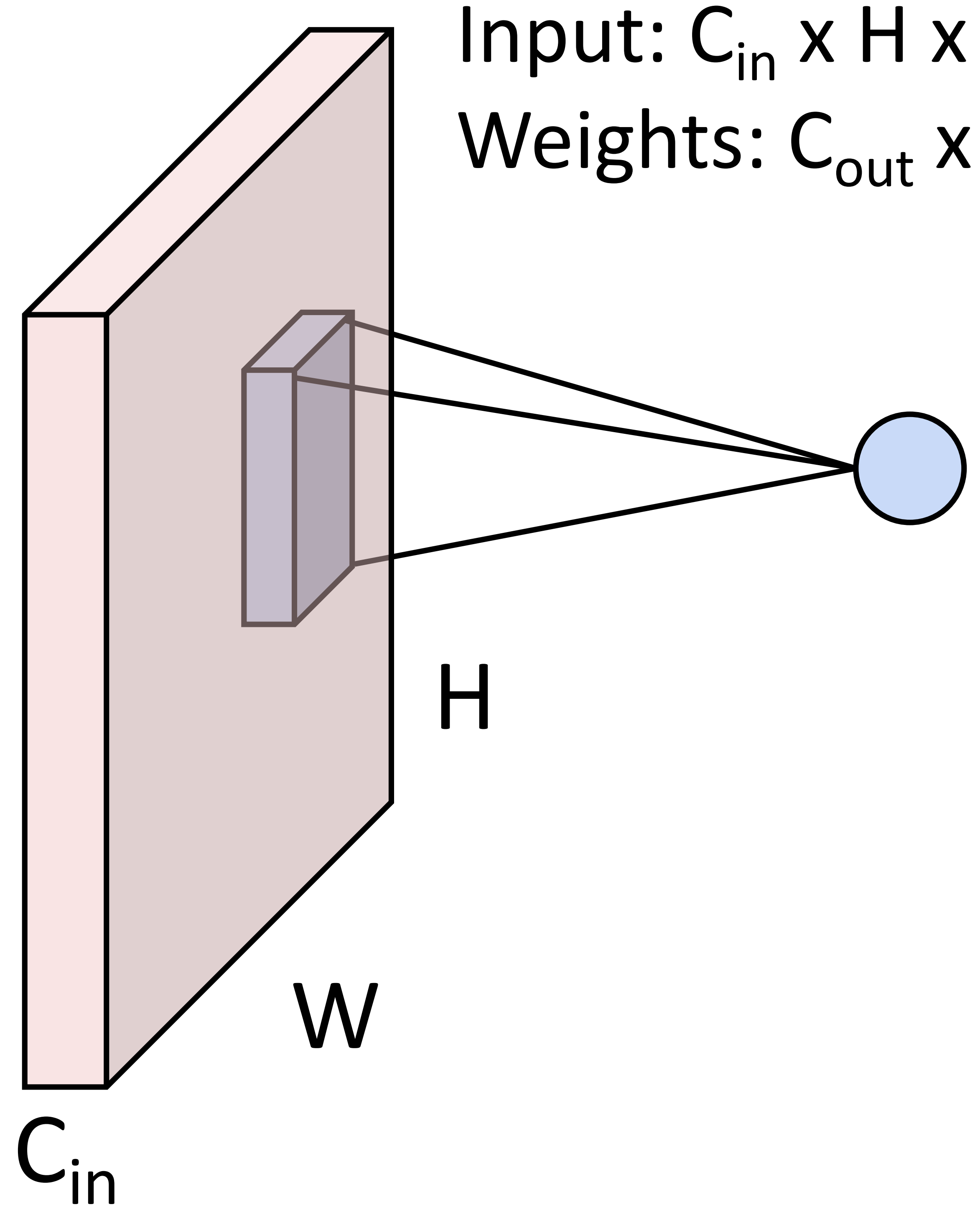
Output size: C_{out} x H' x W' where:

- H' = (H – K + 2P) / S + 1
- W' = (W – K + 2P) / S + 1

Common settings:
$K_H = K_W$ (Small square filters)
P = (K – 1) / 2 ("Same" padding)
C_{in}, C_{out} = 32, 64, 128, 256 (powers of 2)
K = 3, P = 1, S = 1 (3x3 conv)
K = 5, P = 2, S = 1 (5x5 conv)
K = 1, P = 0, S = 1 (1x1 conv)
K = 3, P = 1, S = 2 (Downsample by 2)

Other types of convolution

So far: 2D Convolution



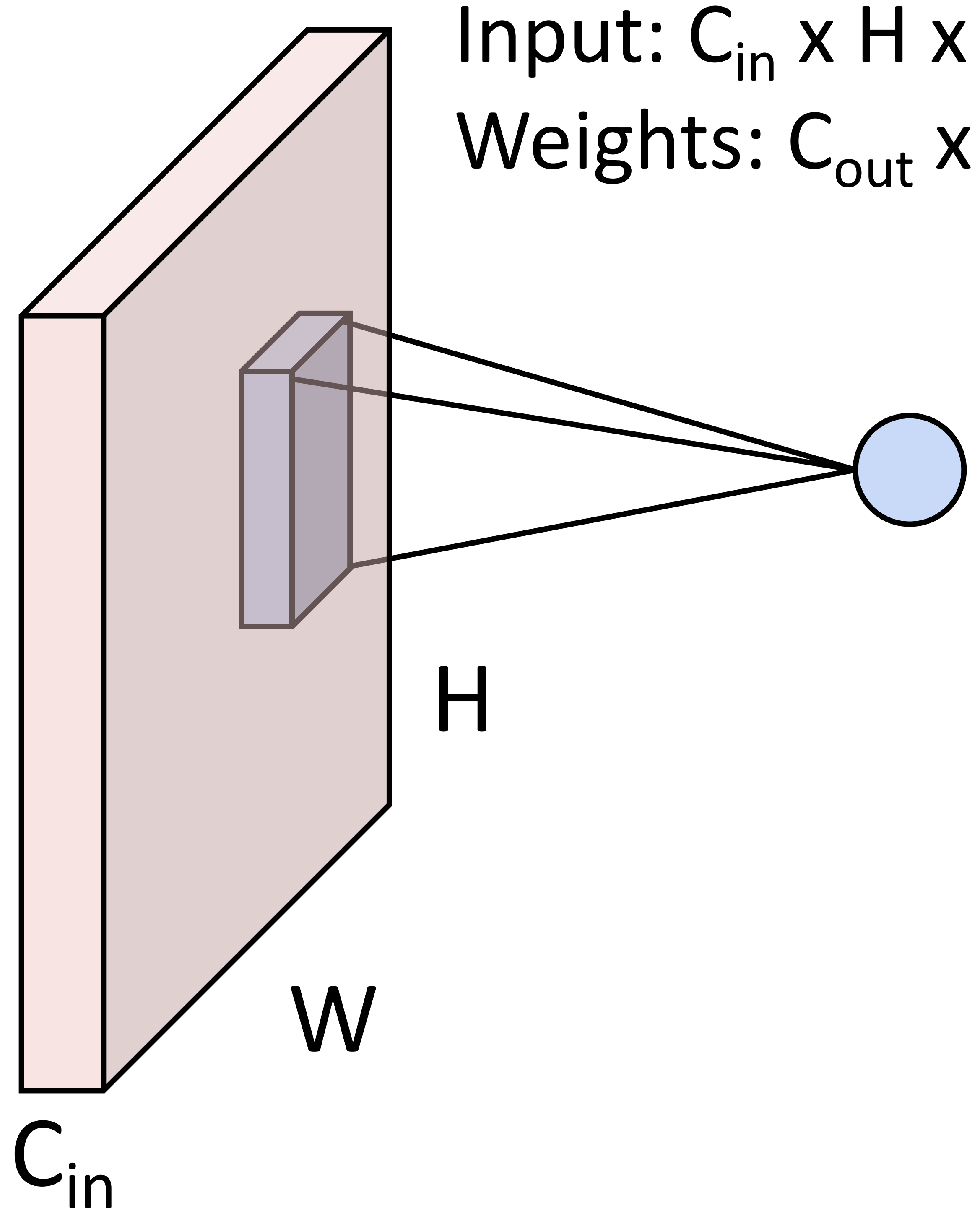
Input: C_{in} x H x W

Weights: C_{out} x C_{in} x K x K

Other types of convolution

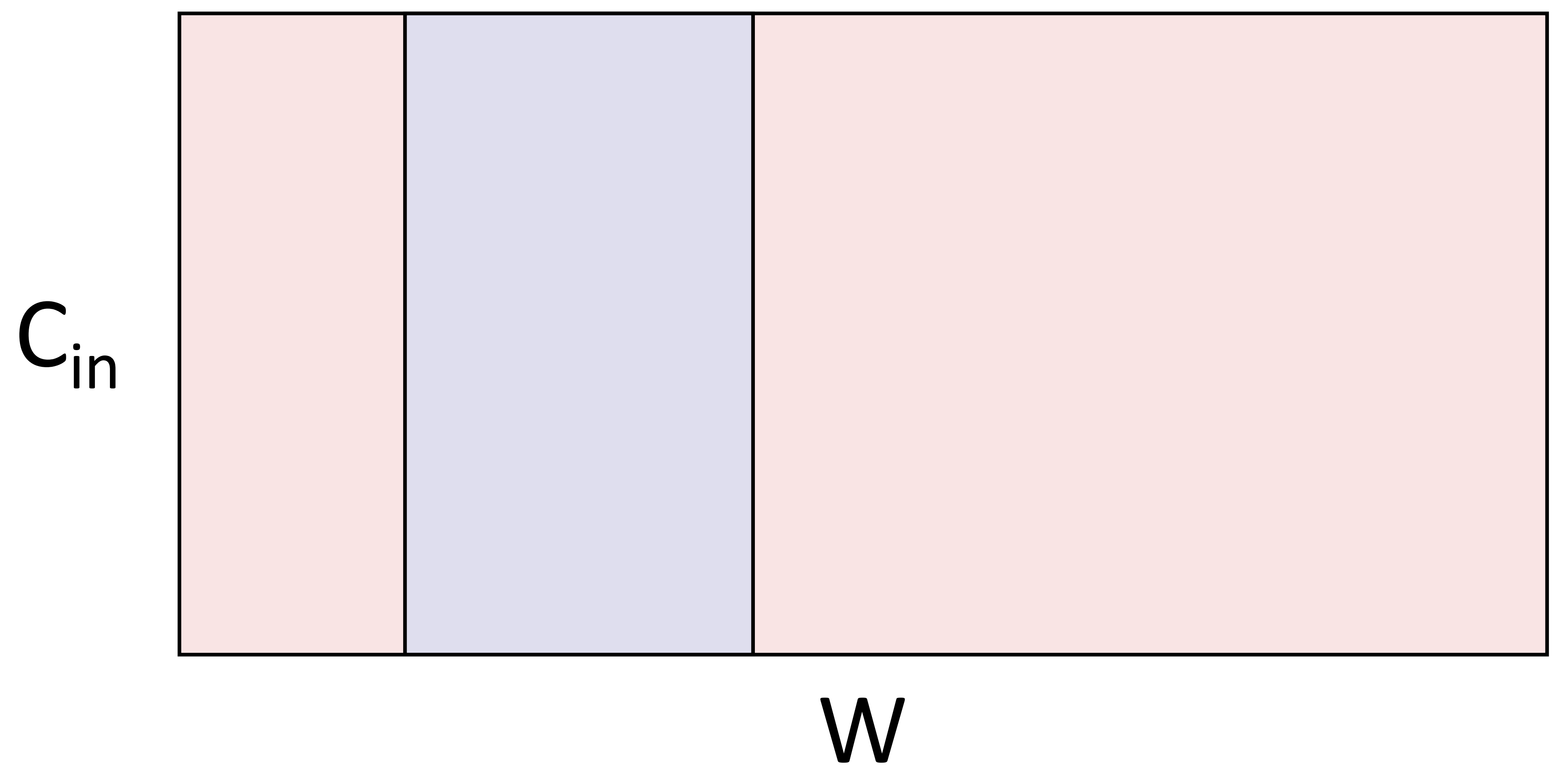
So far: 2D Convolution

Input: C_{in} x H x W
Weights: C_{out} x C_{in} x K x K



1D Convolution

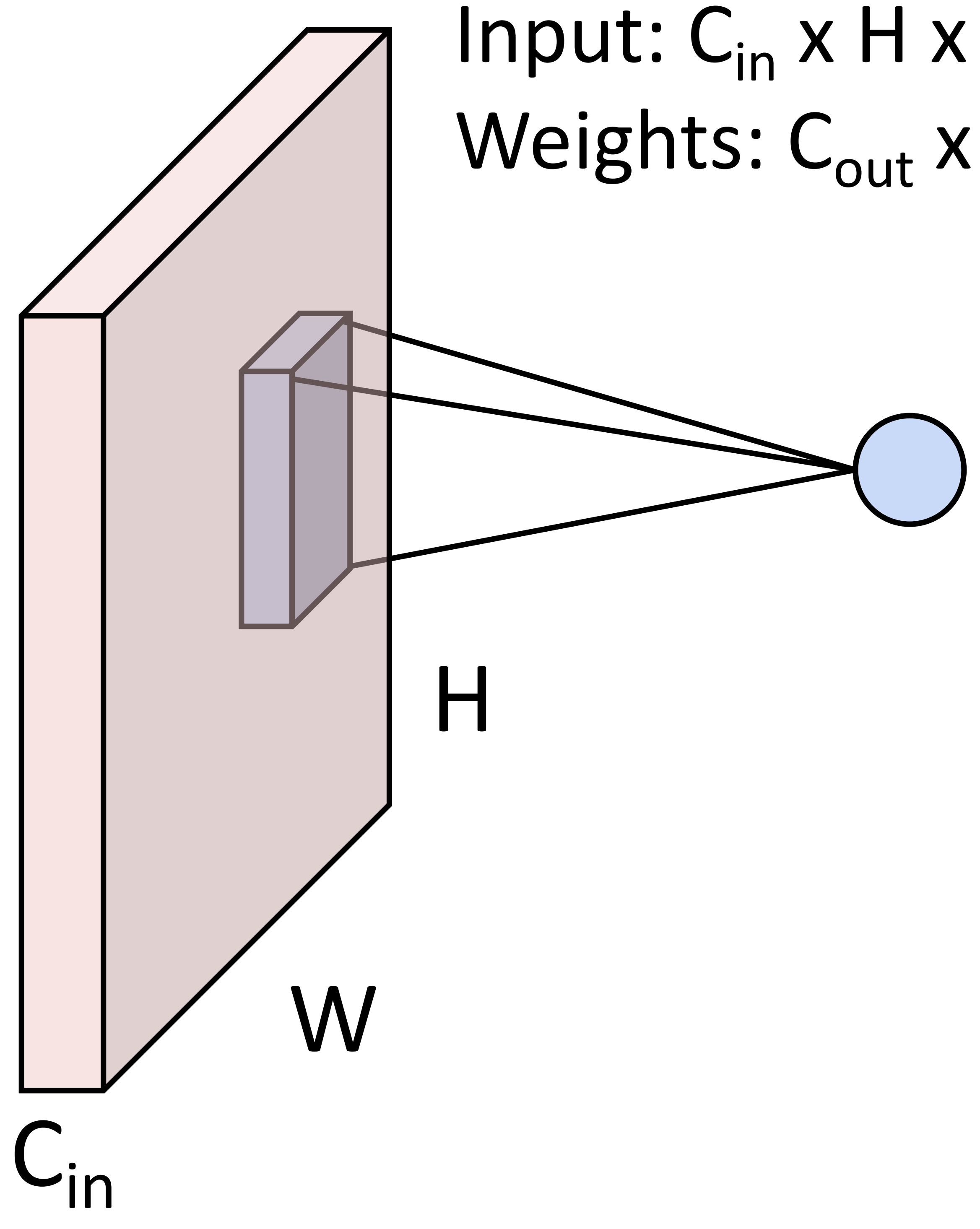
Input: C_{in} x W
Weights: C_{out} x C_{in} x K



Other types of convolution

So far: 2D Convolution

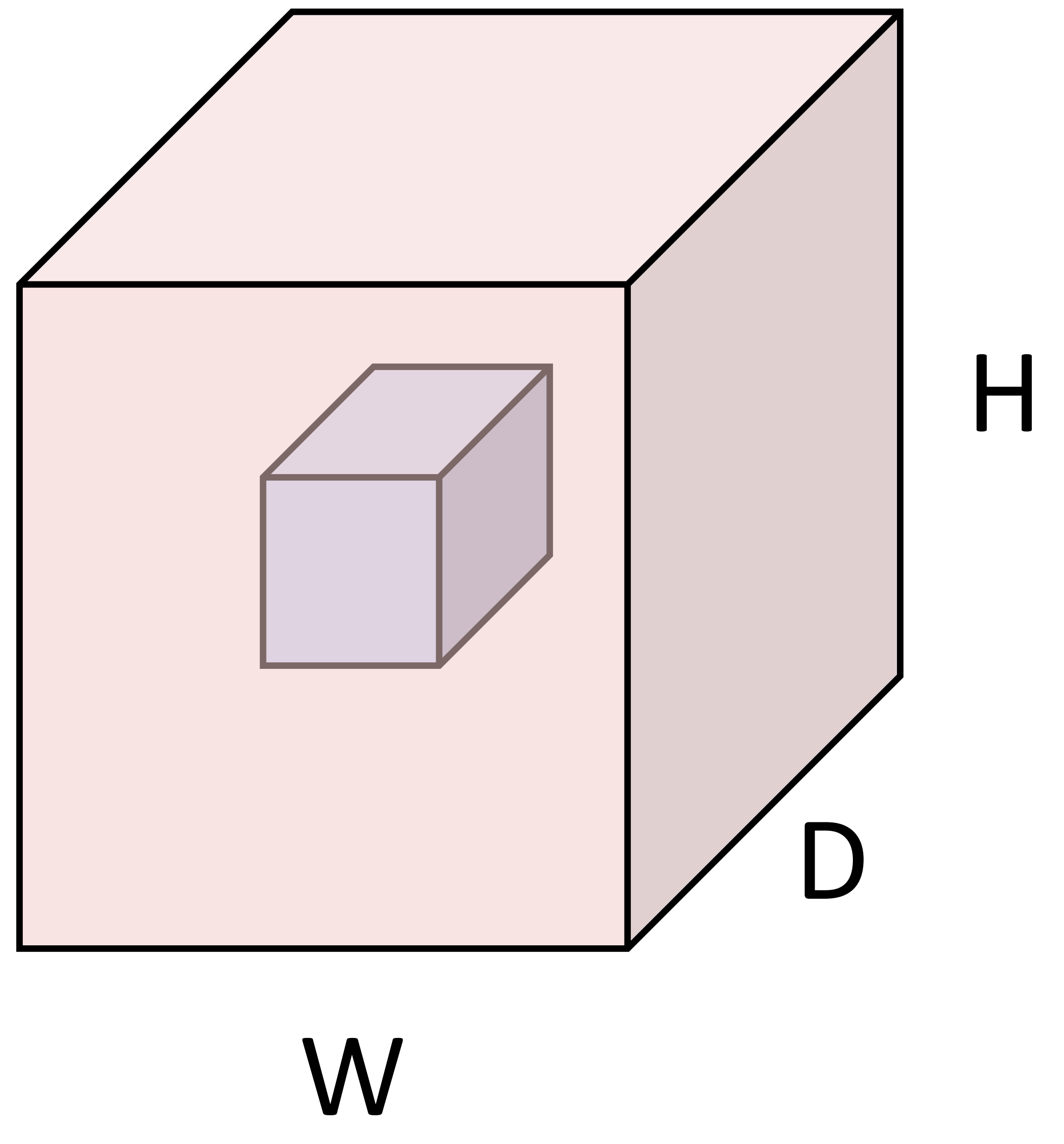
Input: C_{in} x H x W
Weights: C_{out} x C_{in} x K x K



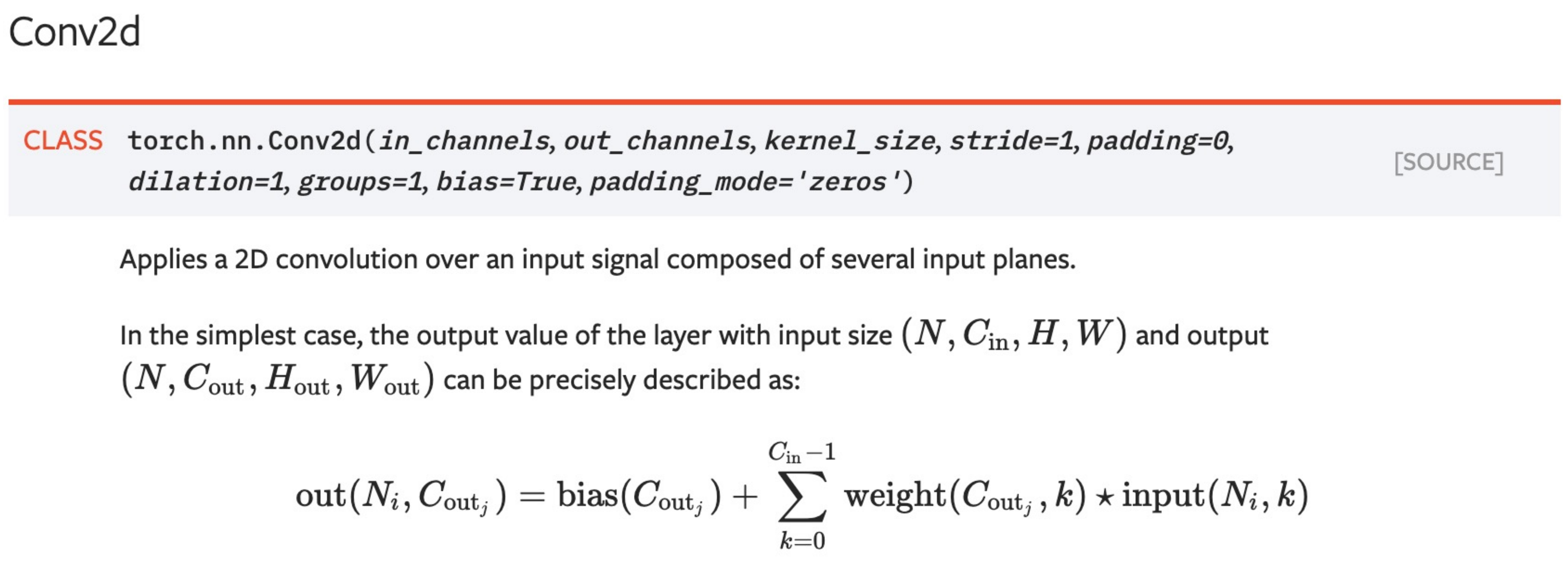
3D Convolution

Input: C_{in} x H x W x D
Weights: C_{out} x C_{in} x K x K x K

C_{in}-dim vector at each point in the volume



PyTorch Convolution Layer



Conv2d

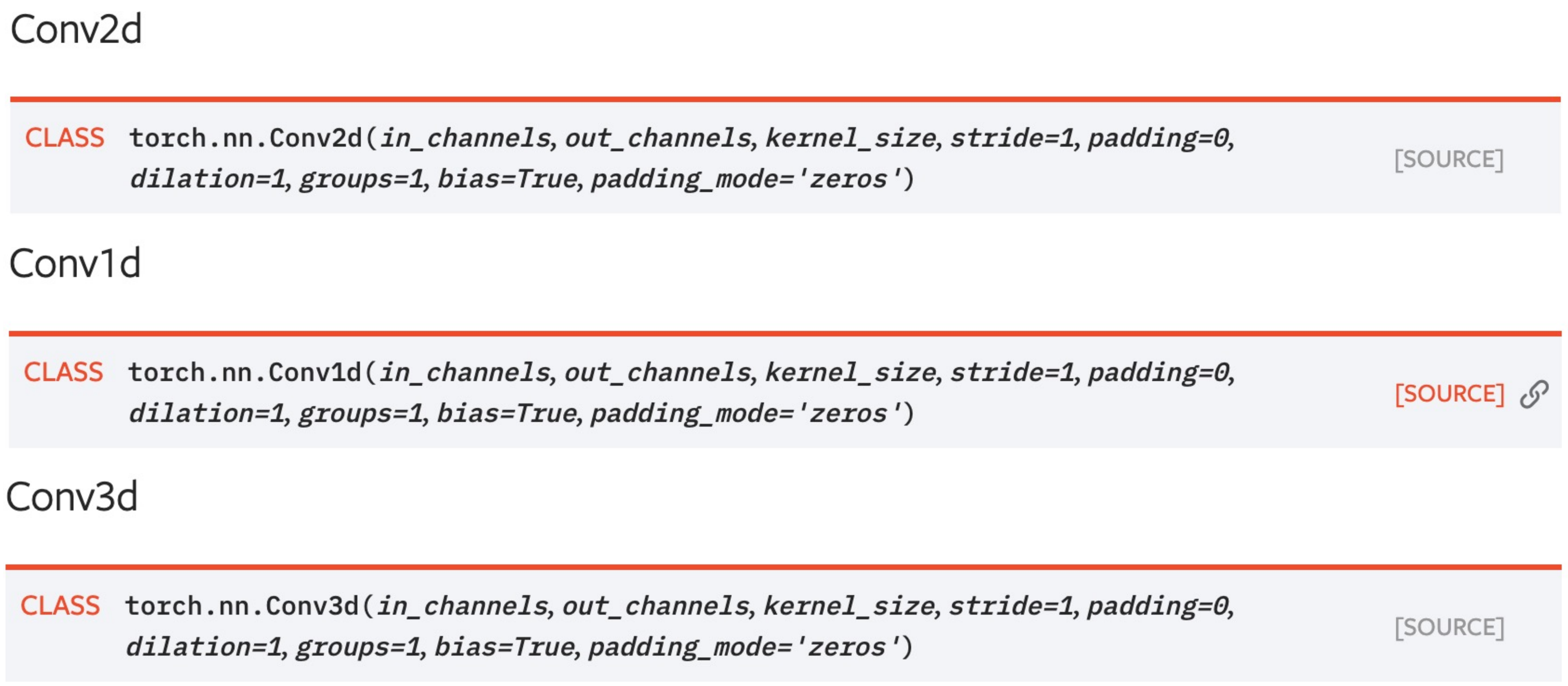
CLASS `torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True, padding_mode='zeros')` [SOURCE]

Applies a 2D convolution over an input signal composed of several input planes.

In the simplest case, the output value of the layer with input size (N, C_{in}, H, W) and output $(N, C_{\text{out}}, H_{\text{out}}, W_{\text{out}})$ can be precisely described as:

$$\text{out}(N_i, C_{\text{out}_j}) = \text{bias}(C_{\text{out}_j}) + \sum_{k=0}^{C_{\text{in}}-1} \text{weight}(C_{\text{out}_j}, k) \star \text{input}(N_i, k)$$

PyTorch Convolution Layer



Conv2d

```
CLASS torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0,
      dilation=1, groups=1, bias=True, padding_mode='zeros')
```
[SOURCE]

Conv1d

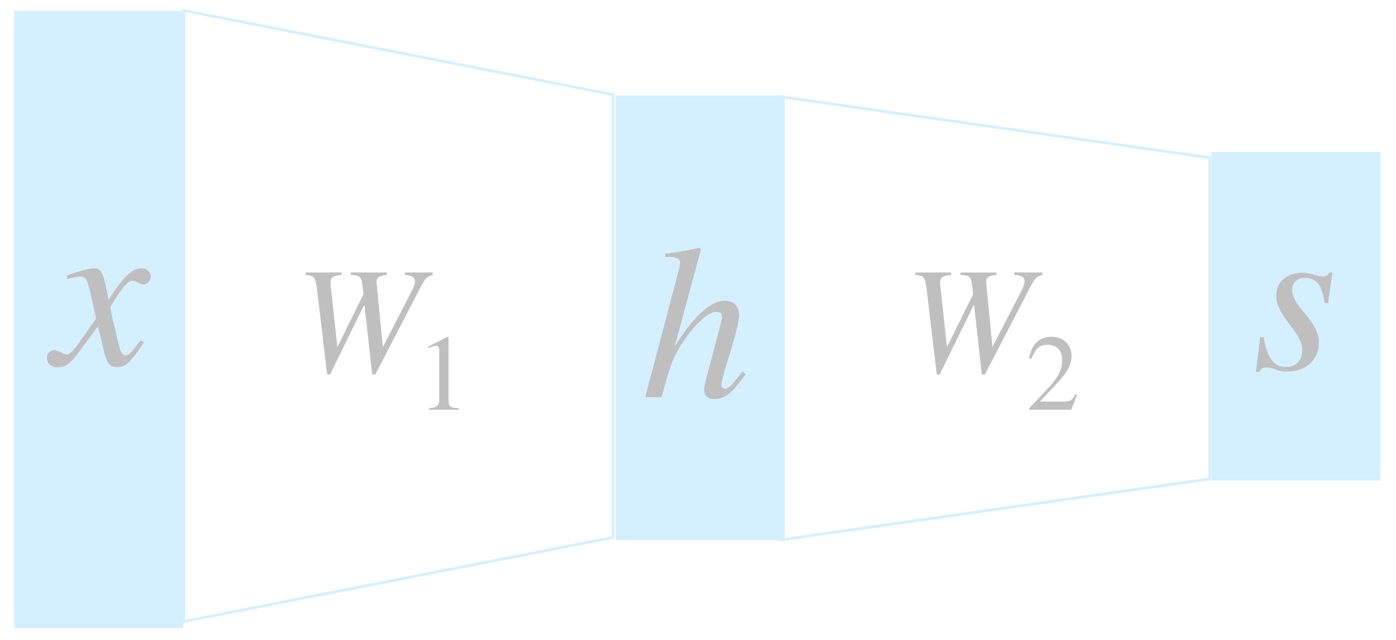
```
CLASS torch.nn.Conv1d(in_channels, out_channels, kernel_size, stride=1, padding=0,
      dilation=1, groups=1, bias=True, padding_mode='zeros')
```
[SOURCE]

Conv3d

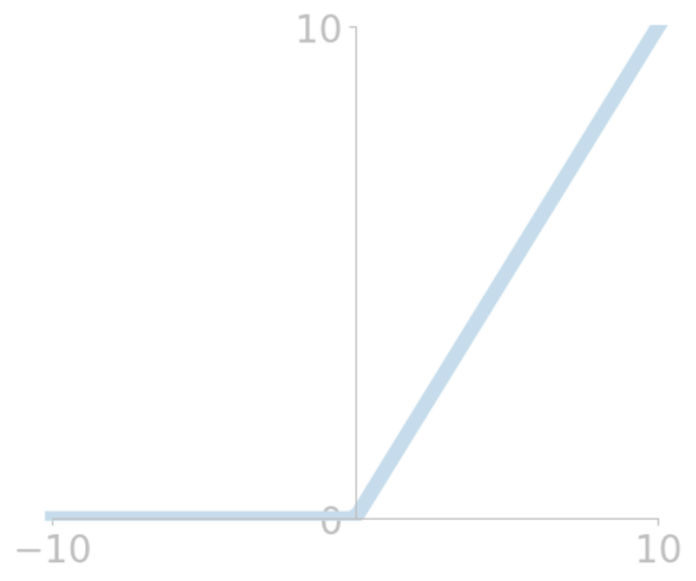
```
CLASS torch.nn.Conv3d(in_channels, out_channels, kernel_size, stride=1, padding=0,
      dilation=1, groups=1, bias=True, padding_mode='zeros')
```
[SOURCE]

Components of Convolutional Neural Networks

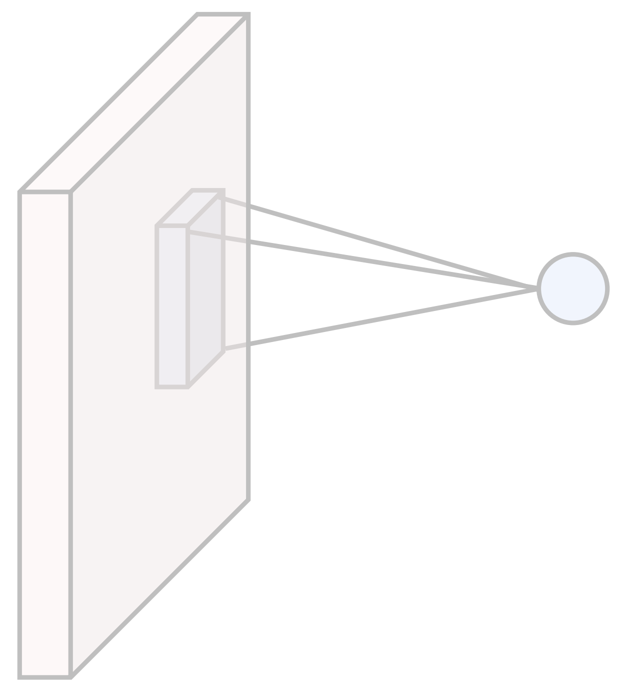
Fully-Connected Layers



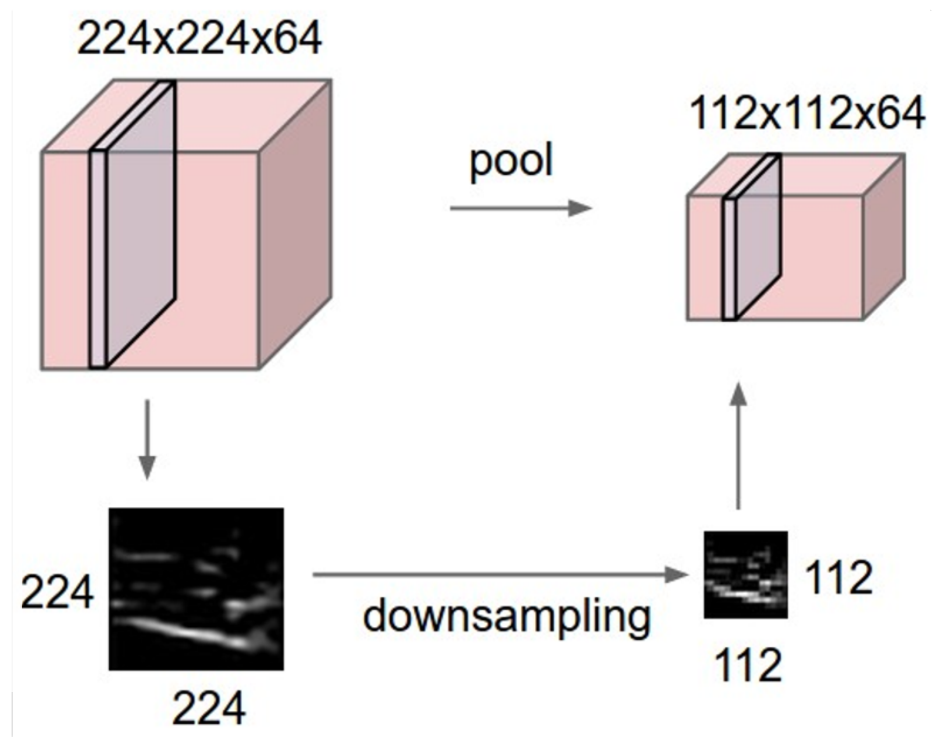
Activation Functions



Convolution Layers



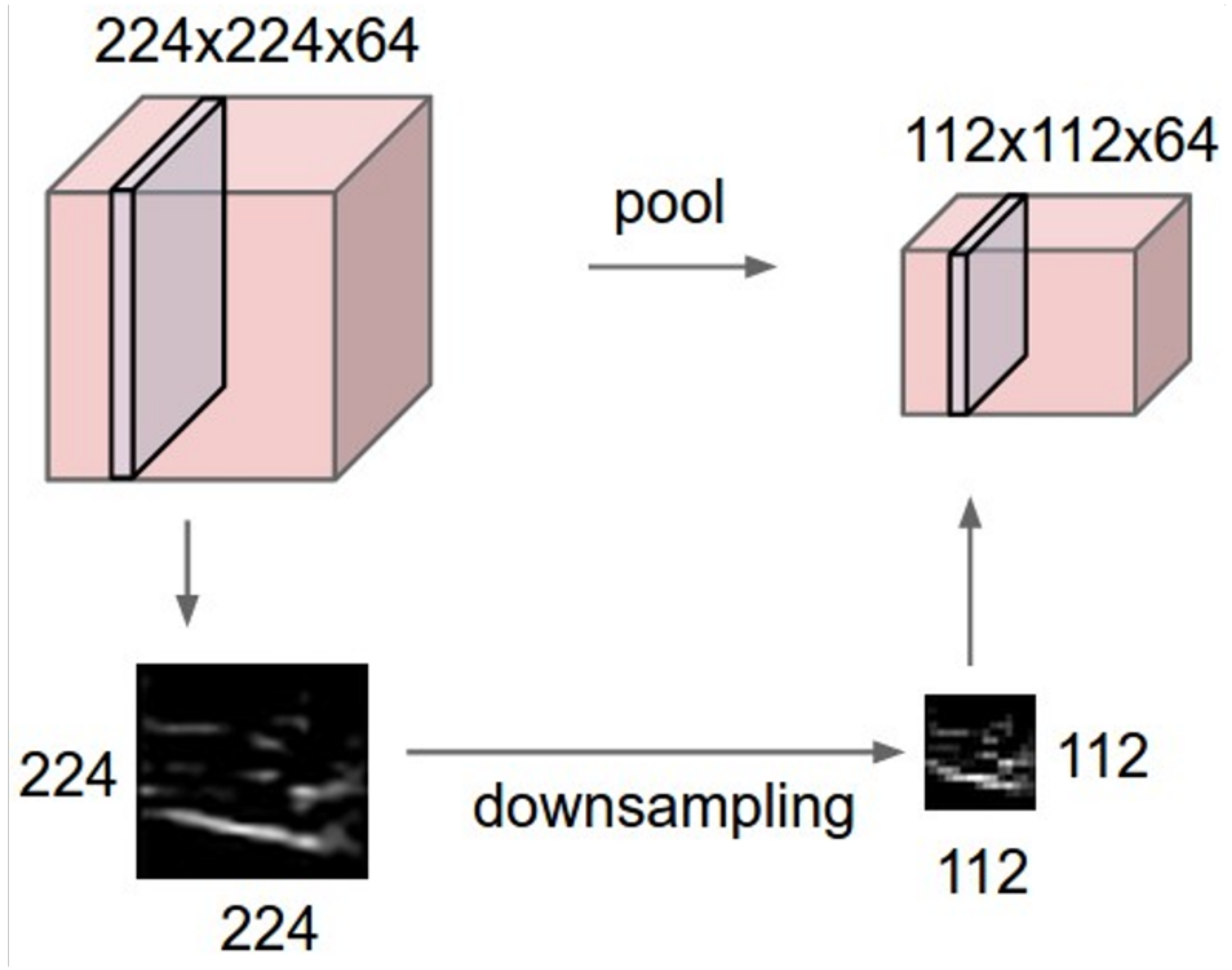
Pooling Layers



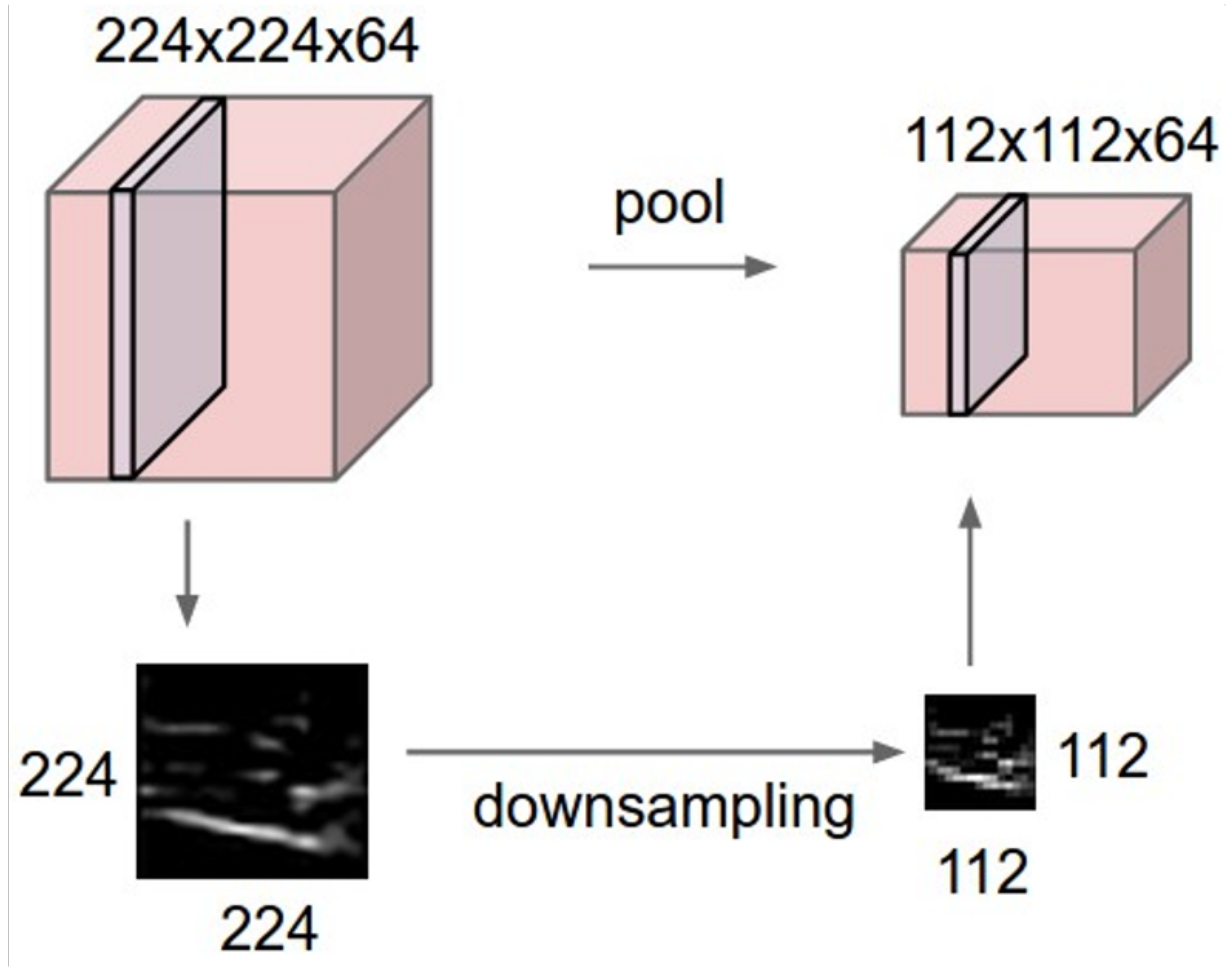
Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Pooling Layers: Another way to downsample

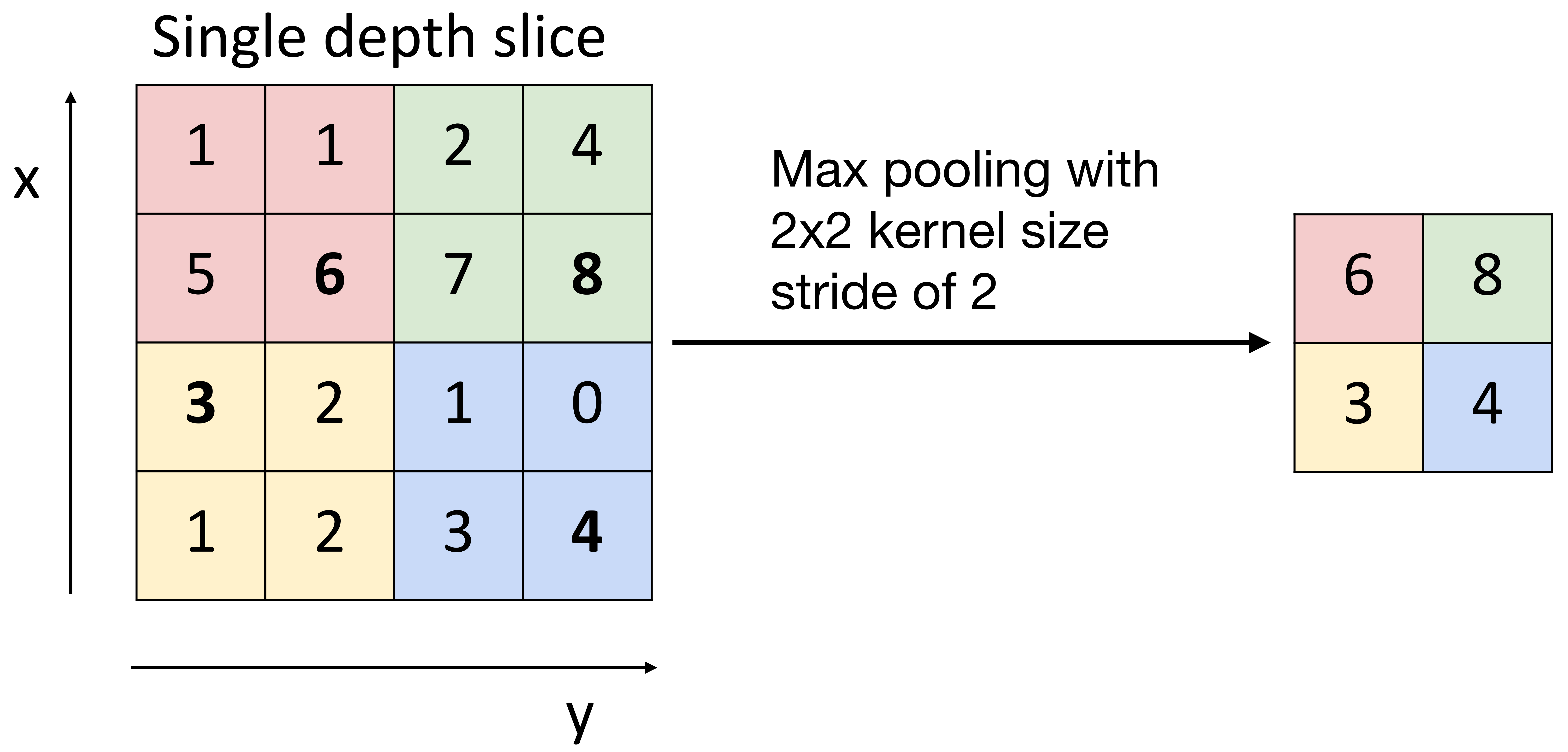


Pooling Layers: Another way to downsample

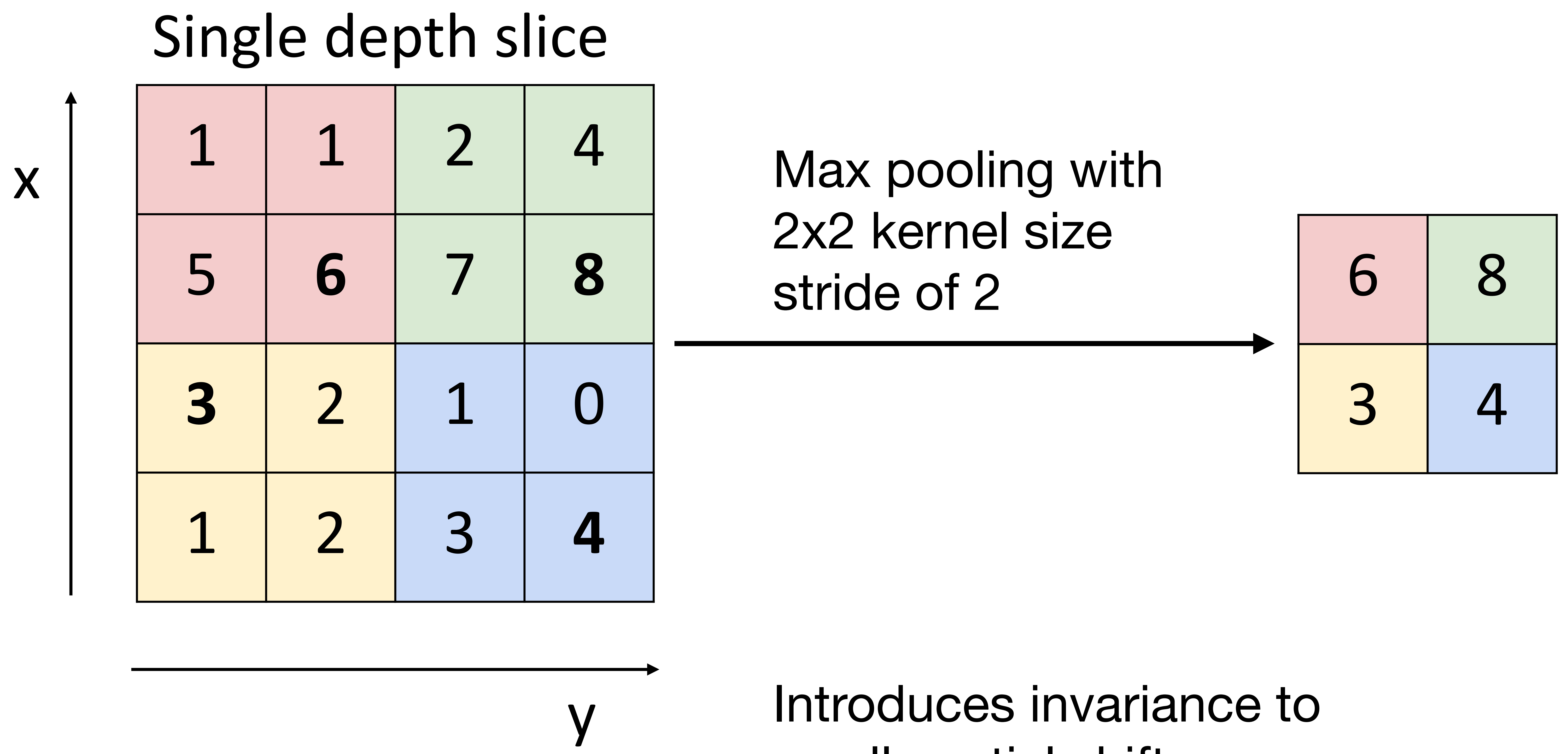


Hyperparameters:
Kernel size
Stride
Pooling function

Max Pooling


Single depth slice
x
y
1
1
2
4
5
6
7
8
3
2
1
0
1
2
3
4
Max pooling with
2x2 kernel size
stride of 2
6
8
3
4

Max Pooling



Introduces invariance to small spatial shifts

No learnable parameters!

Pooling Summary

Input: C x H x W

Hyperparameters:

- Kernel size: K
- Stride: S
- Pooling function (max, avg)

Output: C x H' x W' where

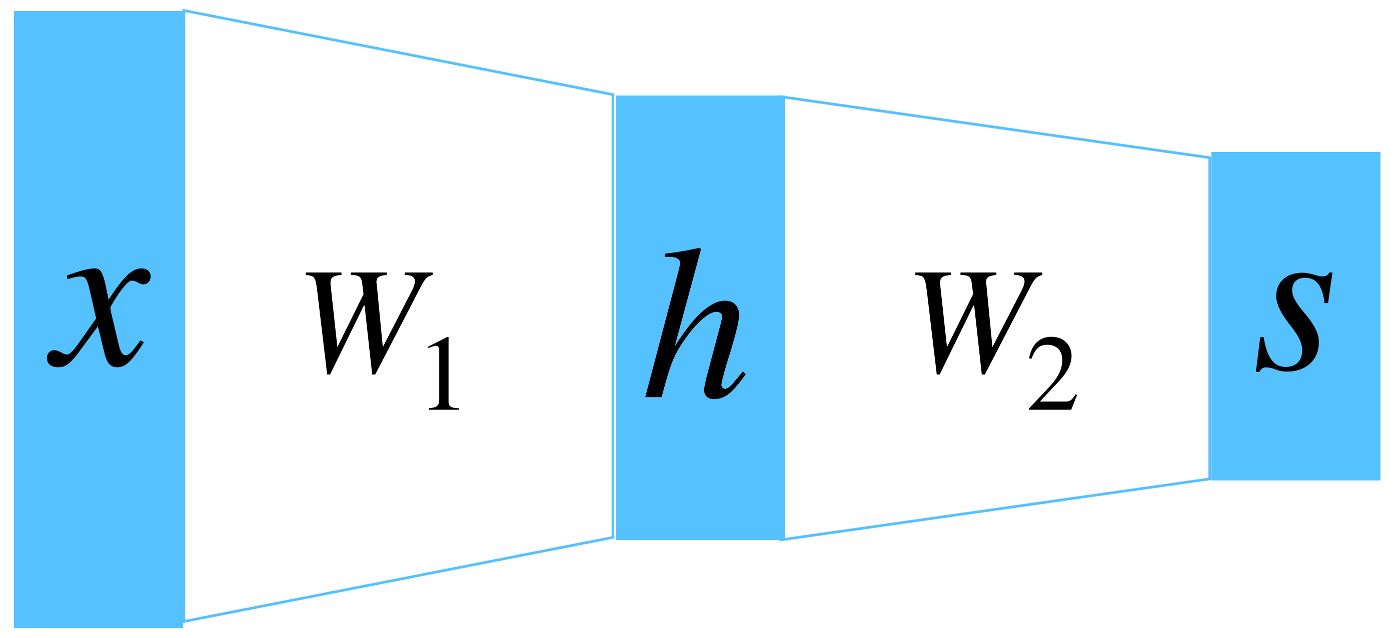
- H' = (H – K) / S + 1
- W' = (W – K) / S + 1

Learnable parameters: None!

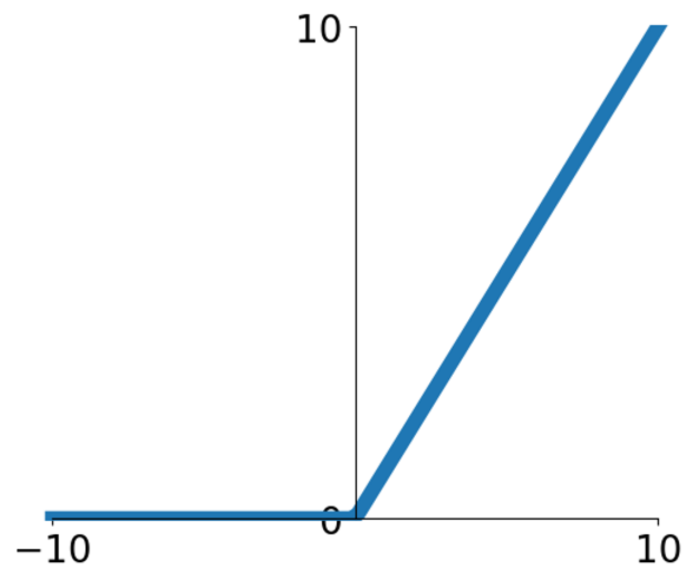
Common settings:
max, K = 2, S = 2
max, K = 3, S = 2 (AlexNet)

Components of Convolutional Neural Networks

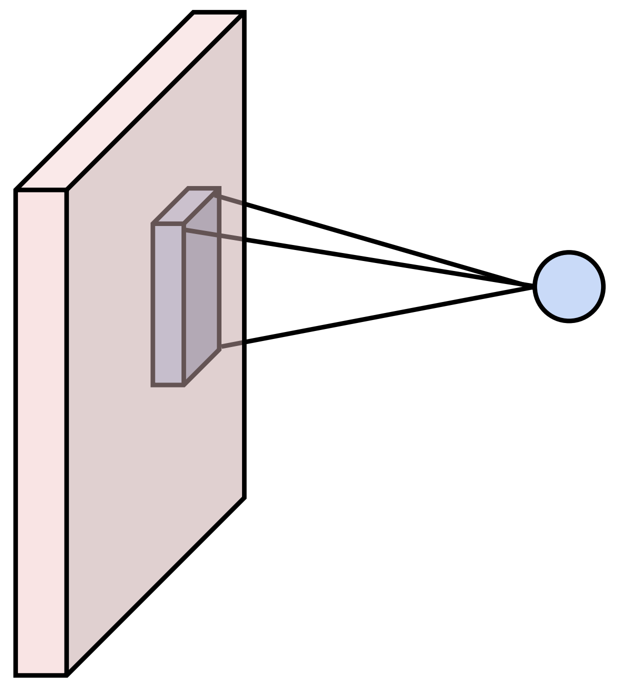
Fully-Connected Layers



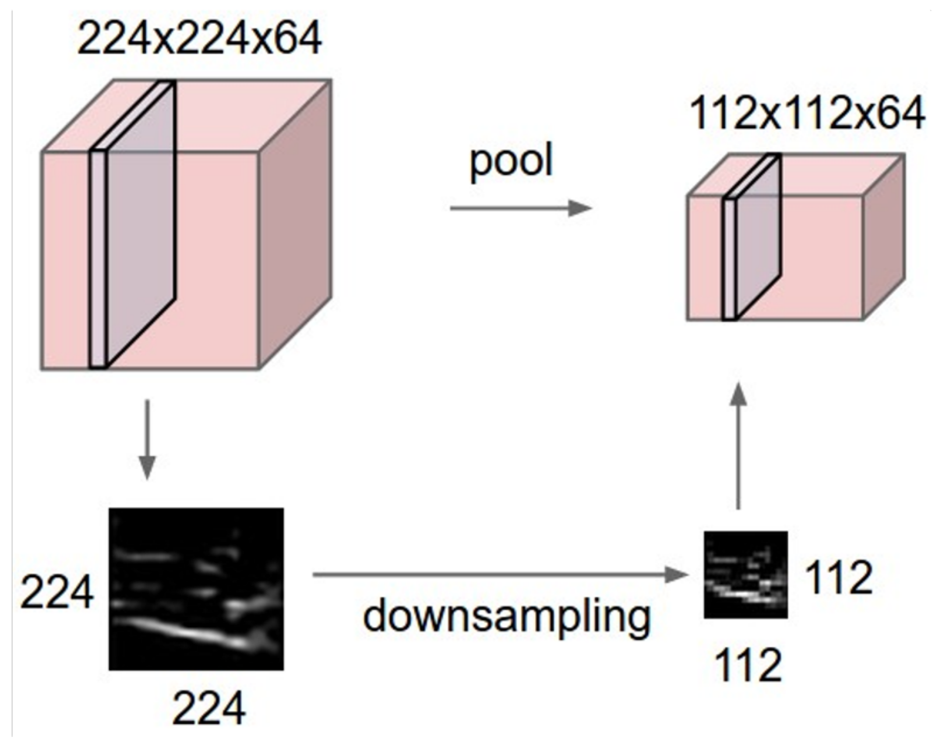
Activation Functions



Convolution Layers



Pooling Layers



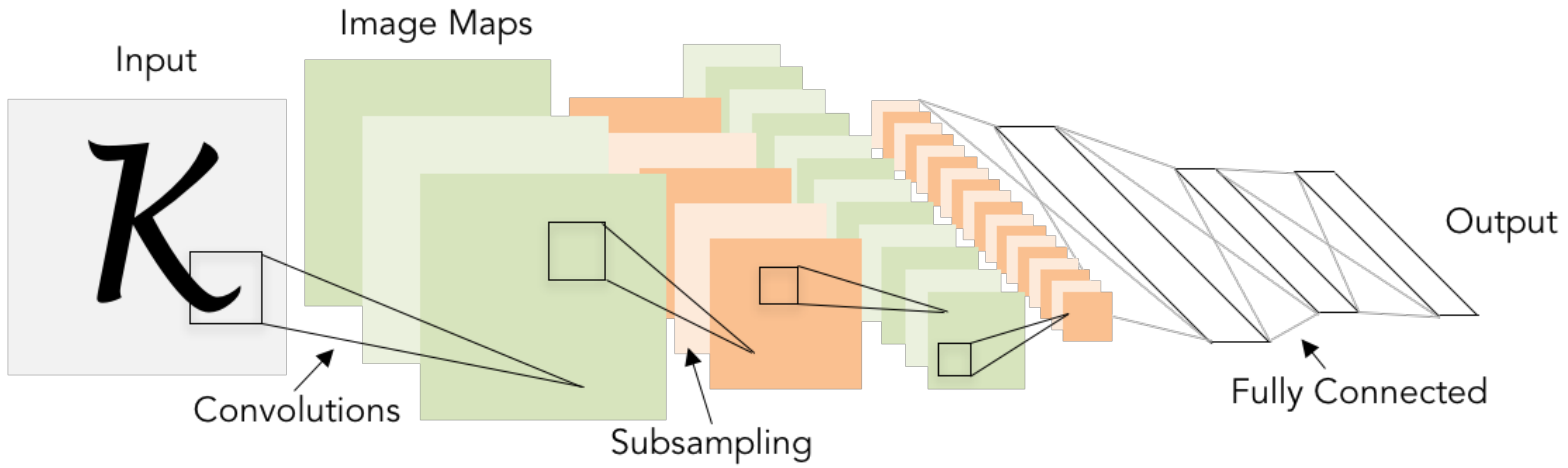
Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Convolutional Neural Networks

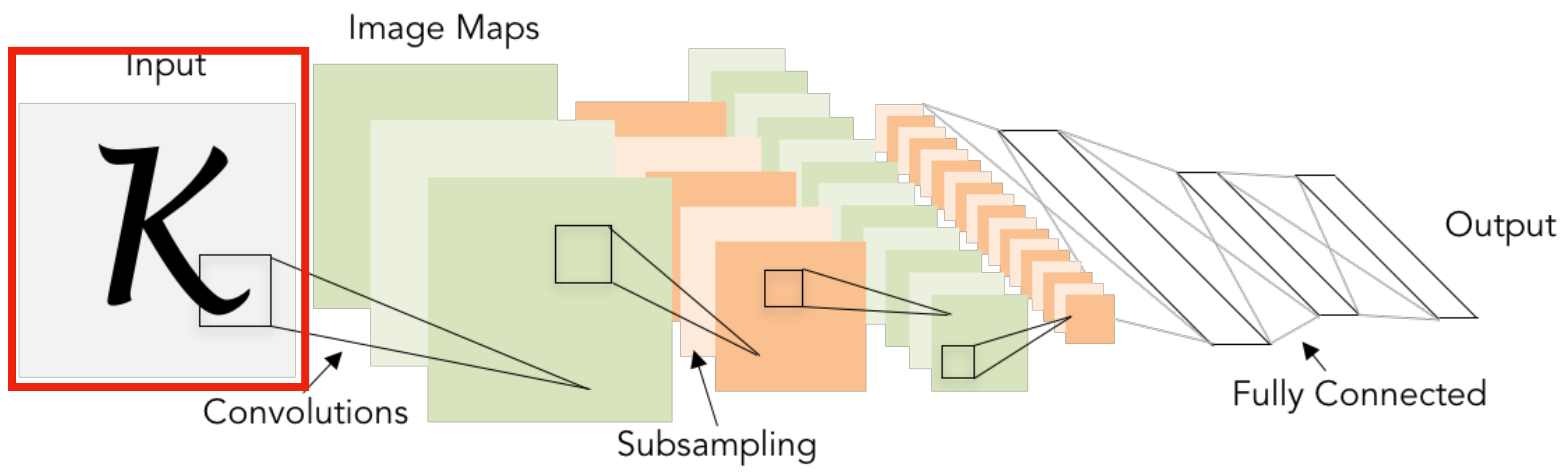
Classic architecture: [Conv, ReLU, Pool] x N, flatten, [FC, ReLU] x N, FC

Example: LeNet-5



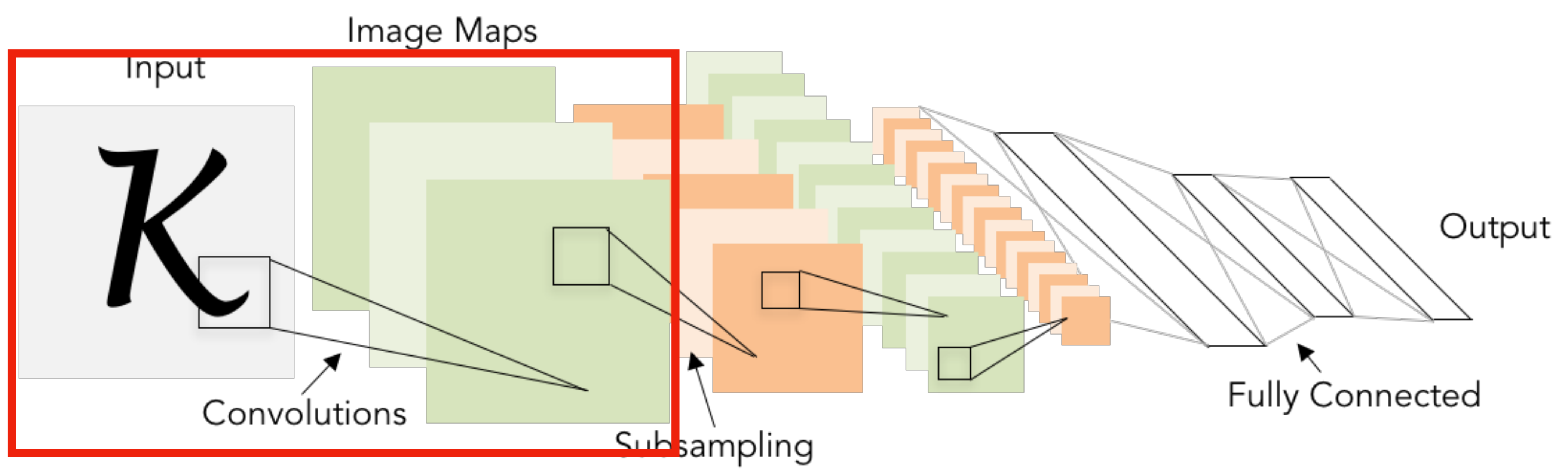
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	



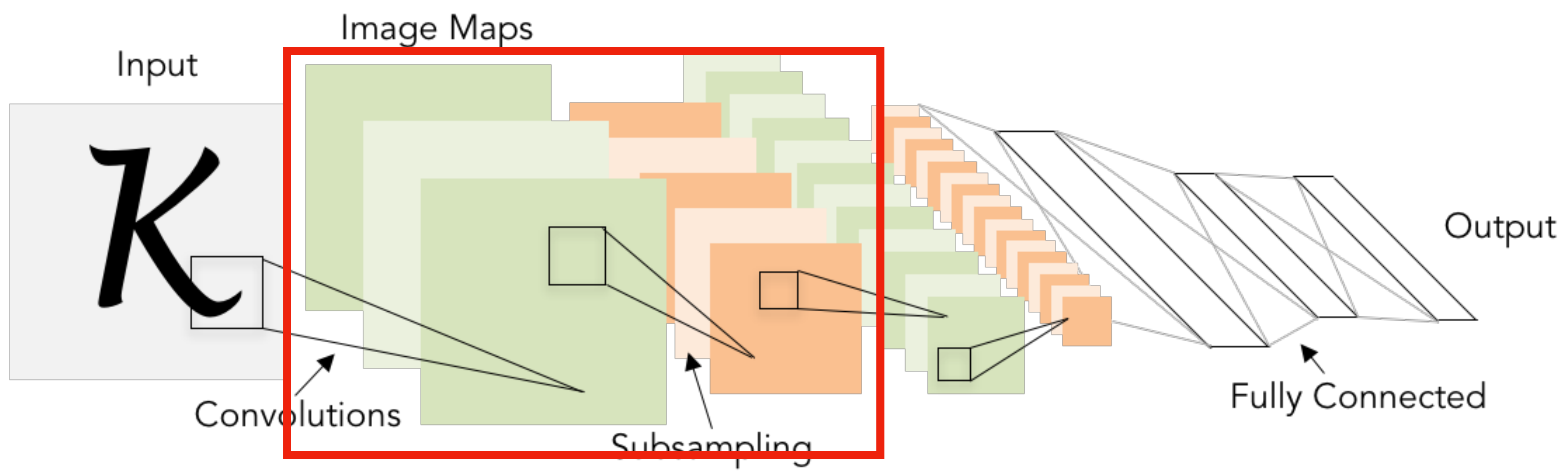
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	



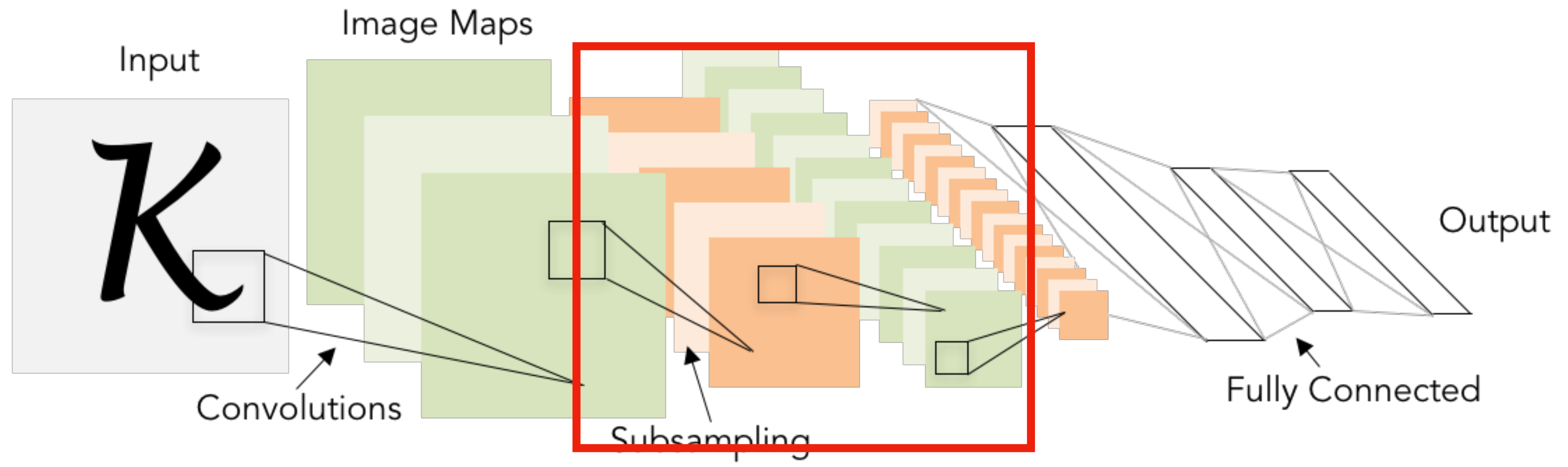
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	



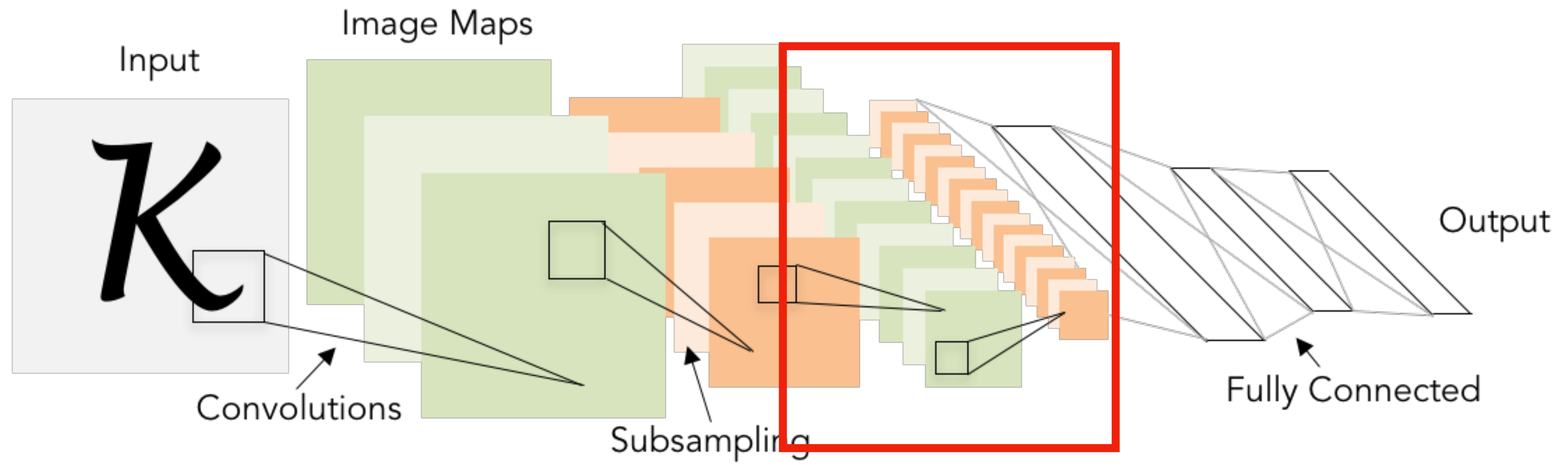
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	



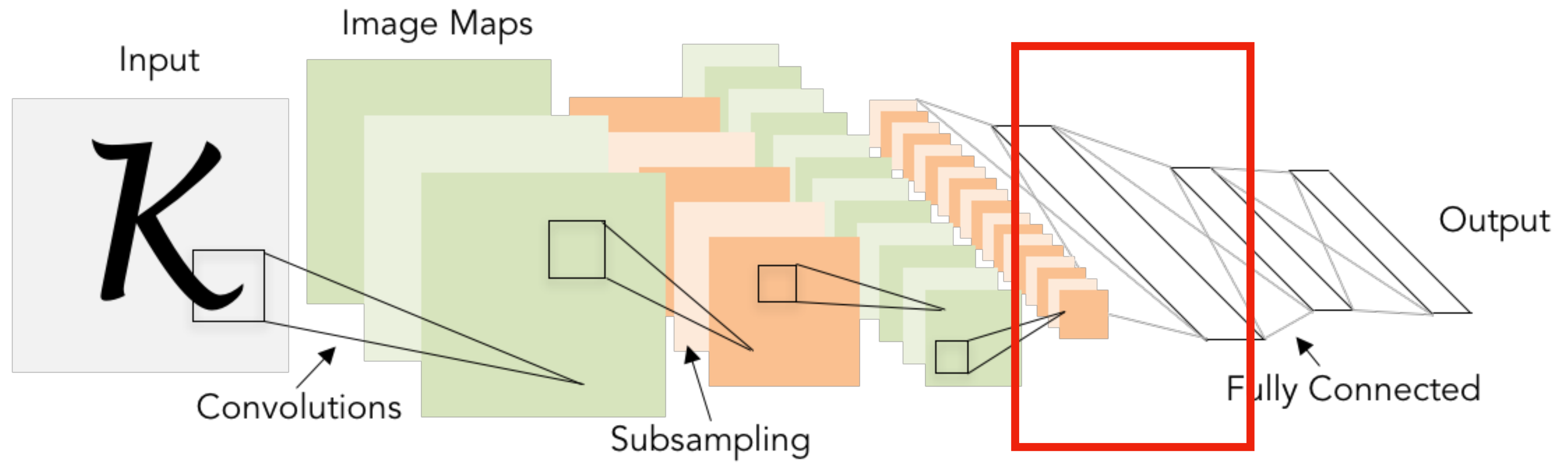
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	



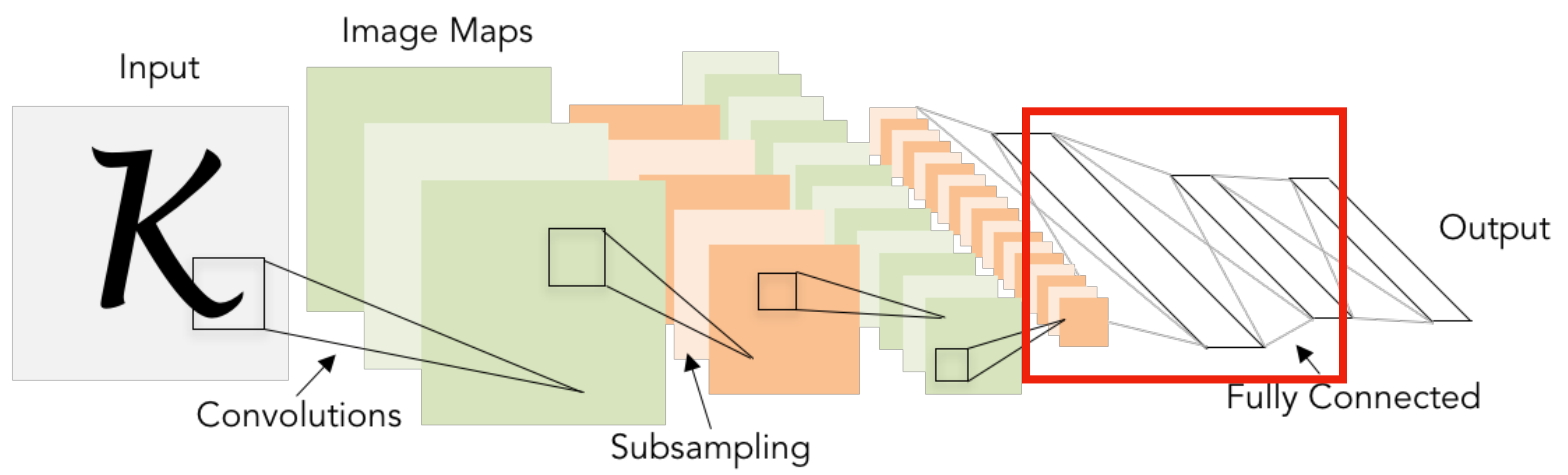
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	



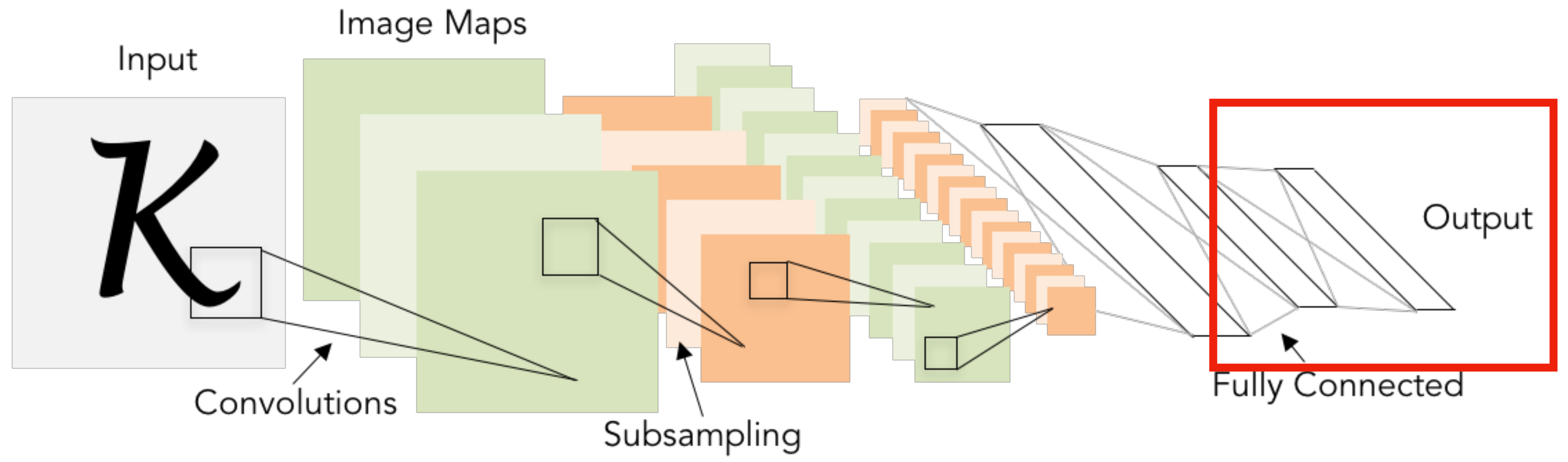
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	
Linear (2450 -> 500)	500	2450 x 500
ReLU	500	



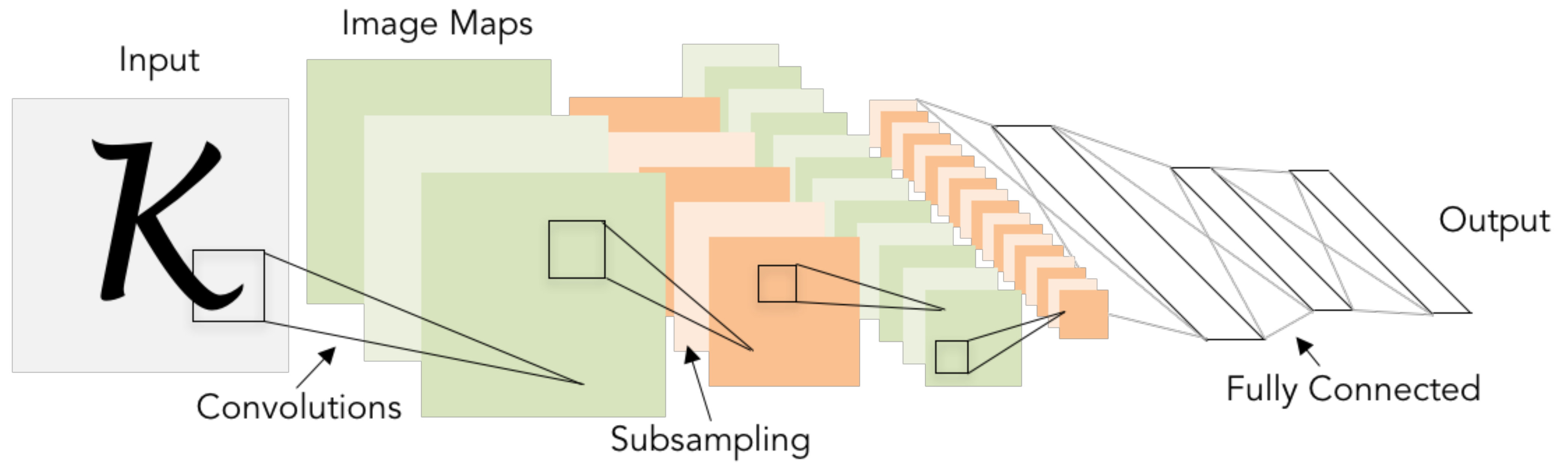
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	
Linear (2450 -> 500)	500	2450 x 500
ReLU	500	
Linear (500 -> 10)	10	500 x 10



Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	
Linear (2450 -> 500)	500	2450 x 500
ReLU	500	
Linear (500 -> 10)	10	500 x 10



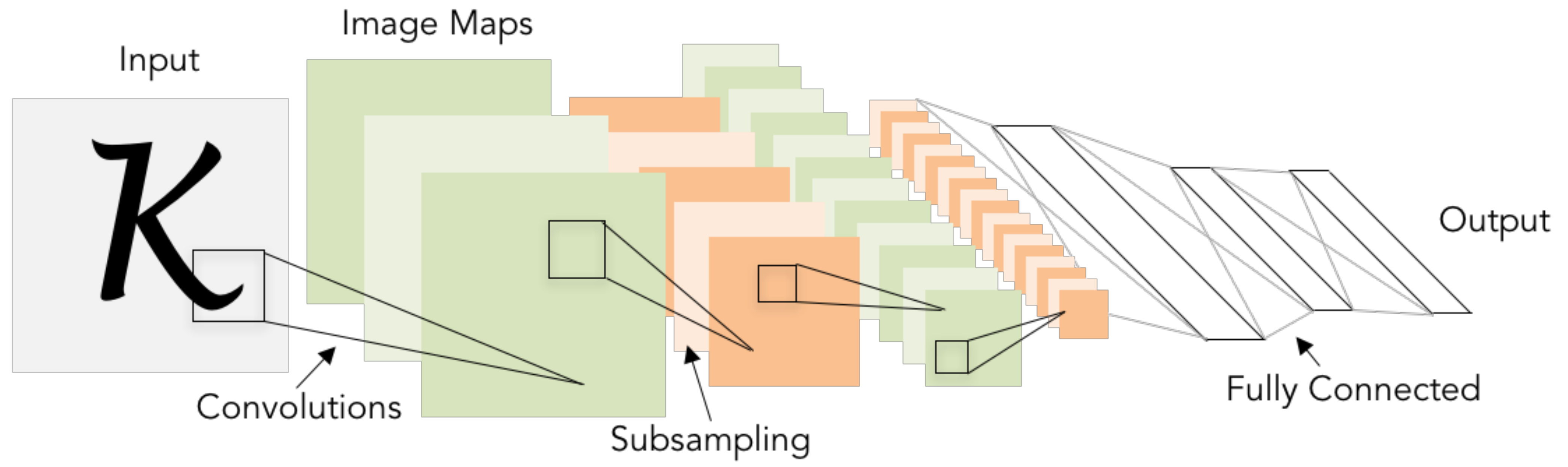
As we progress through the network:

Spatial size decreases
(using pooling or striped convolution)

Number of channels increases
(total "volume" is preserved!)

Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	
Linear (2450 -> 500)	500	2450 x 500
ReLU	500	
Linear (500 -> 10)	10	500 x 10



As we progress through the network:

Spatial size **decreases**
(using pooling or striped convolution)

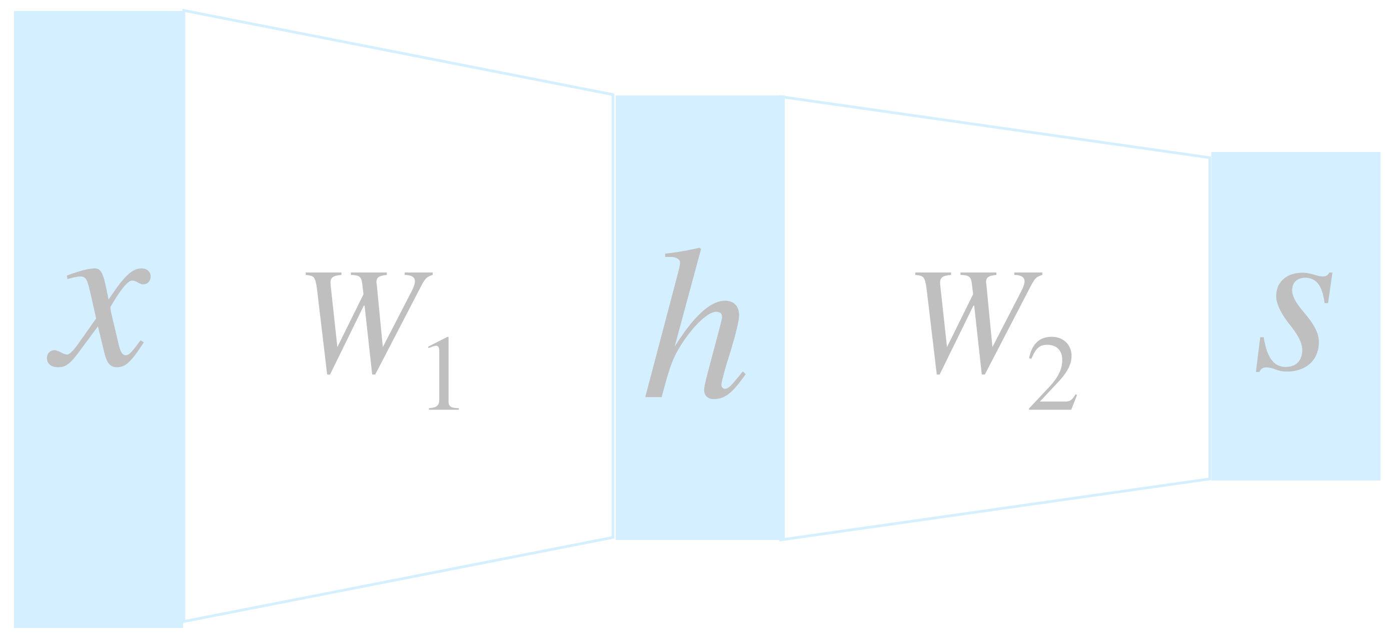
Number of channels **increases**
(total “volume” is preserved!)

Some modern architectures
break this trend—stay tuned!

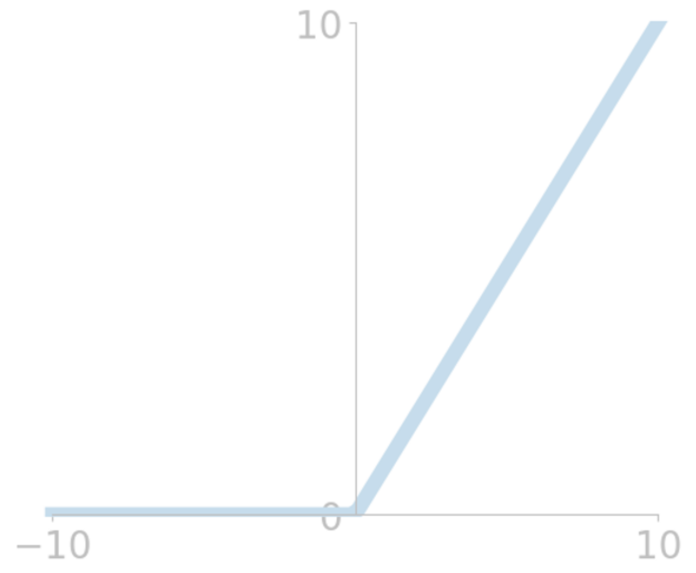
Problem: Deep Networks very hard to train

Components of Convolutional Neural Networks

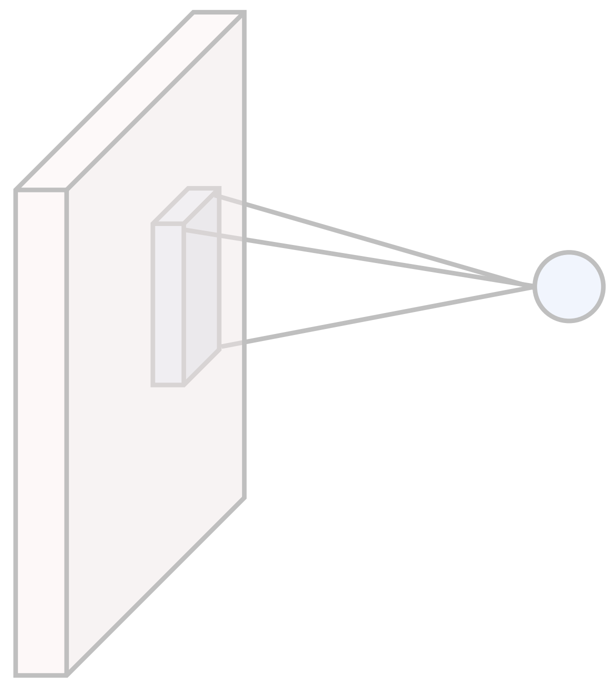
Fully-Connected Layers



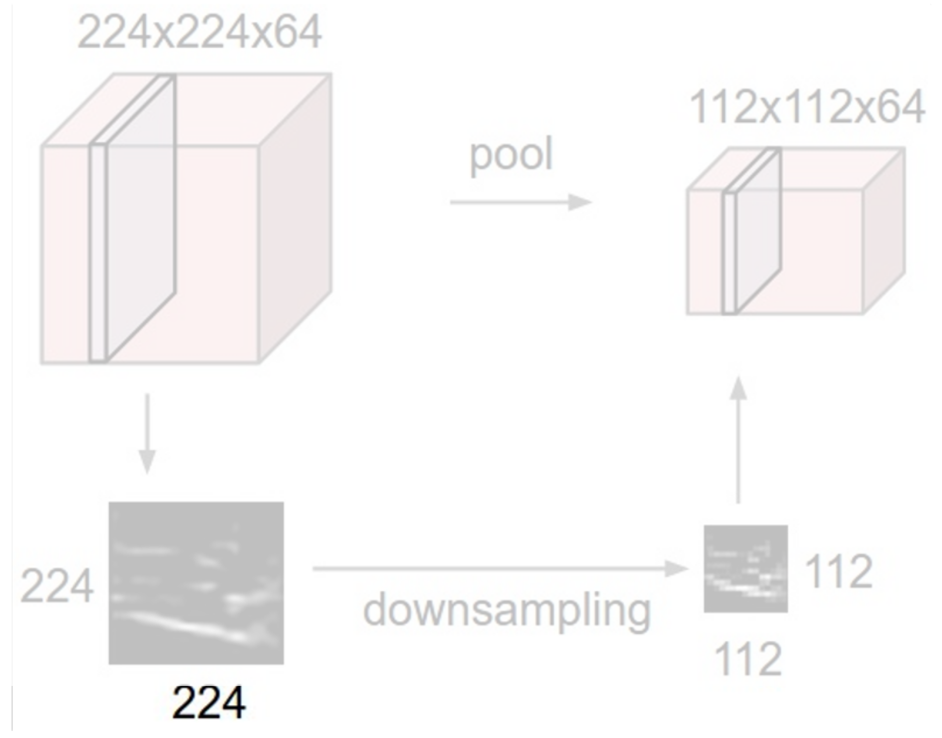
Activation Functions



Convolution Layers



Pooling Layers



Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Batch Normalization

Idea: "Normalize" the outputs of a layer so they have zero mean and unit variance

Why? Helps reduce "internal covariate shift", improves optimization results

We can normalize a batch of activations using:

$$\hat{x} = \frac{x - E[x]}{\sqrt{Var[x]}}$$

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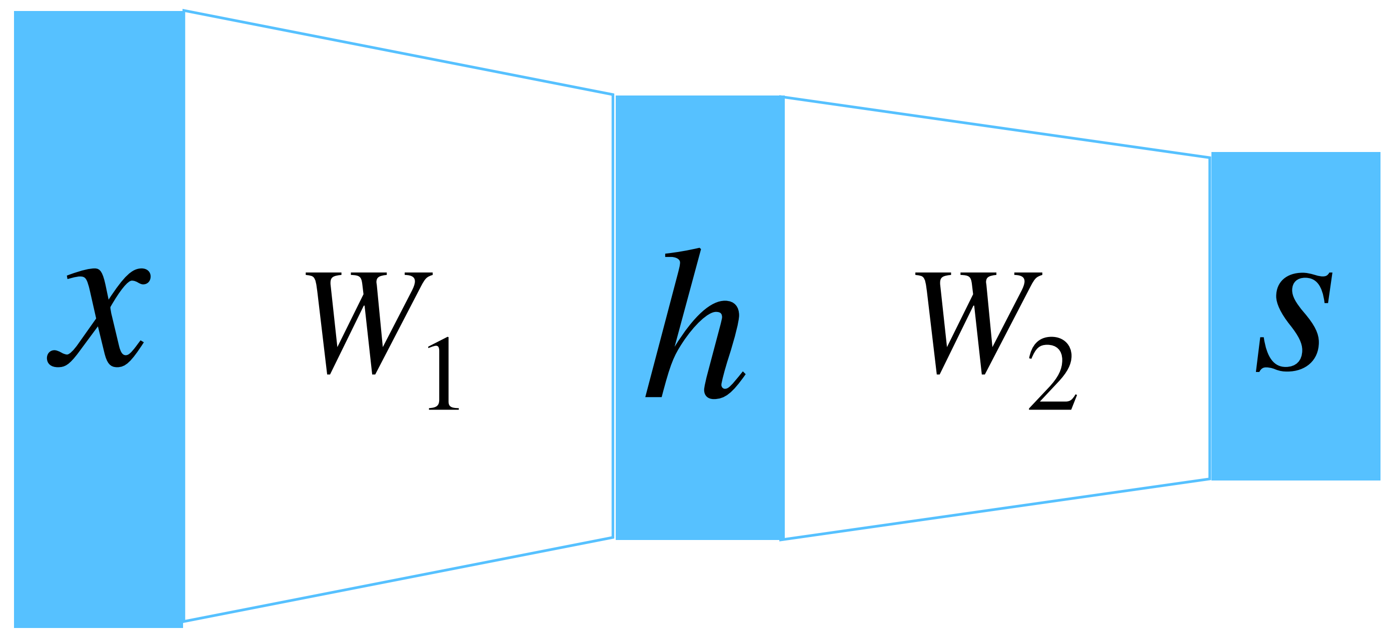
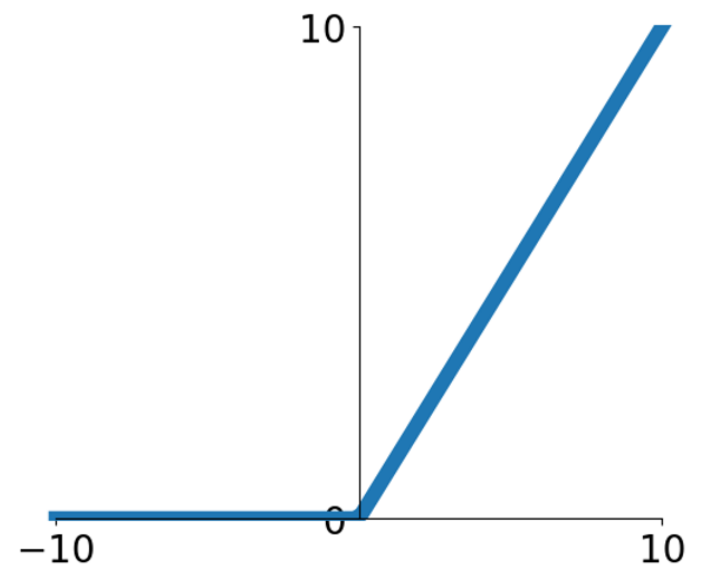
This is a **differentiable function**, so we can use it as an operator in our networks and backdrop through it!

Summary: Components of Convolutional Network

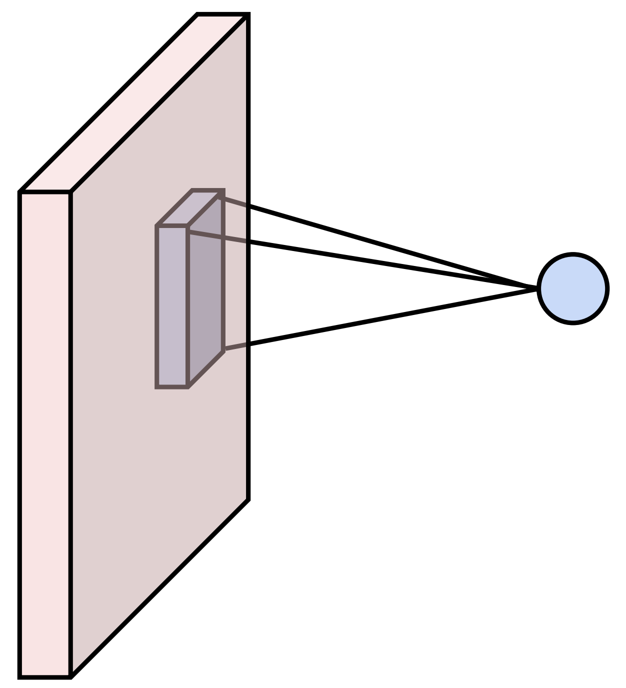
Fully-Connected Layers



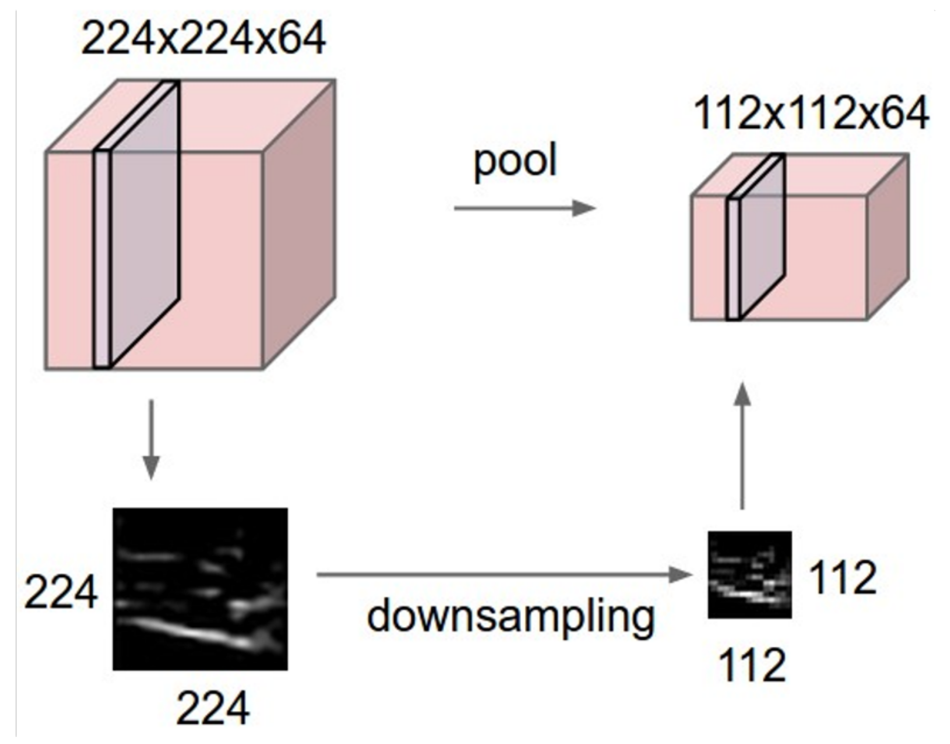
Activation Functions



Convolution Layers



Pooling Layers

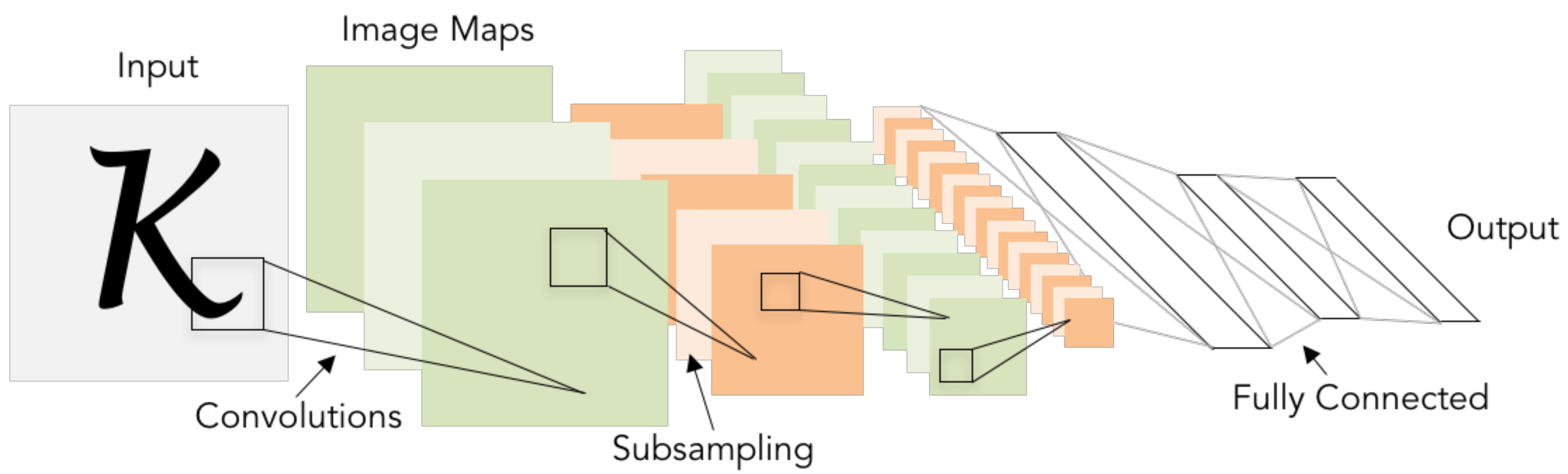


Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Summary: Components of Convolutional Network

Problem: What is the right way to combine all these components?



Next time: CNN Architectures

Final Project Overview

- Research-oriented final project
    - Instead of a final exam!

- Objectives
    - Gain experience reading literature
    - Reproduce published results
    - Propose a new idea and test the results!

Final Project Overview

- Research-oriented final project
  - Instead of a final exam!

Can be completed in teams of 1-3 people

- Objectives
  - Gain experience reading literature
  - Reproduce published results
  - Propose a new idea and test the results!

DR

Final Project Deliverables

1. A written paper review
2. In-class paper presentation
3. Reproduce published results
4. Extend results with new idea, technique or dataset
5. Document results in written report

(1) Paper Review and (2) Presentation

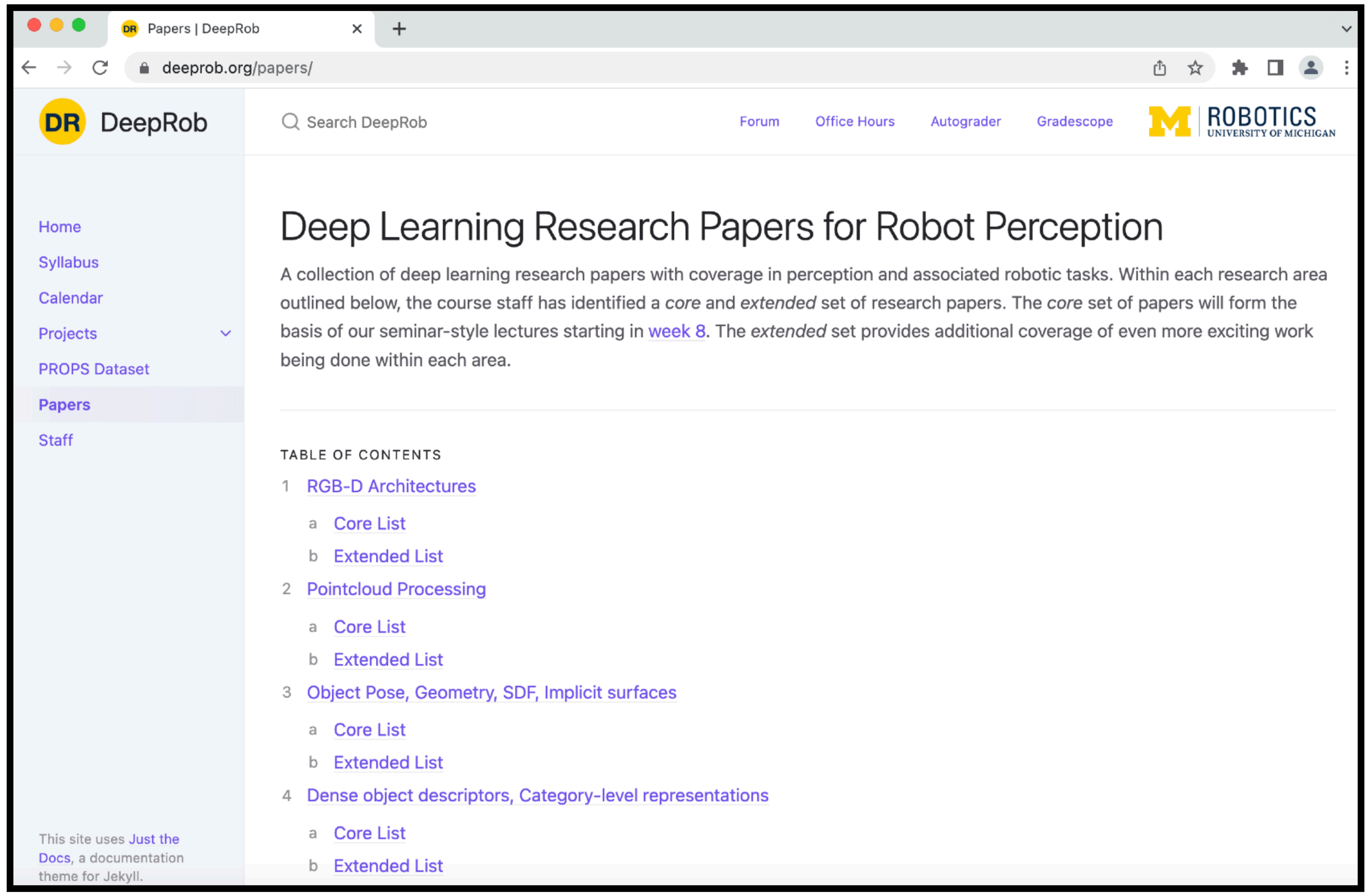
Final project teams will be based on overlapping interest

Students will choose from the 'core' list of papers on course website

Each team will be assigned one of the 'core' papers to review and present in-class

The 1-page paper review will be due **1-week before** the scheduled presentation

Presentation schedule will be based on paper topic as shown in course calendar



Deep Learning Research Papers for Robot Perception

A collection of deep learning research papers with coverage in perception and associated robotic tasks. Within each research area outlined below, the course staff has identified a *core* and *extended* set of research papers. The *core* set of papers will form the basis of our seminar-style lectures starting in week 8. The *extended* set provides additional coverage of even more exciting work being done within each area.

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This site uses Just the Docs, a documentation theme for Jekyll.

More details on review and presentation criteria in following lectures

(3) Paper Reproduction and (4) Extension

Each team will choose a paper relating to deep learning and robot perception

Doesn’t have to be same paper you presented in class

Then reimplement and reproduce at least one of the paper’s published results **(not necessarily all the results)**

Then, each team will test one of their own ideas!

By extending the paper’s model using new architecture or technique or dataset

Your chance to experiment with deep learning and contribute to the field!

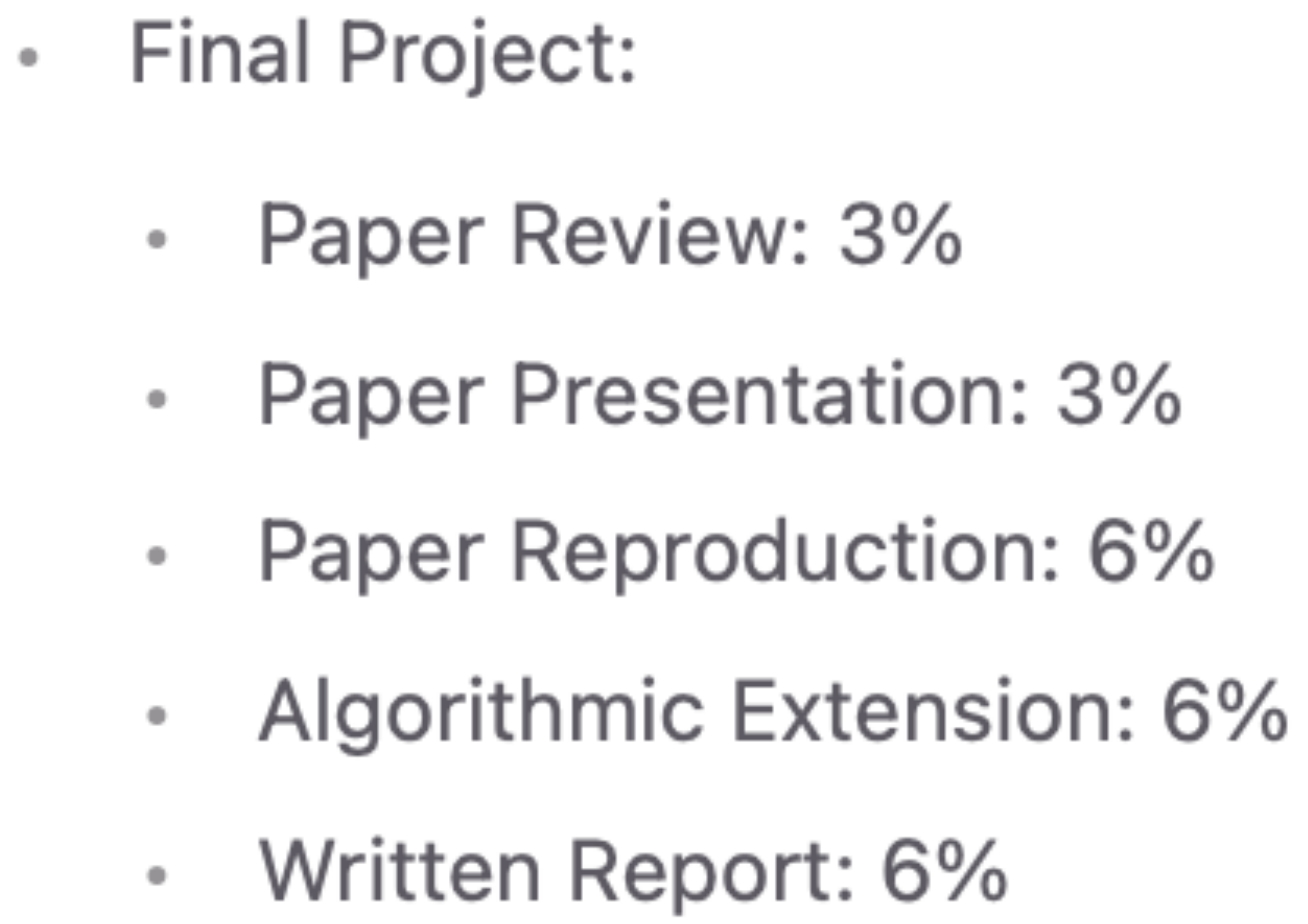
More details on reproduction and extension in following lectures

(5) Project Report

- The final deliverable for your final project
- A 1-2 page paper
  - What problem within robot perception or manipulation?
  - What work has been done in this area?
  - What approach did you investigate?
  - What questions and directions exist for future work?

More details on report in following lectures

Final Project Grading Overview



- Final Project:
  - Paper Review: 3%
  - Paper Presentation: 3%
  - Paper Reproduction: 6%
  - Algorithmic Extension: 6%
  - Written Report: 6%

More details on report in following lectures

DeepRob

Lecture 7
Convolutional Neural Networks
University of Michigan and University of Minnesota

Slides adapted from Justin Johnson's Deep Learning for Computer Vision course 91