THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532L):
Multimodal Learning with Vision, Language and Sound

Lecture 4: Convolutional Neural Networks (Part 1)

Course **Logistics**

— **Azure credits** have been distributed

— Instructions for using Azure are on Piazza

— **Office hours** (Shikib) on Wednesday (January 17th) 1-2pm

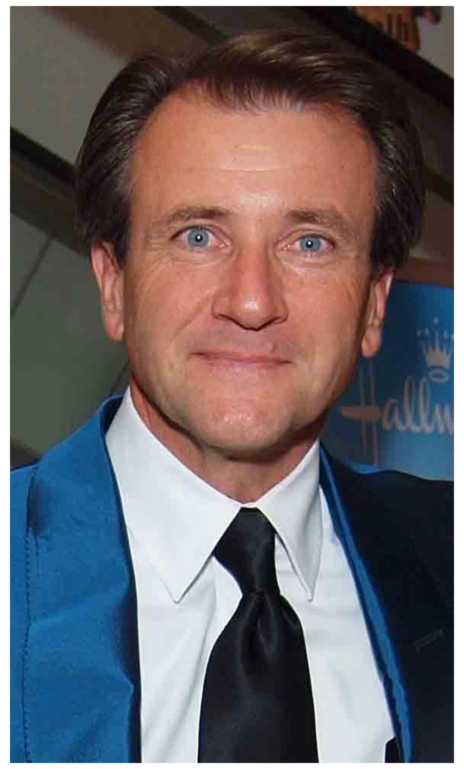
— Assignment 1 grading

— Assignment 2 will be out today (on CNNs)

— Start thinking about **papers**

— Start thinking about **project** and forming groups (proposal is in ~month)

Research **Projects**

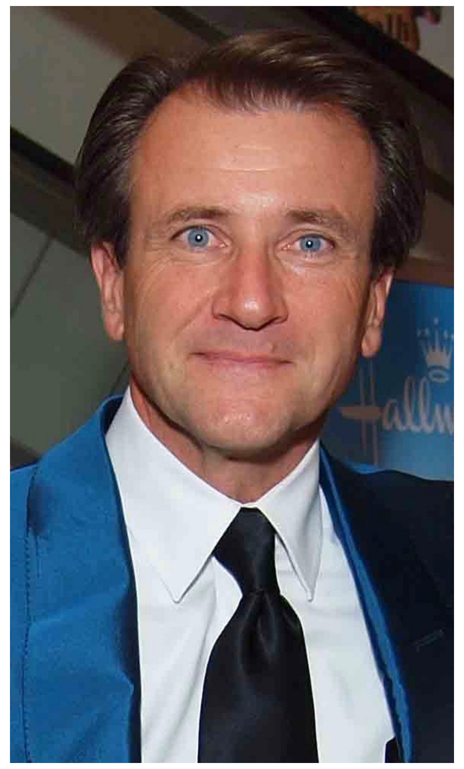


Robert Herjavec
(Canadian businessman and investor)
Shark Tank

Research **Projects**

Business

“A good **entrepreneur** can take a mediocre **idea** and make it great, a bad entrepreneur will take the best idea and run it into a ground.”



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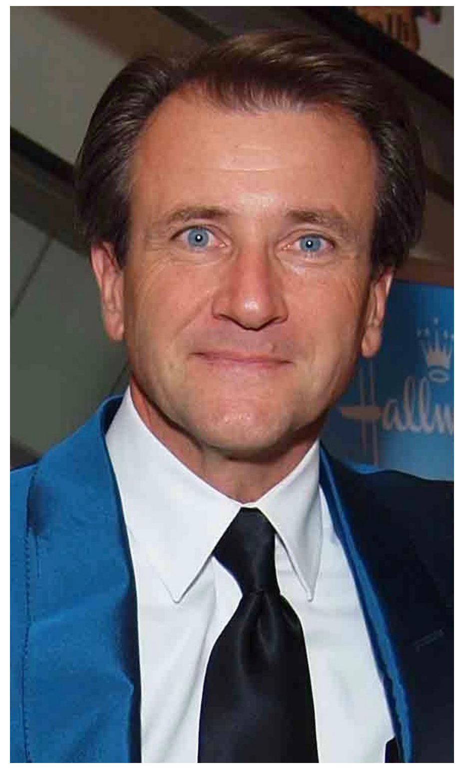

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Research

“A good **idea** can make a mediocre **project** great, a bad idea will take the best project and run it into a ground.” — Me

Research **Projects** Ideas Levels of Abstraction

I want to **solve vision** / language / etc.

Marvin Minsky

Research **Projects** Ideas Levels of Abstraction

I want to **solve vision** / language / etc.

I want to do X (e.g., **image captioning**)

- This is excellent if **X** is something no one has done or thought about and is important (guaranteed success)
- Requires **forward thinking**, knowledge of the field
- A sure way to get tenure
- Difficult to do as the field matures

Rosland Picard, MIT — Affective Computing

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— **Perspective:** come up with an idea or the insight that you truly believe and test it

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— Helps to bringing knowledge from other fields (field cross pollination)

Research **Projects** Ideas Levels of Abstraction

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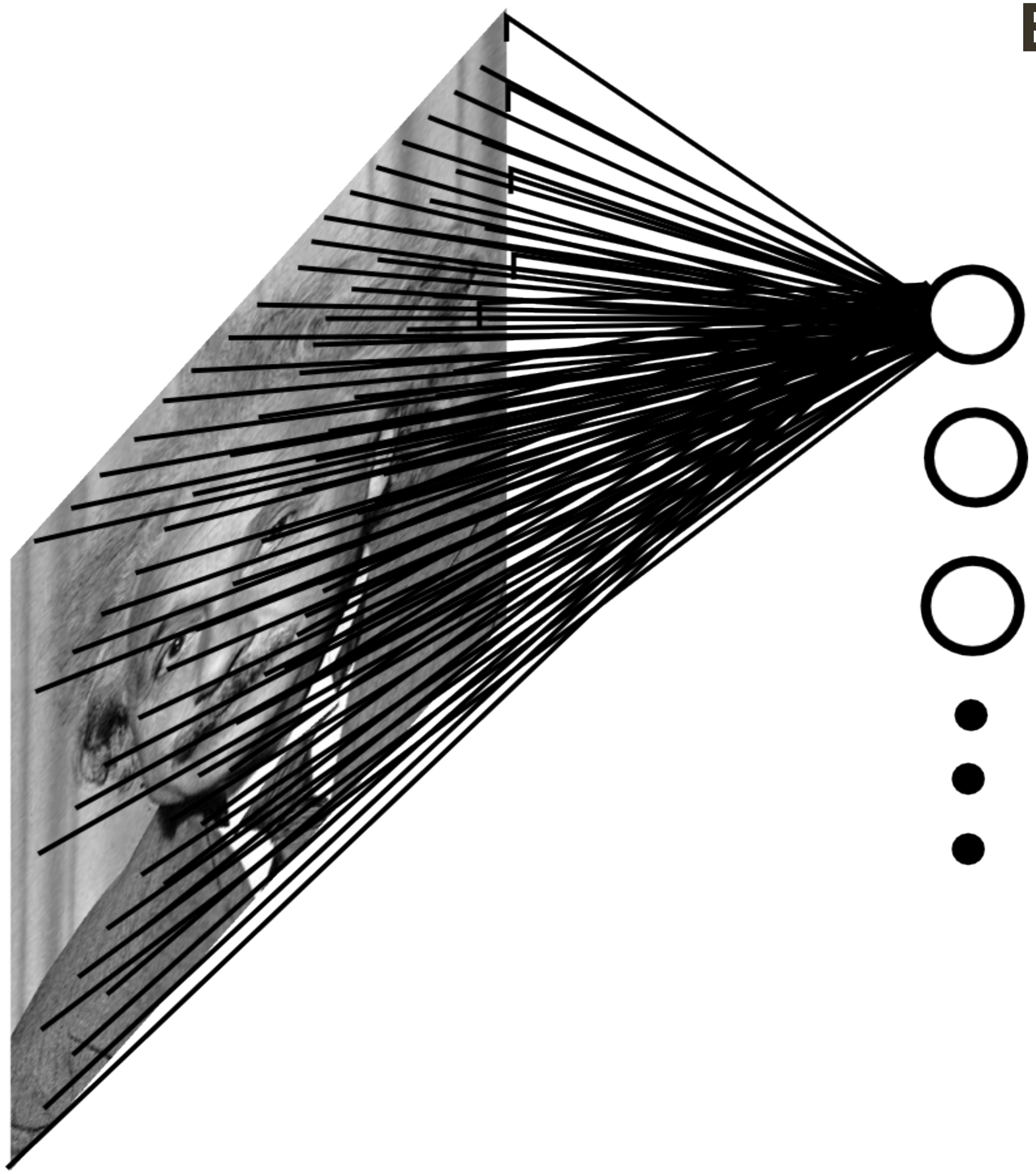
Mathematical **formulation**

Implementation / engineering

Experimental testing

On to **todays** lecture …

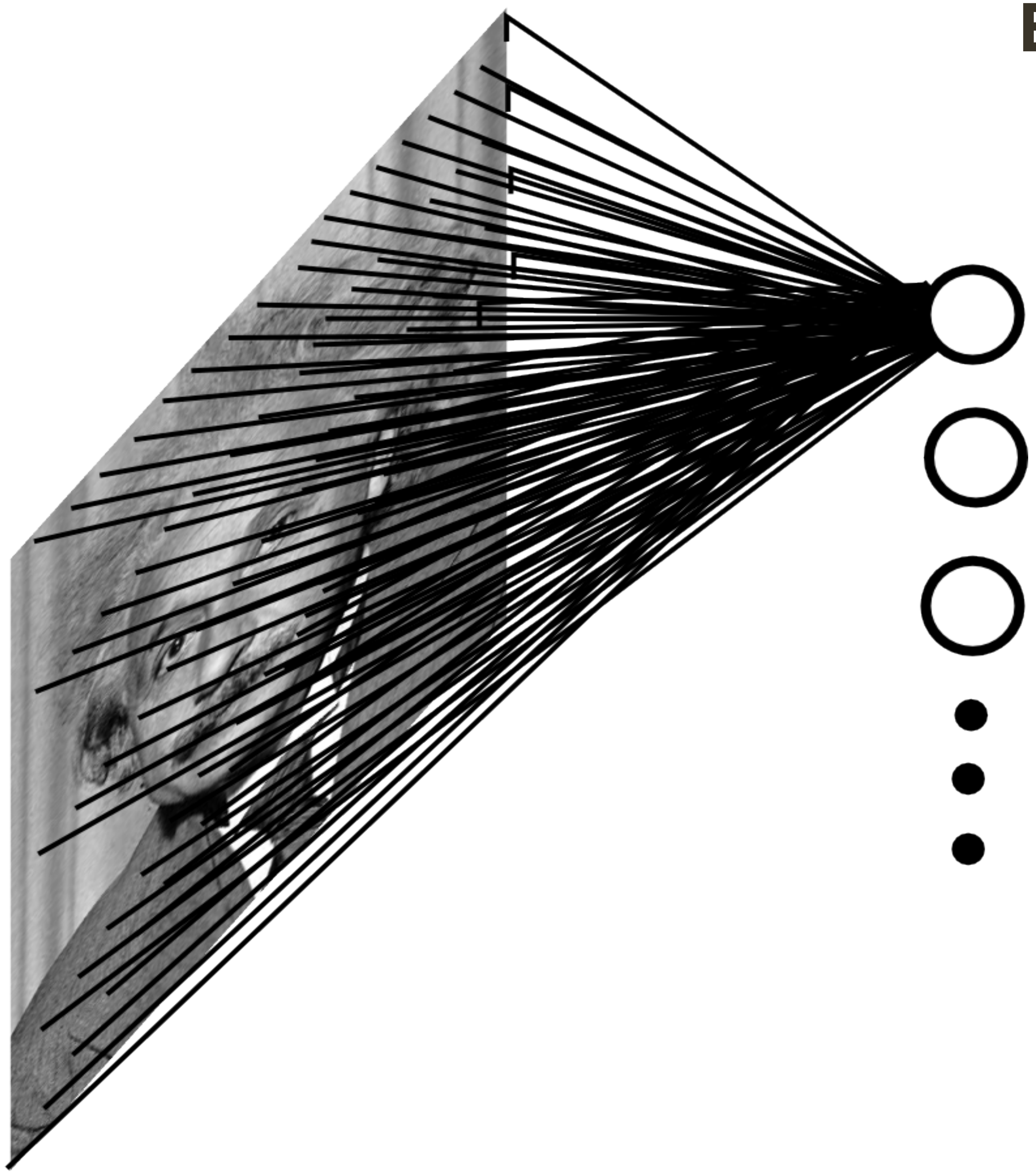
Fully Connected Layer



Example: 200 x 200 image (small)
x 40K hidden units

* slide from Marc'Aurelio Renzato

Fully Connected Layer



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= ~ **2 Billion** parameters (for one layer!)

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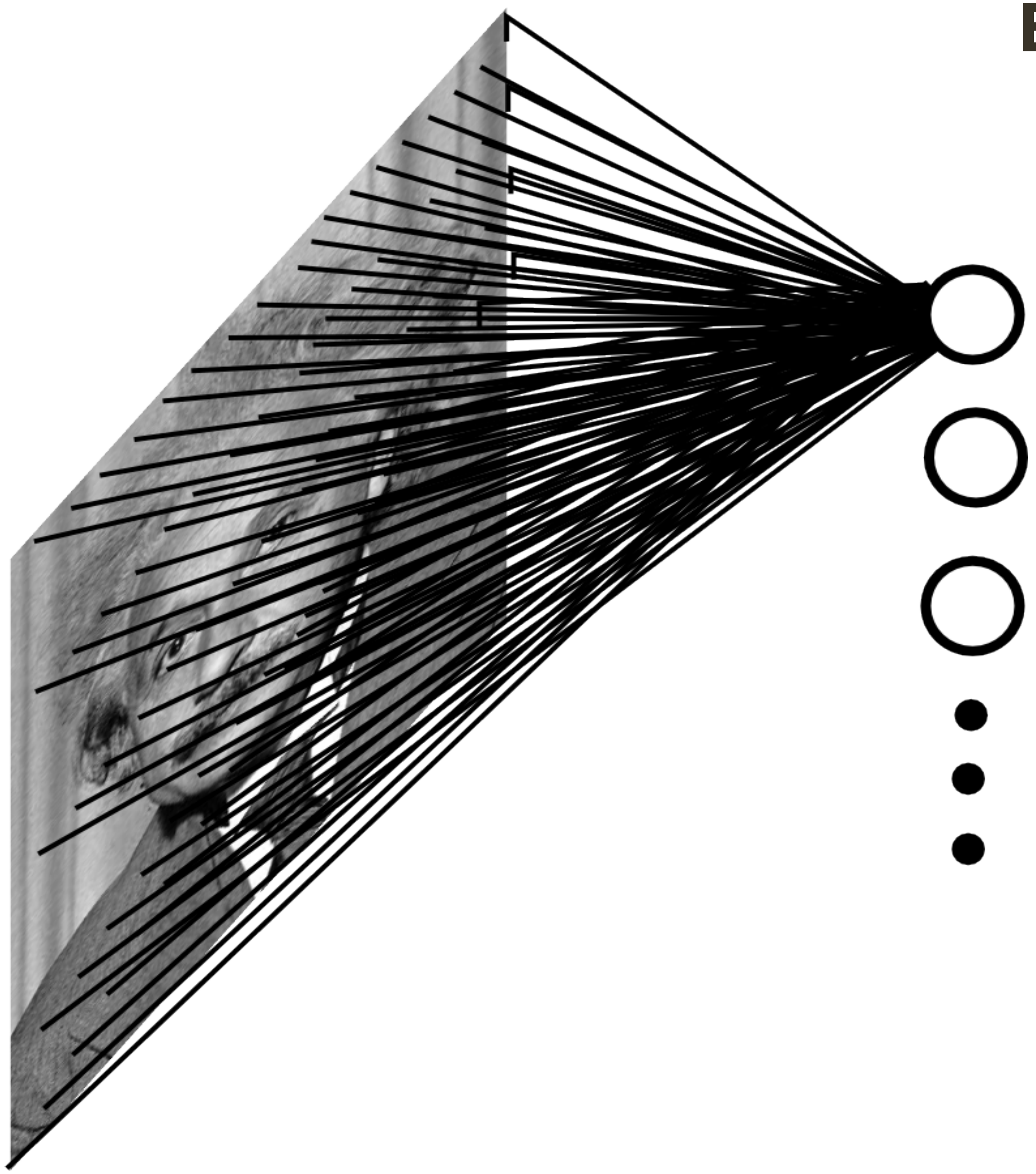

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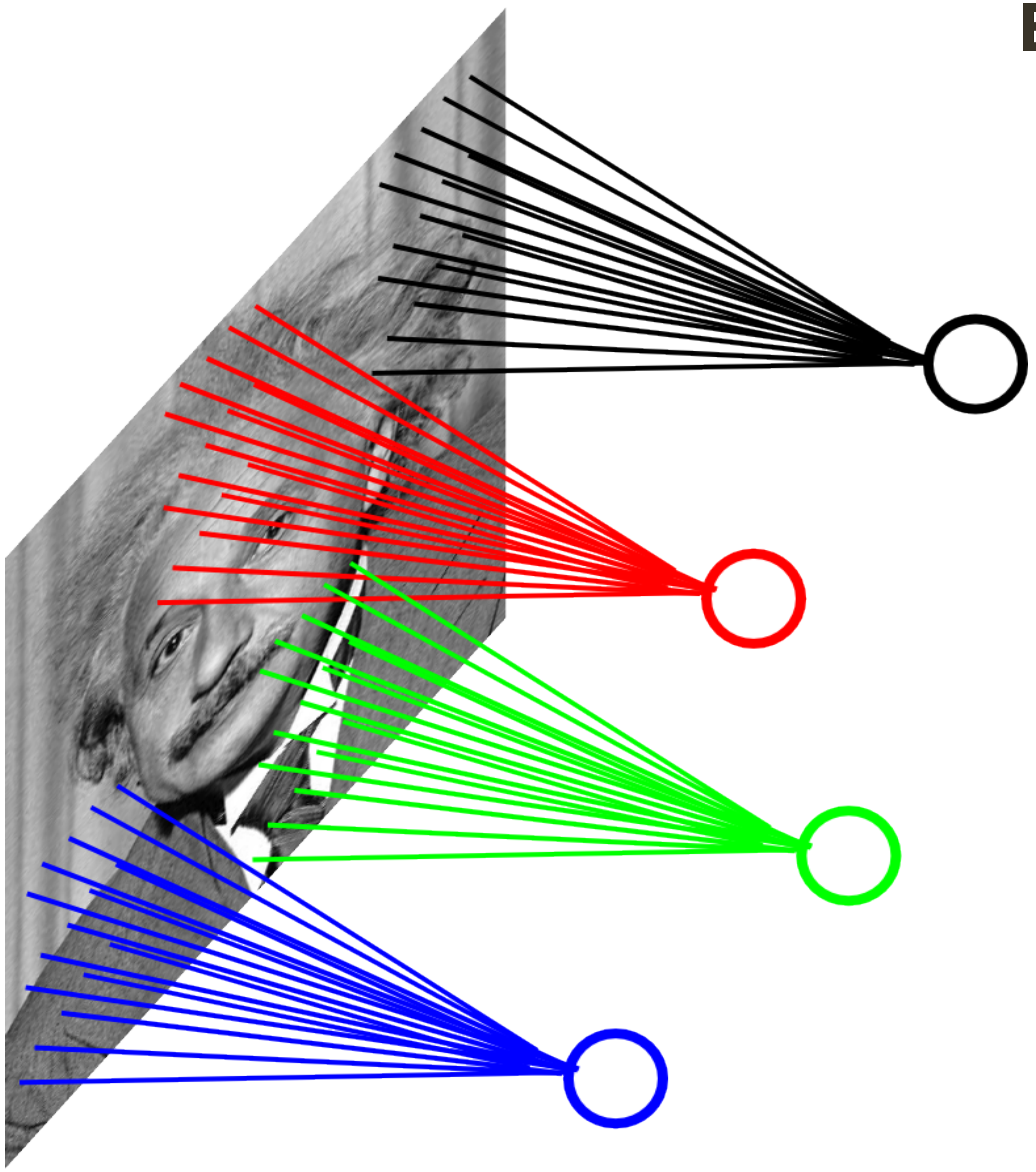
Spatial correlations are generally local

Waste of resources + we don't have enough data to train networks this large

* slide from Marc'Aurelio Renzato

Locally Connected Layer



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Filter size: 10 x 10

= ~ **4 Million** parameters

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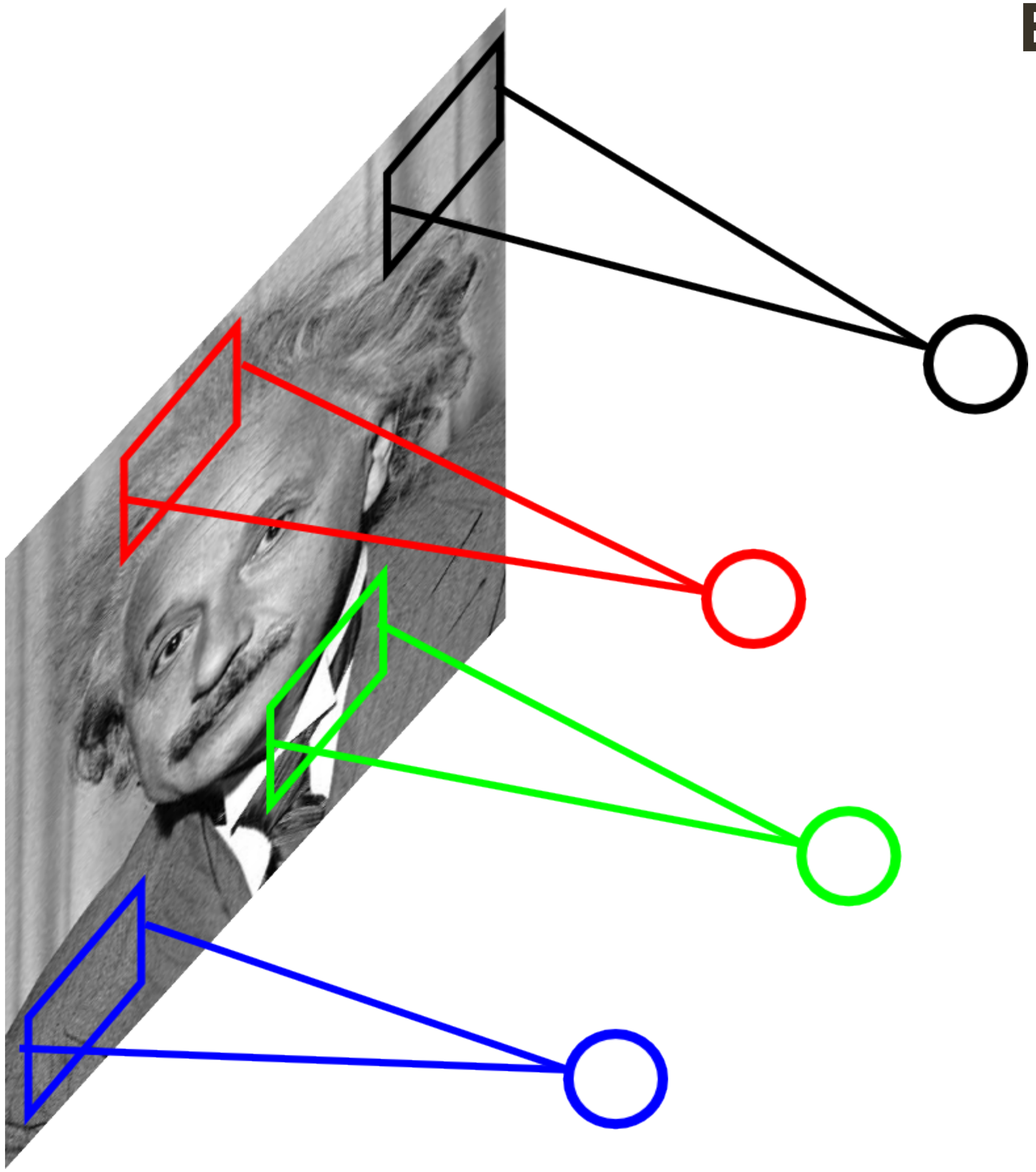
Locally Connected Layer



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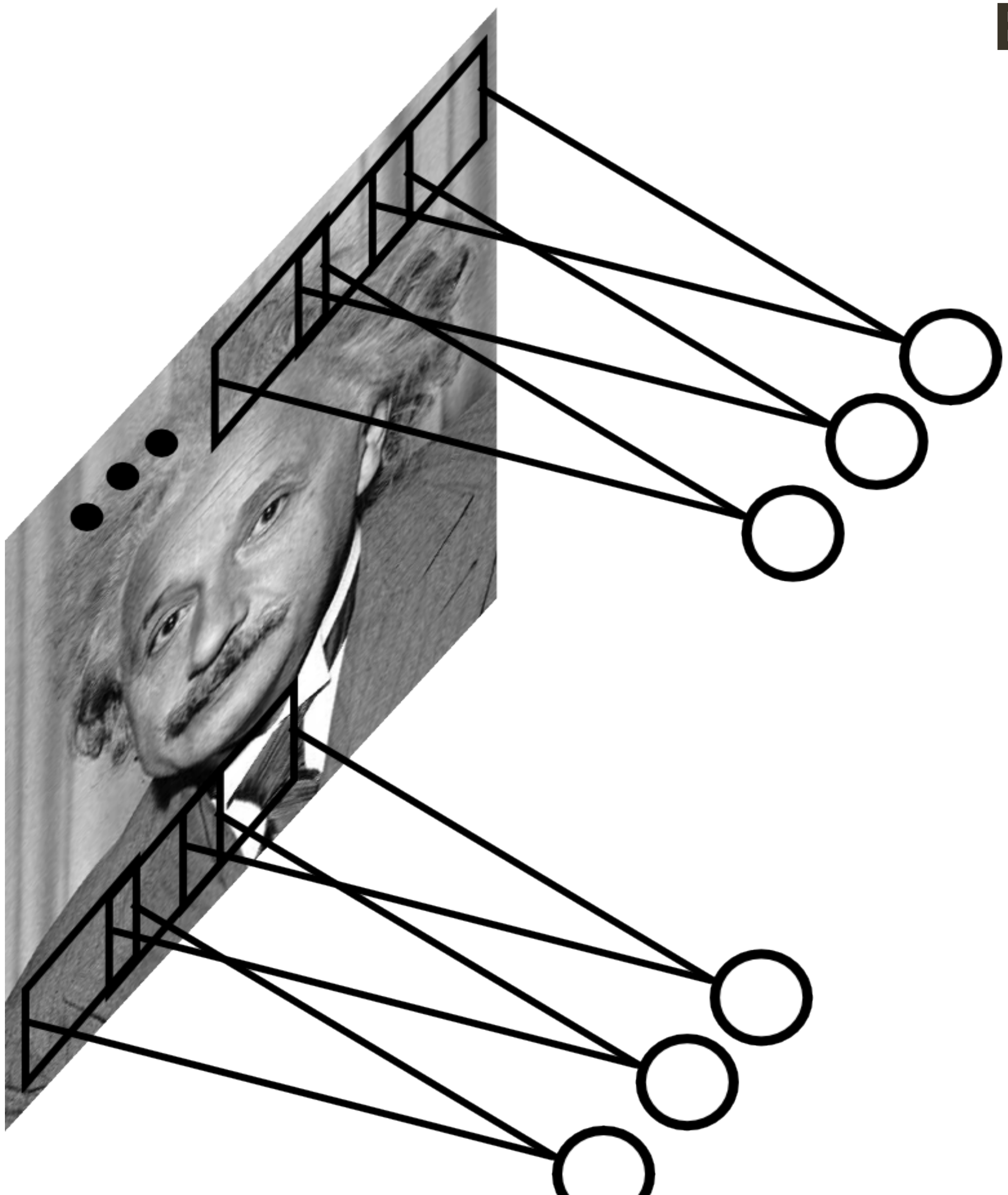
Stationarity — statistics is similar at different locations

* slide from Marc'Aurelio Renzato

Convolutional Layer



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Share the same parameters across the locations (assuming input is stationary)

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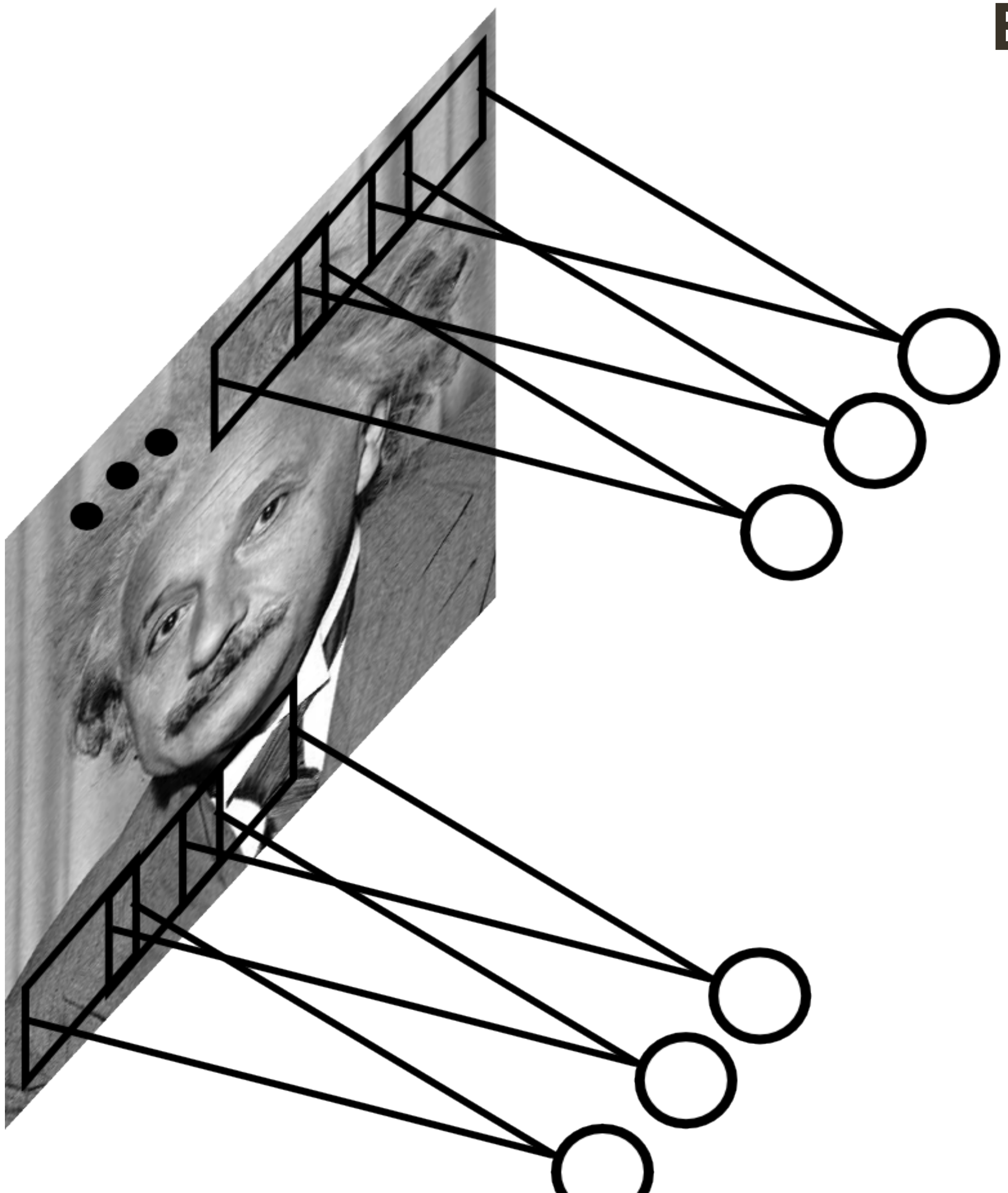

Example: 200 x 200 image (small)
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Filter size: 10 x 10

= ~ **~~4 Million~~** parameters

= 100 parameters

Share the same parameters across the locations (assuming input is stationary)

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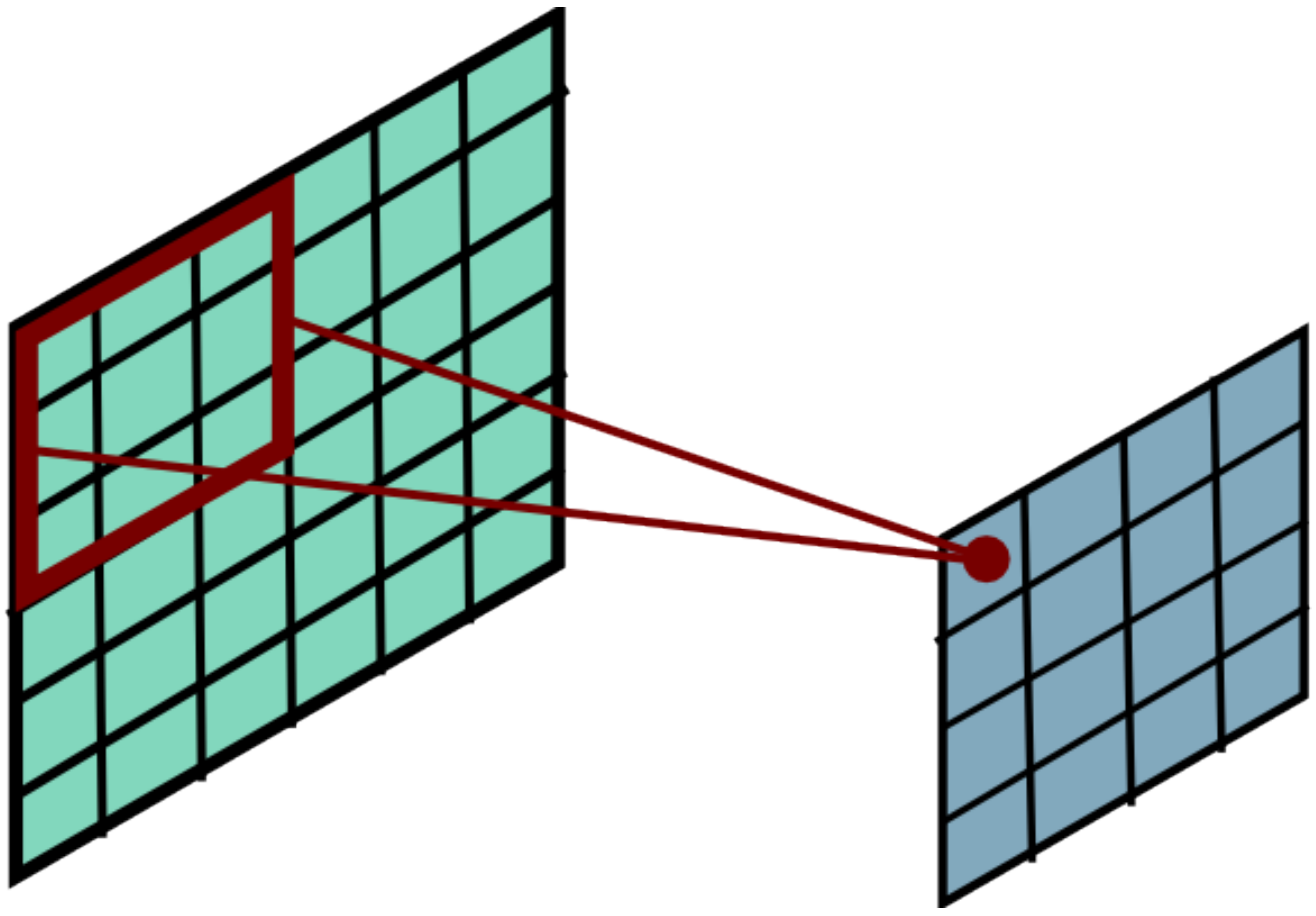

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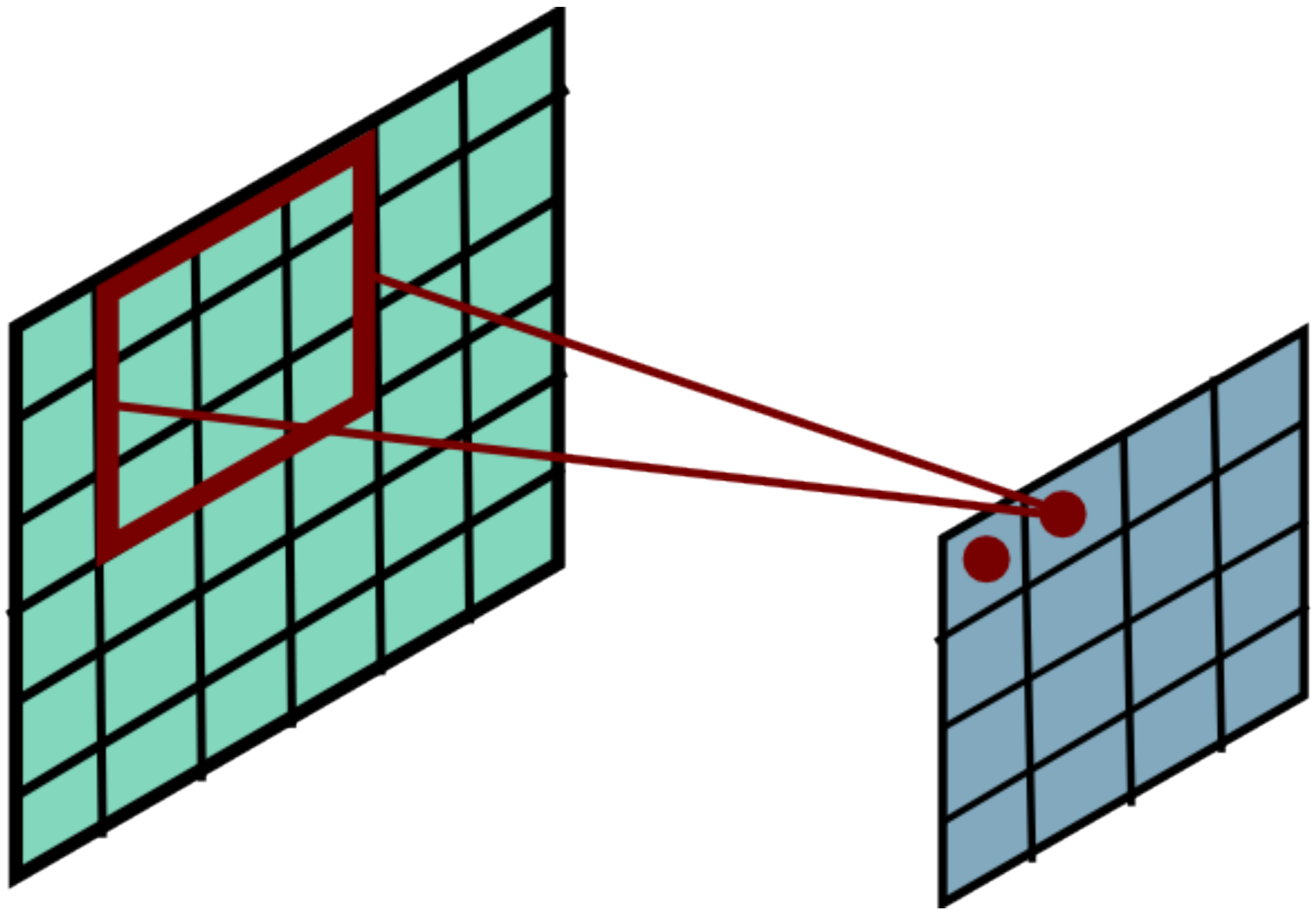

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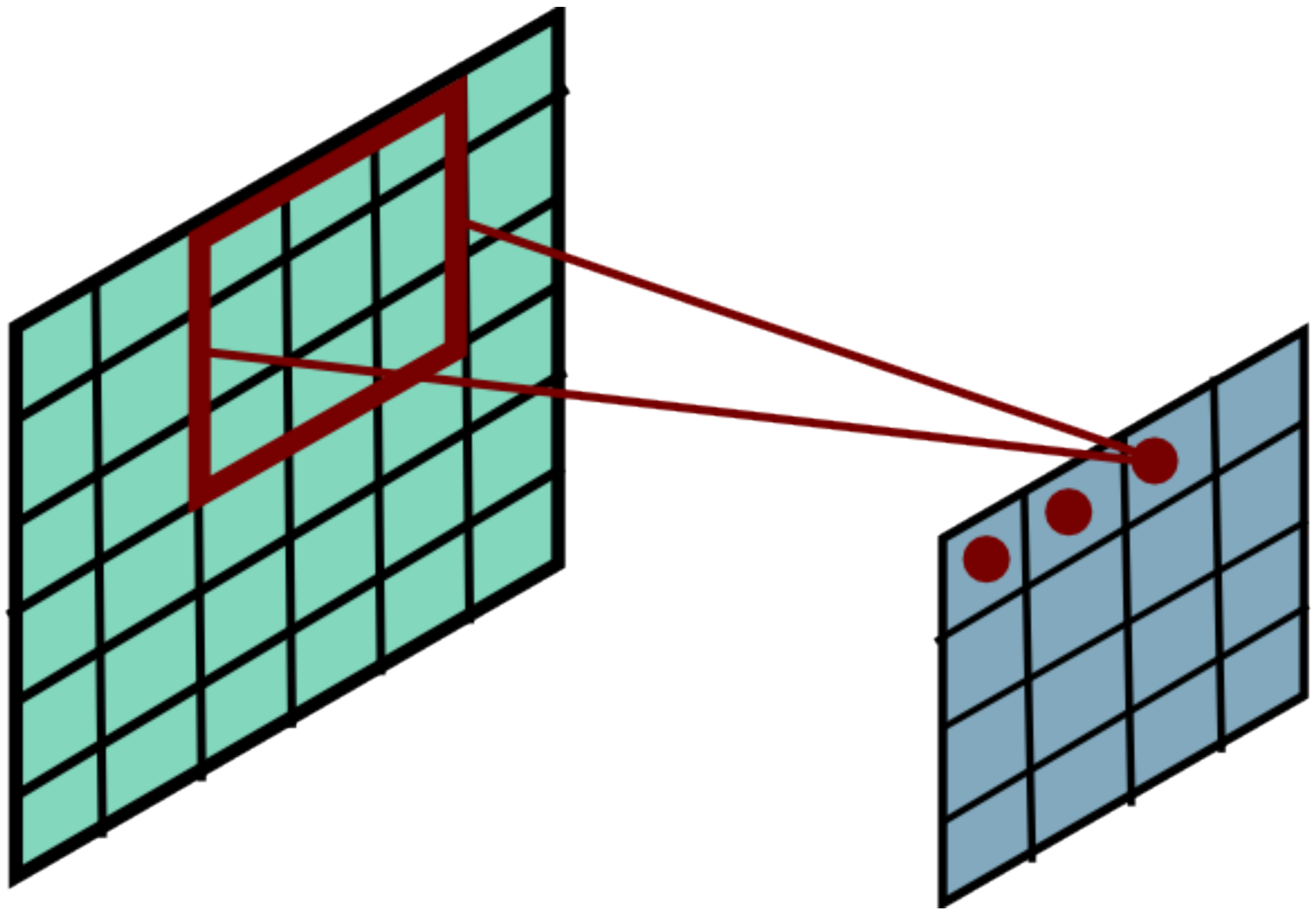

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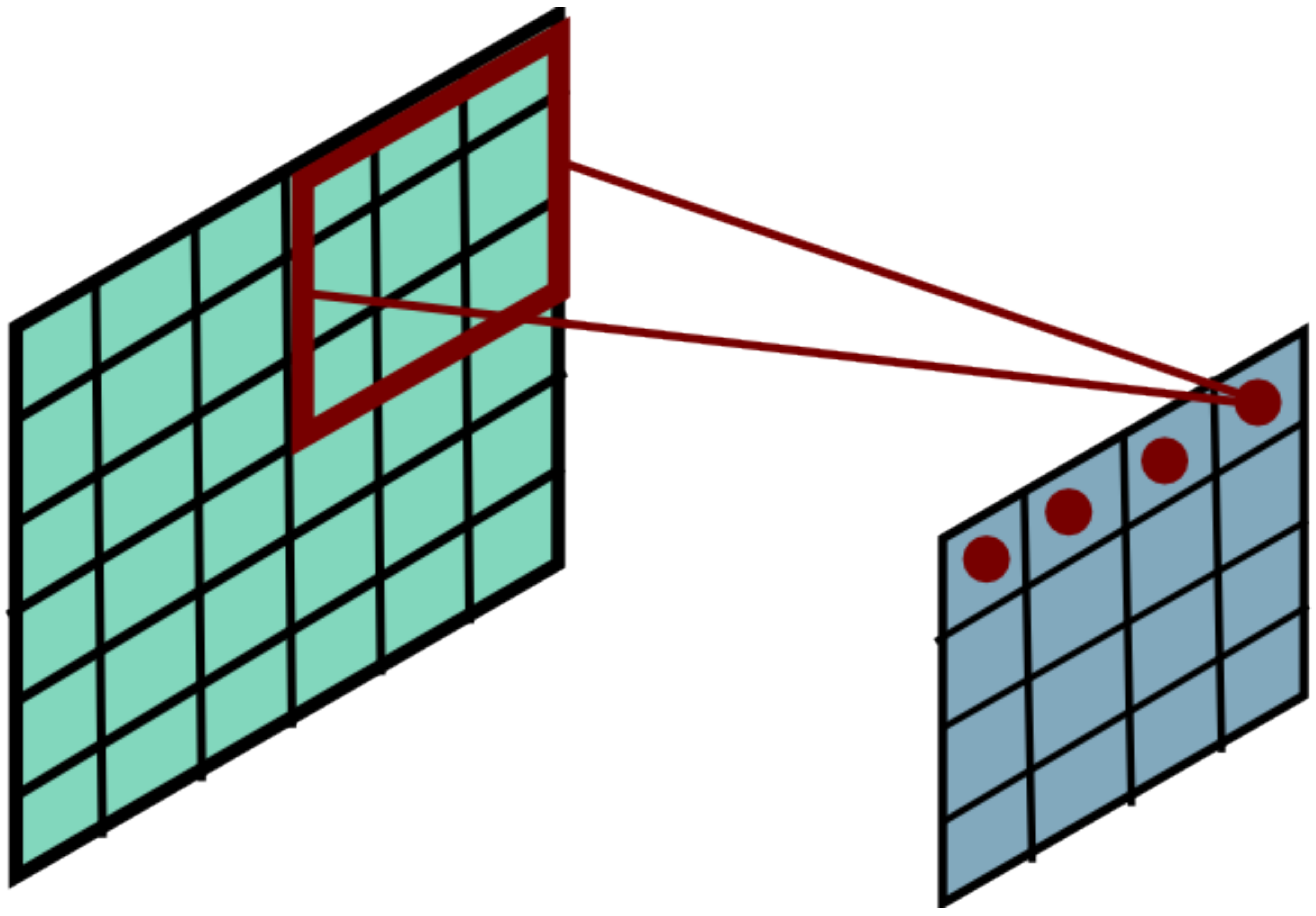

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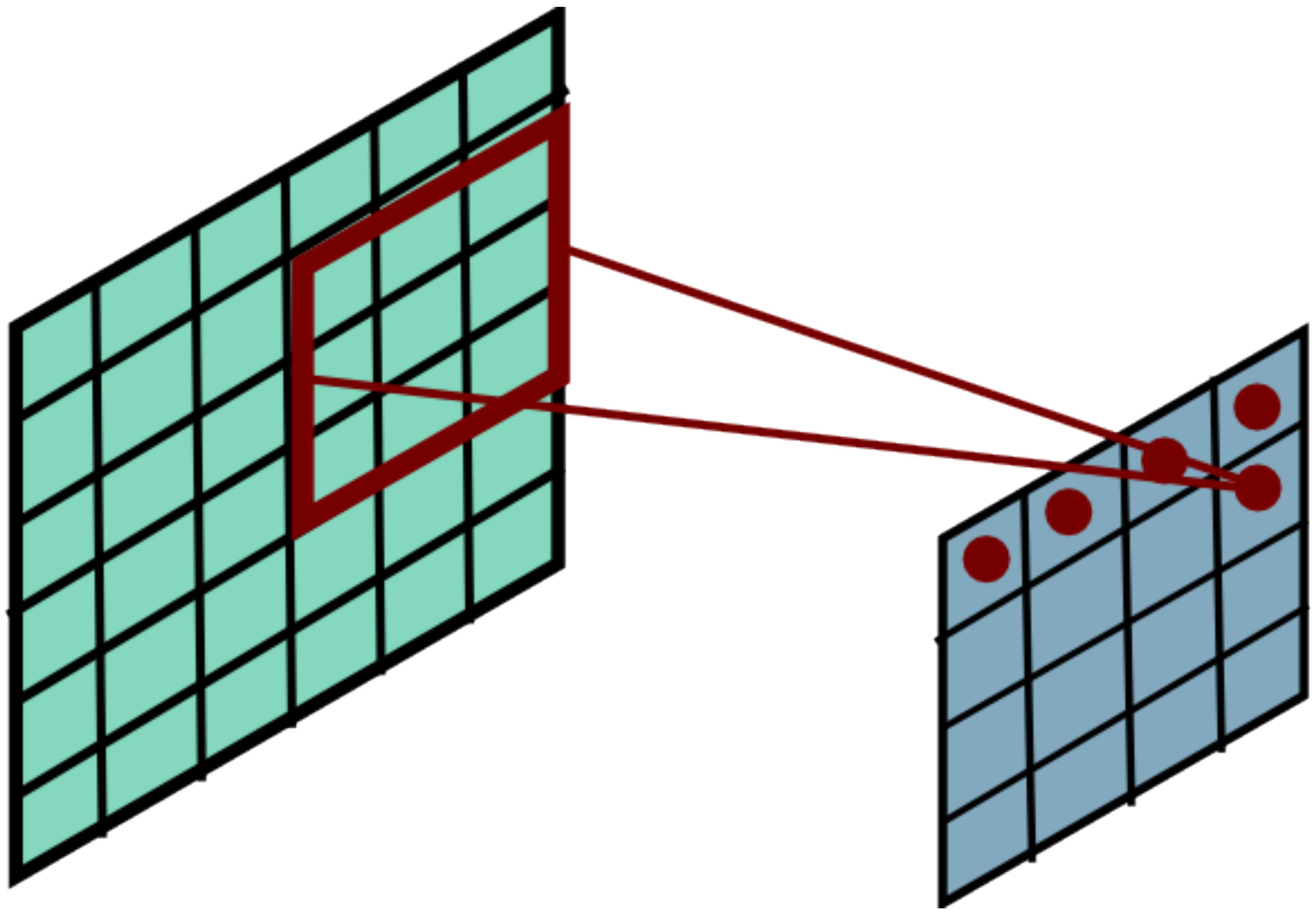

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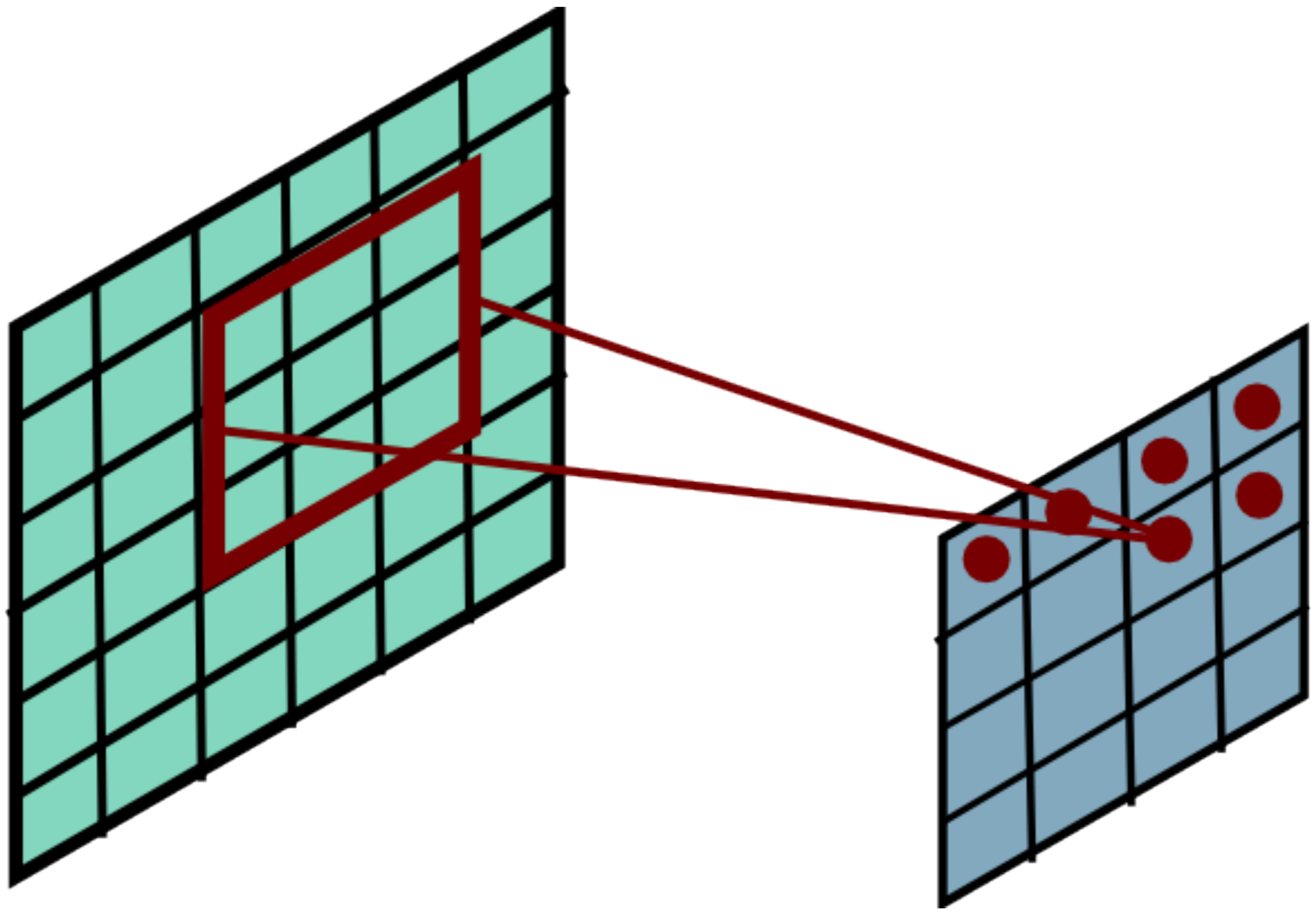

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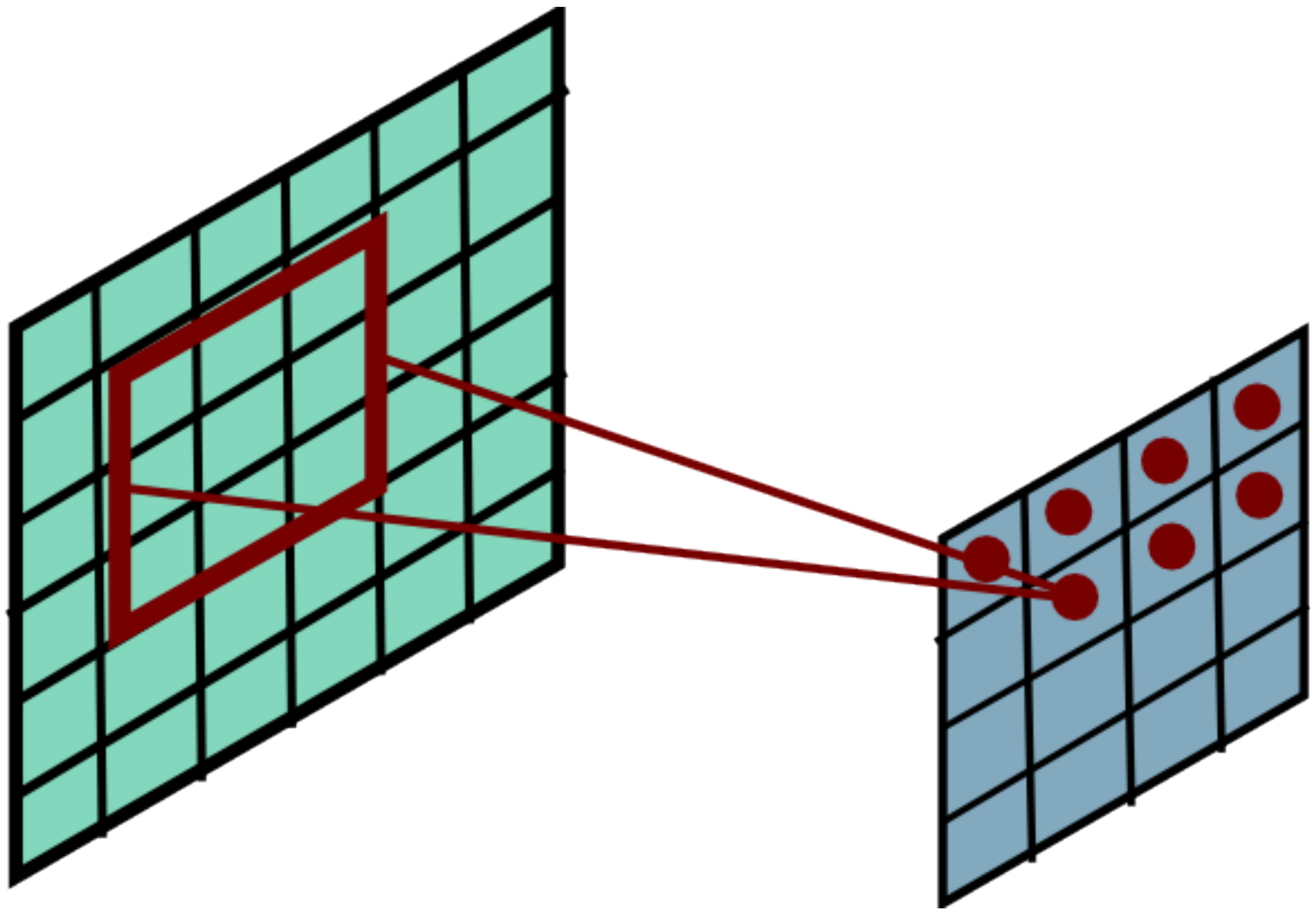

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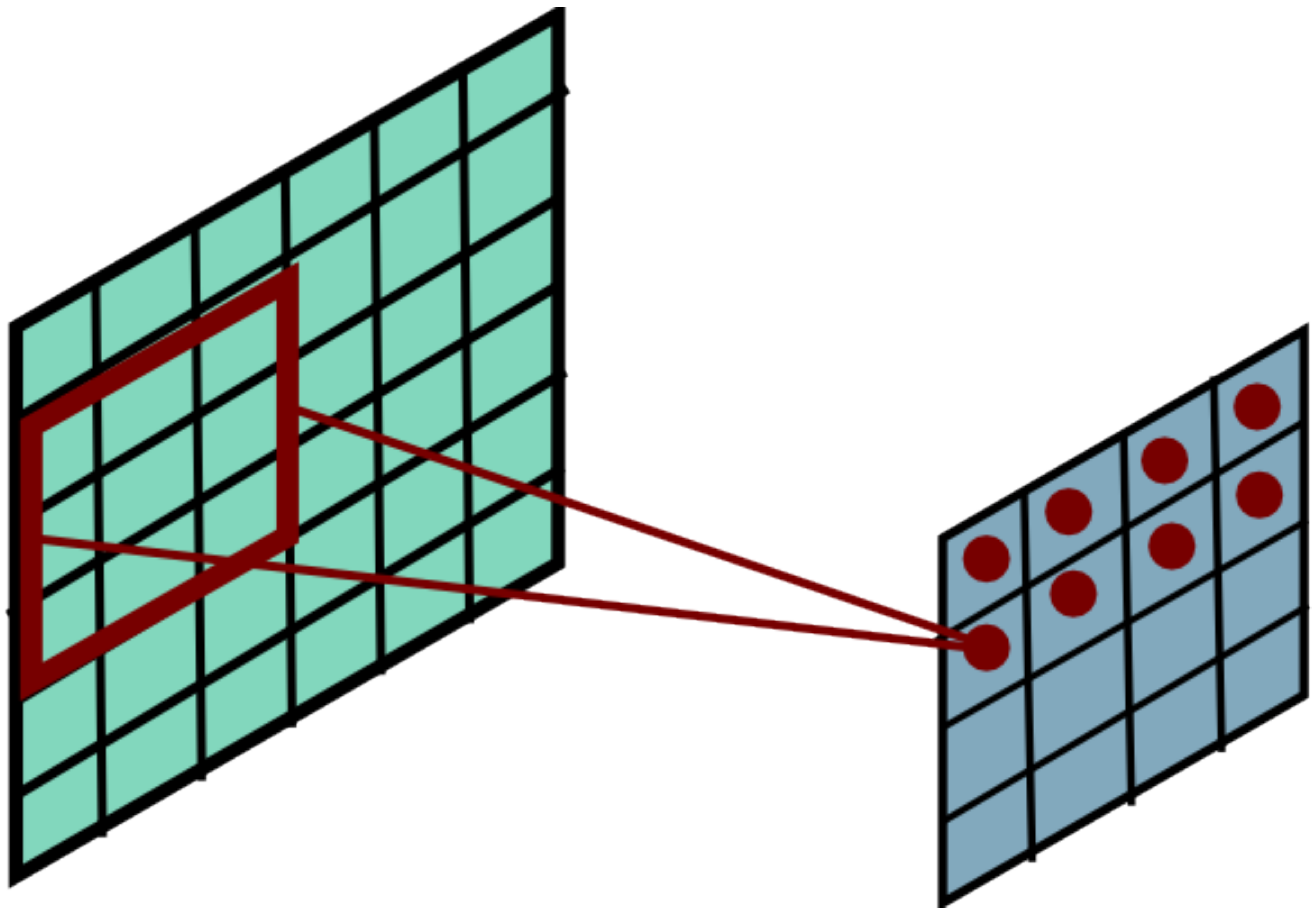

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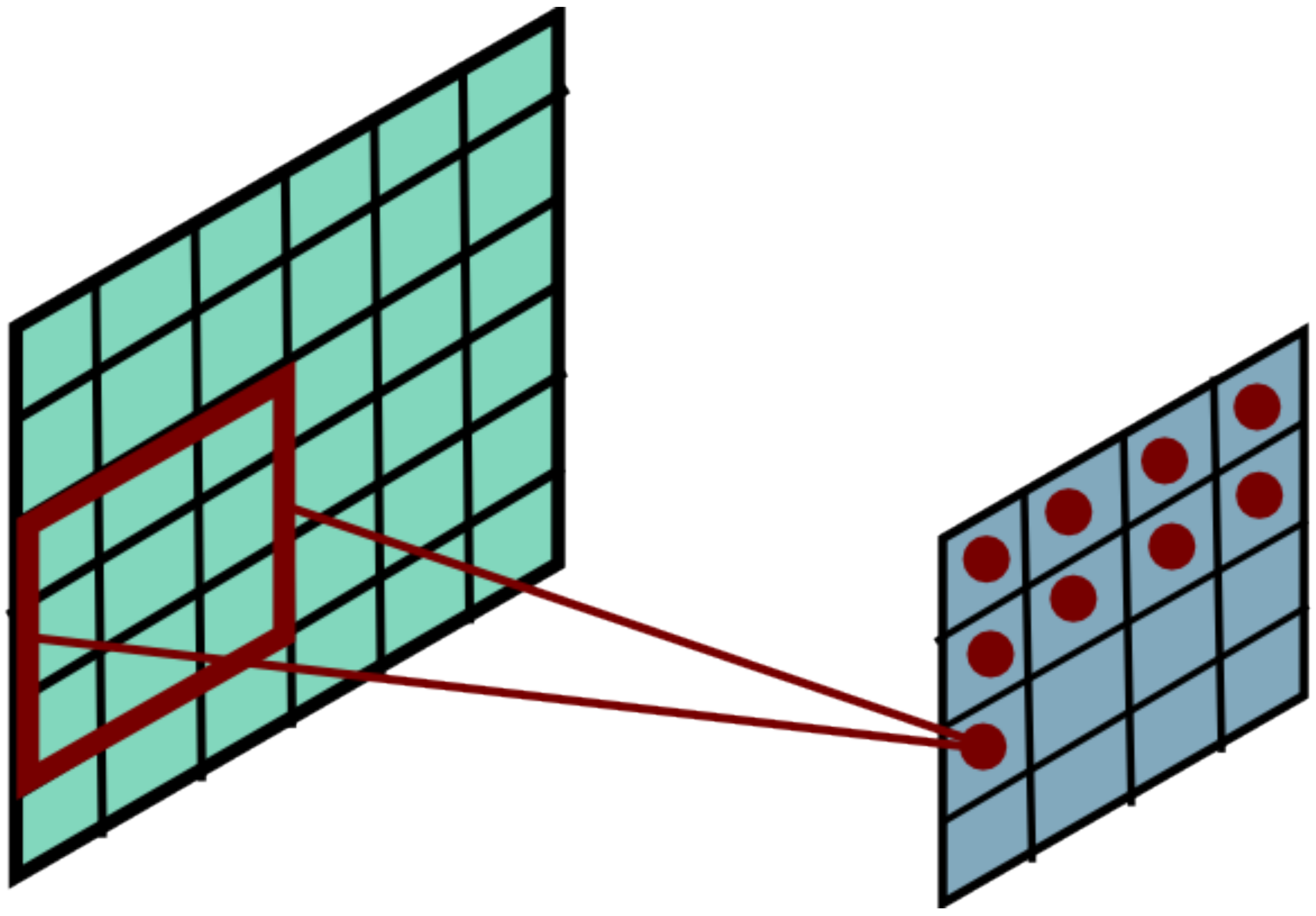

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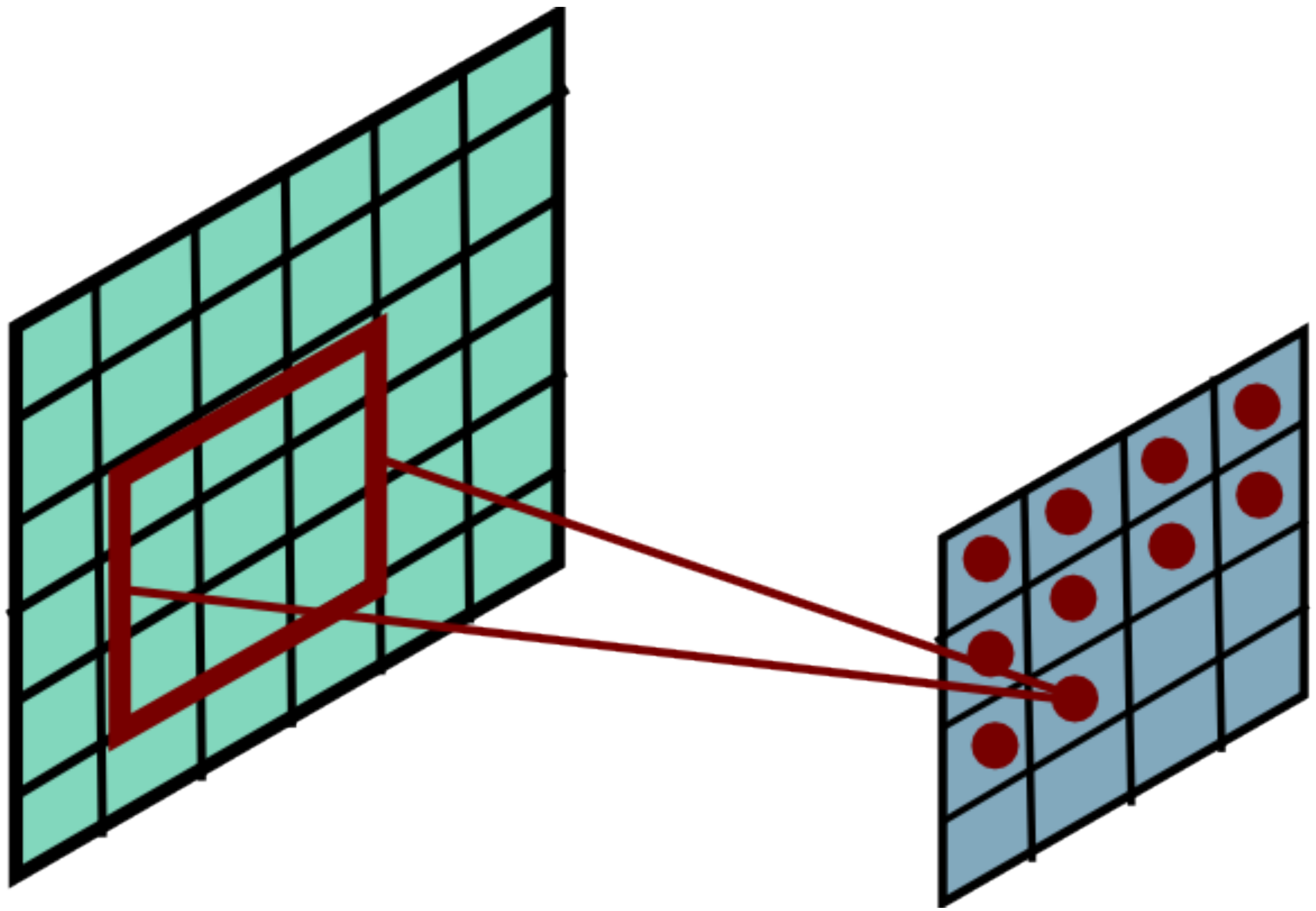

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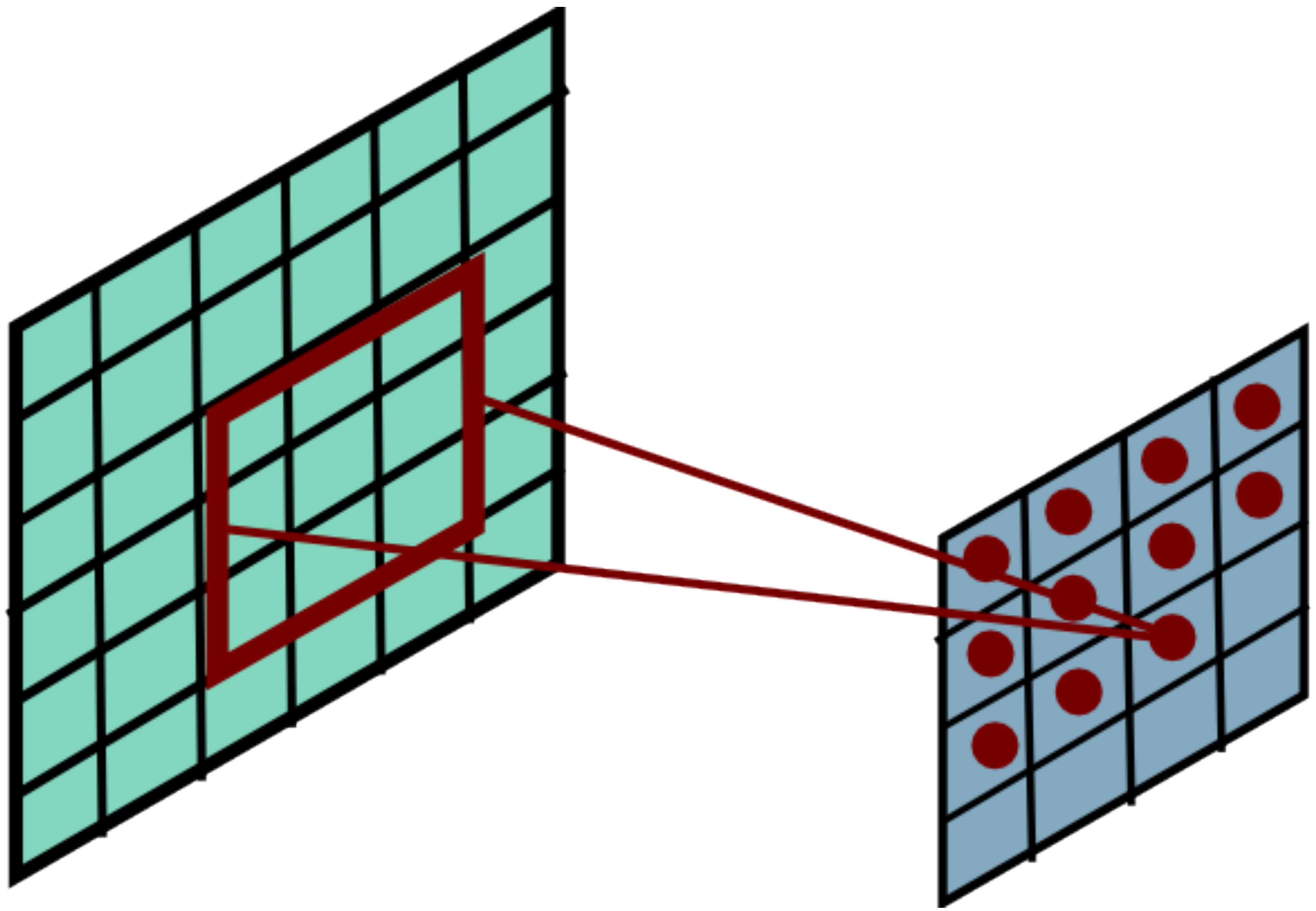

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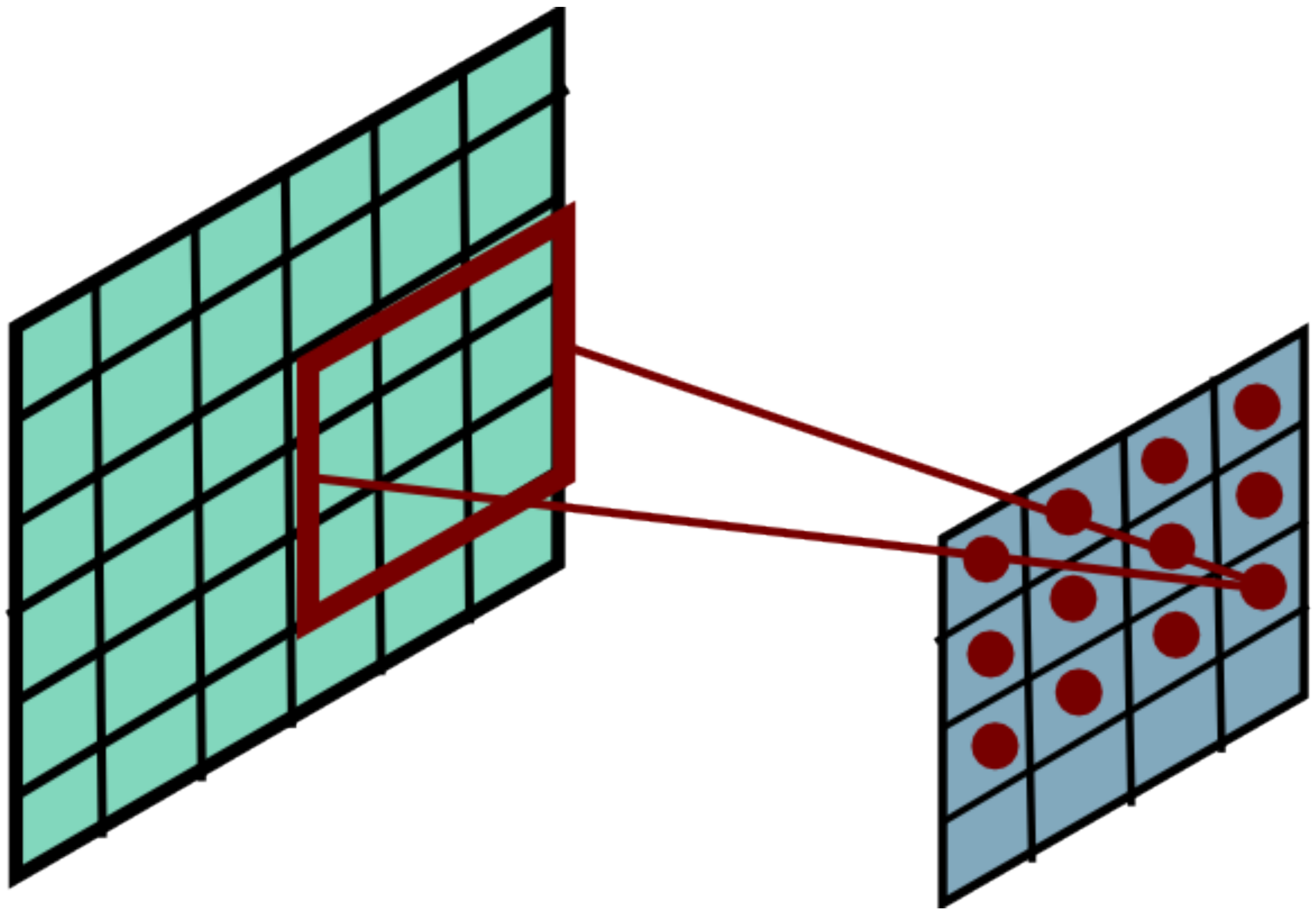

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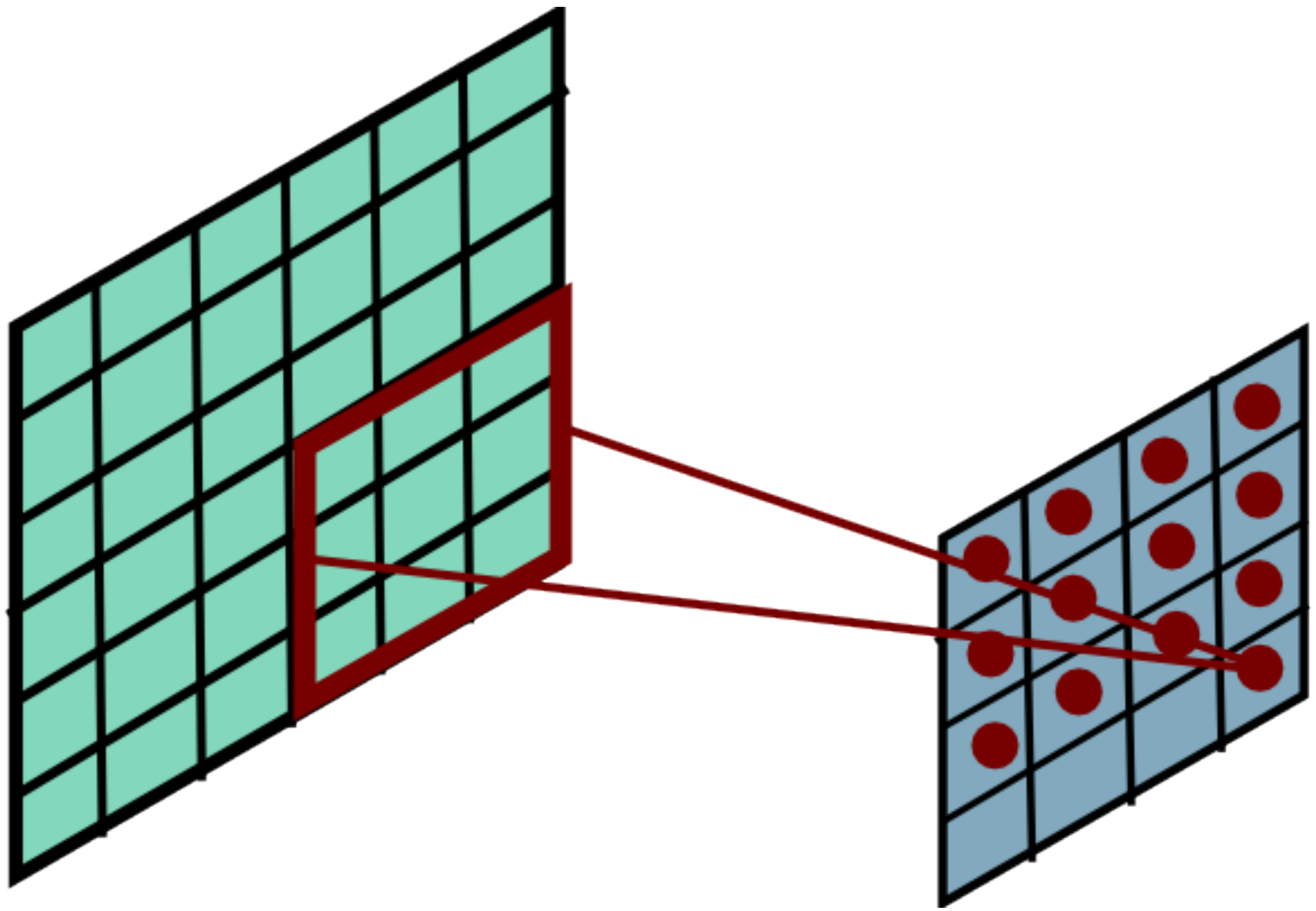

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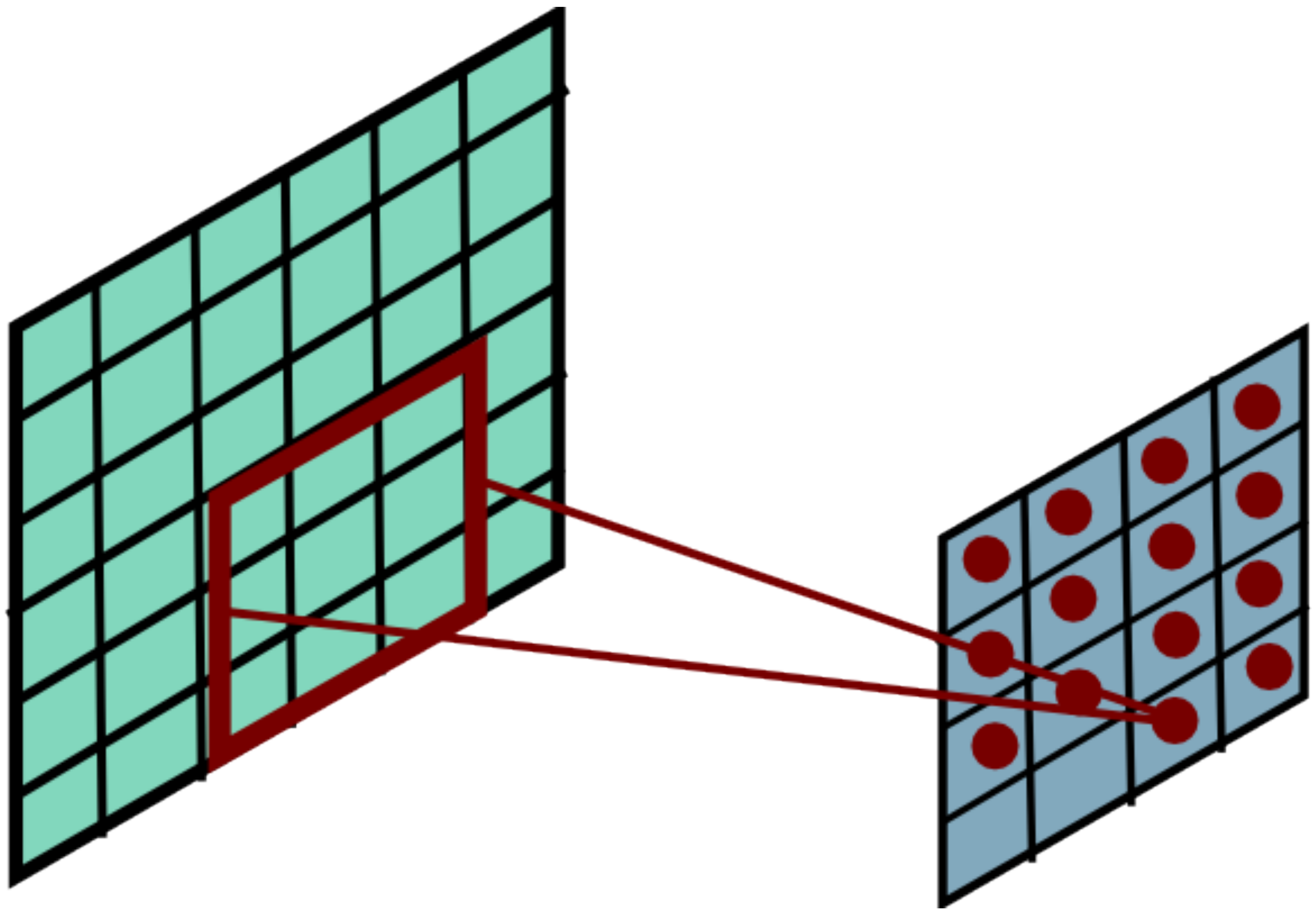

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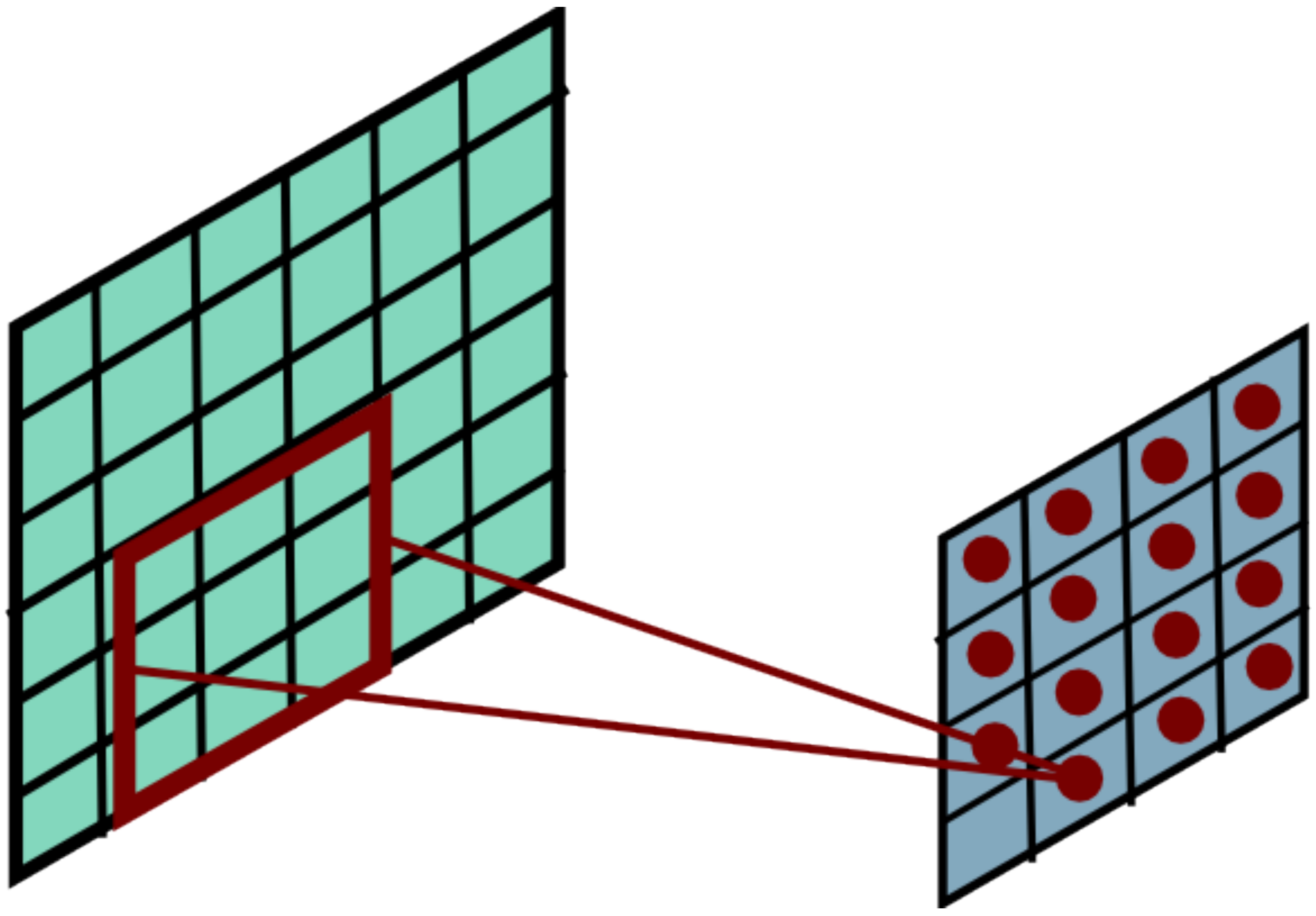

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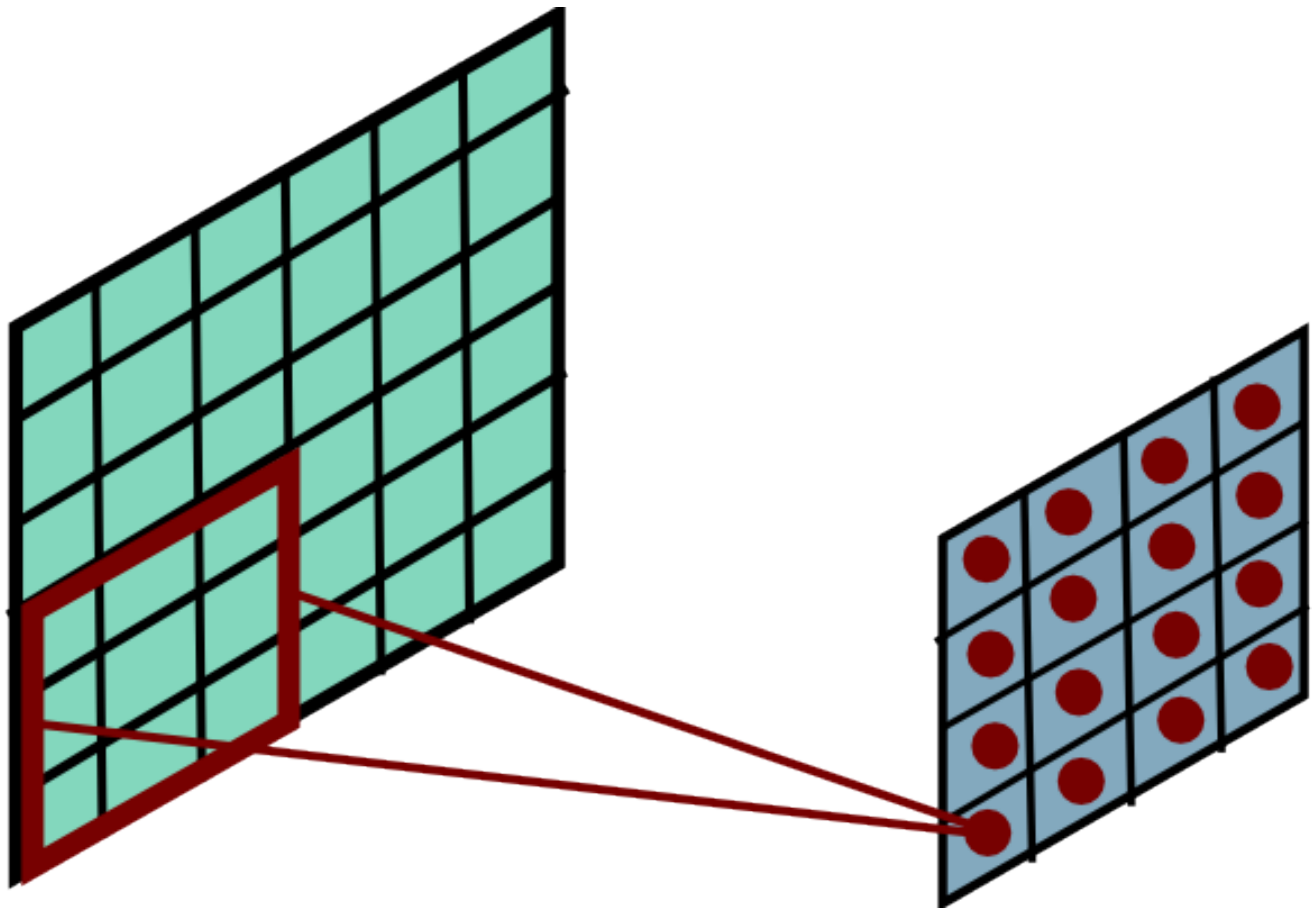

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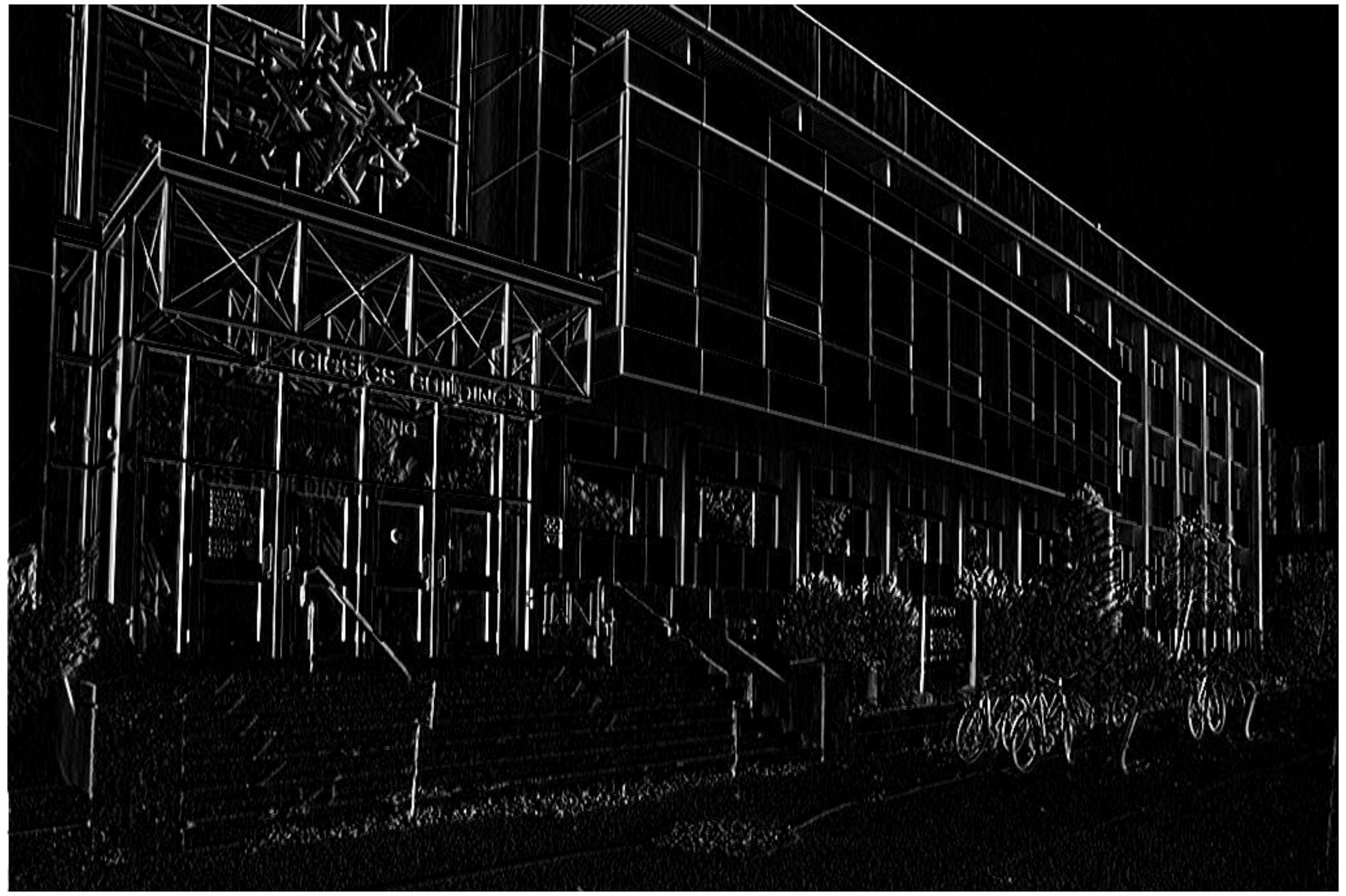
Convolution Layer

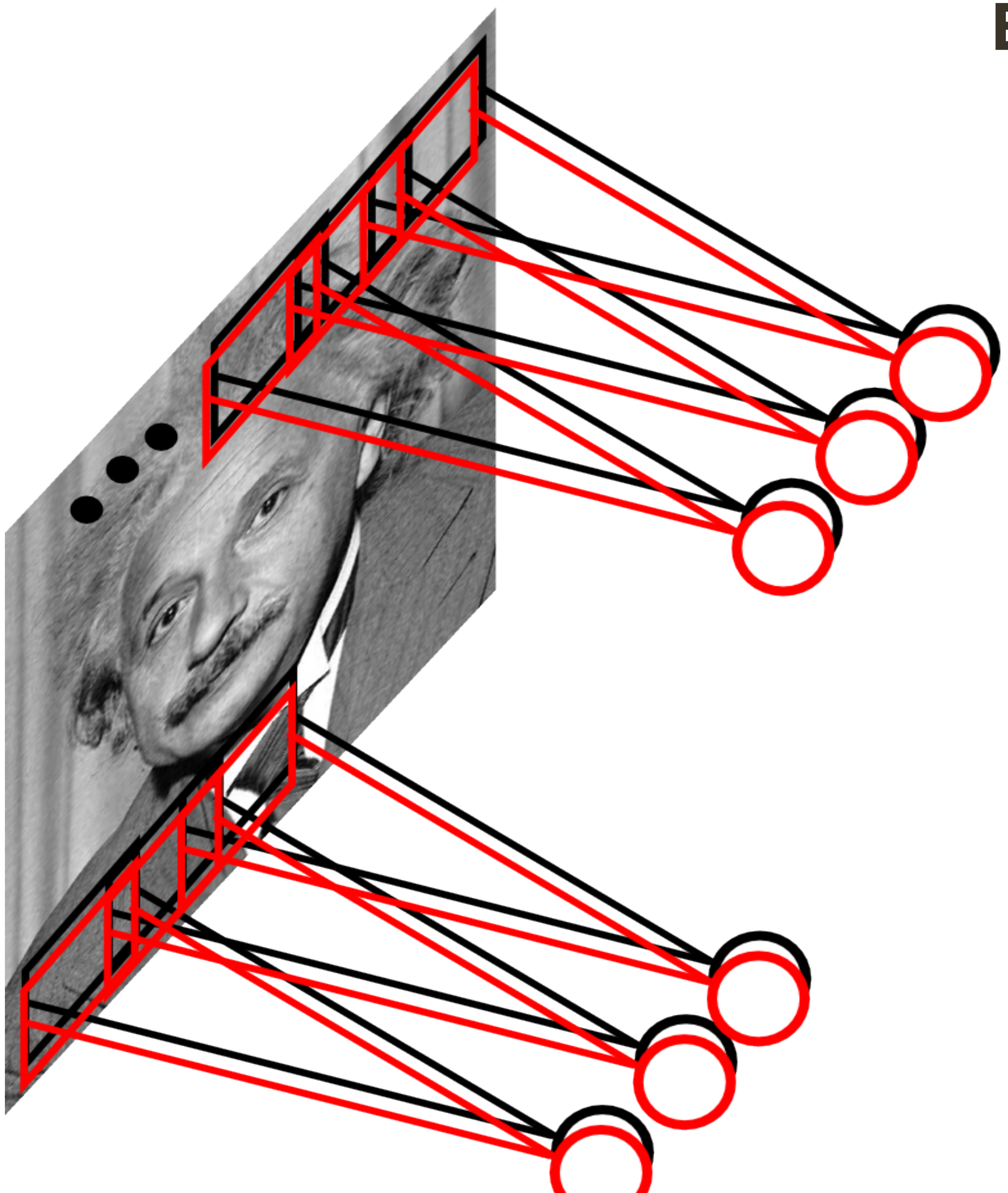
$$\star \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \longrightarrow$$



Convolution Layer

$$\star \begin{bmatrix} 0.11 & 0.11 & 0.11 \\ 0.11 & 0.11 & 0.11 \\ 0.11 & 0.11 & 0.11 \end{bmatrix} \rightarrow$$

Convolutional Layer



Example: 200 x 200 image (small)
x 40K hidden units

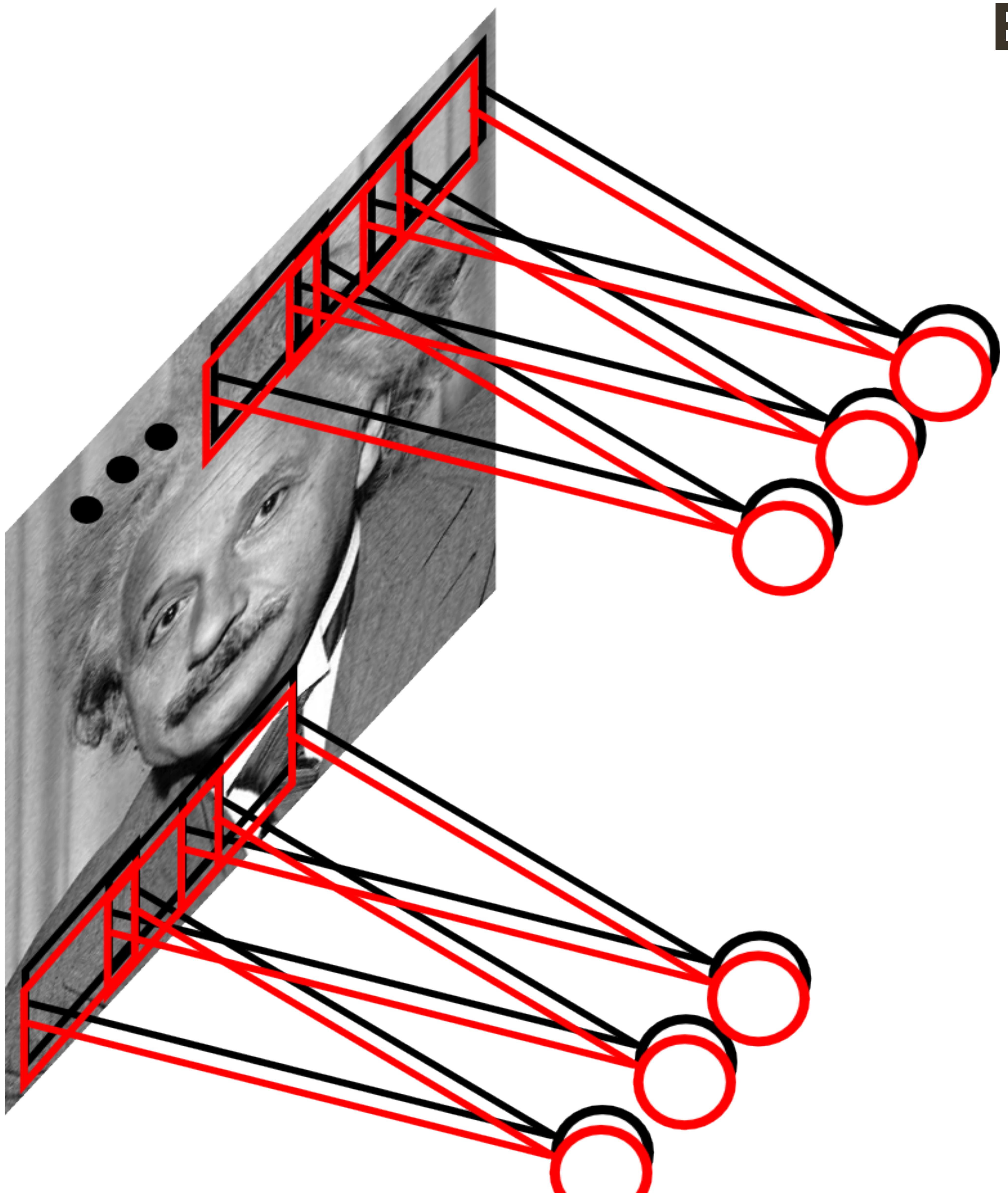
Filter size: 10 x 10

# of filters: 20

Learn **multiple filters**

* slide from Marc'Aurelio Renzato

Convolutional Layer



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= 2000 parameters

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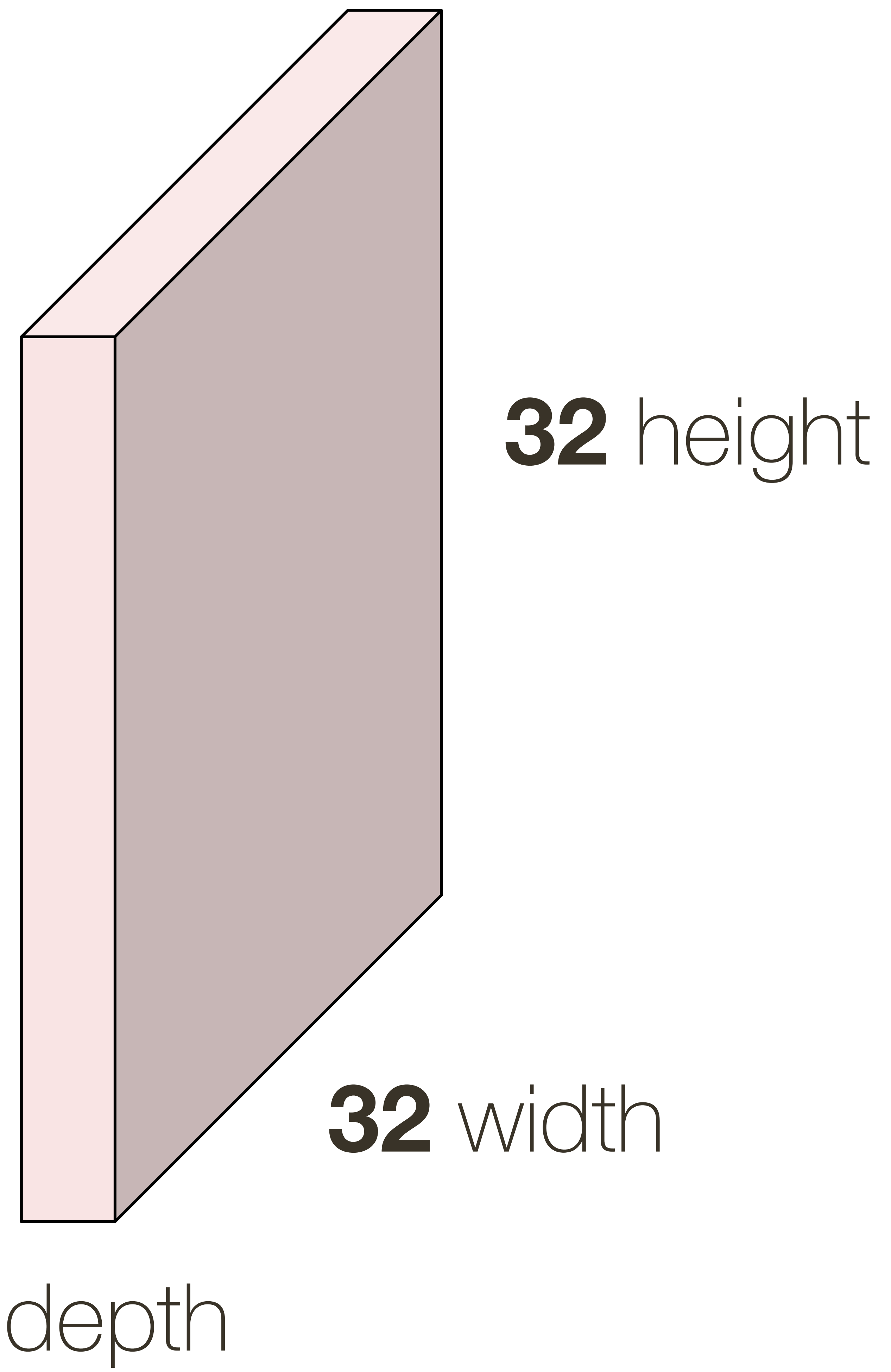
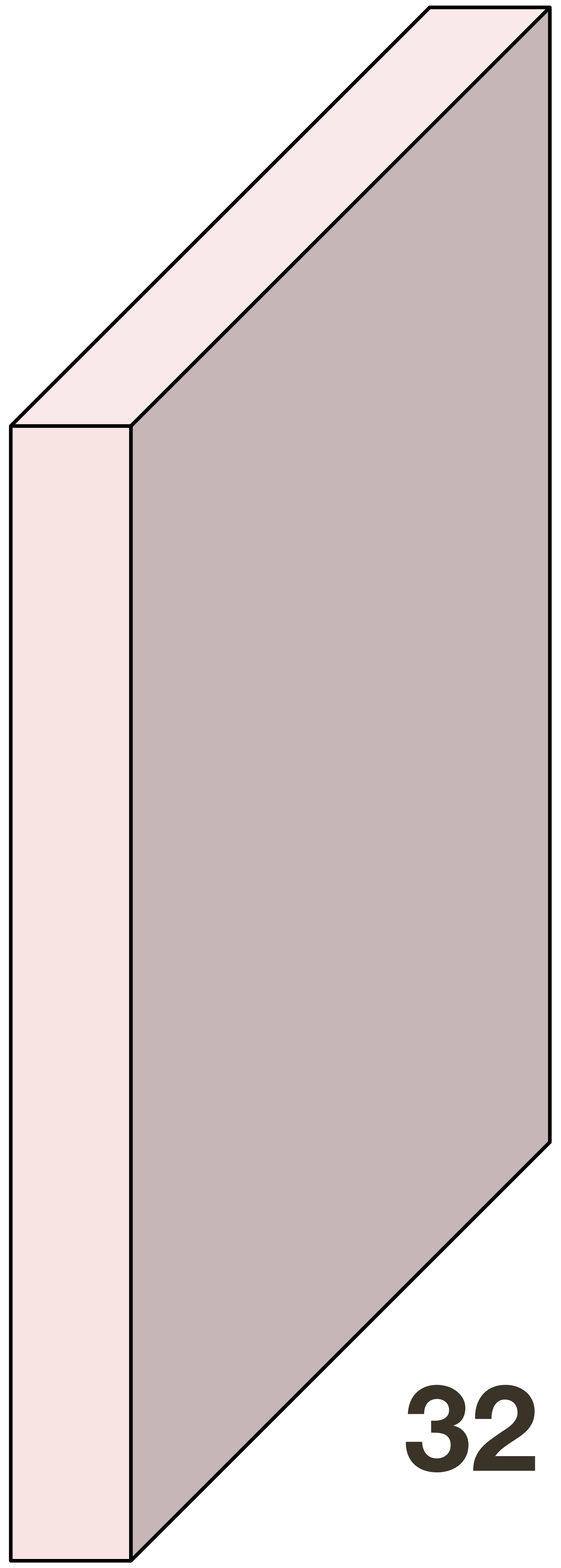
Convolutional Layer

32 x 32 x 3 **image** (note the image preserves spatial structure)



Convolutional Layer

32 x 32 x 3 **image**

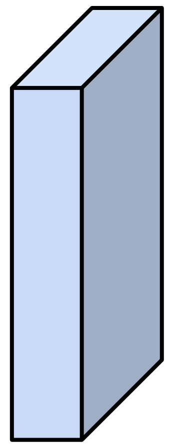


32 height

32 width

3 depth

5 x 5 x 3 **filter**



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

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer

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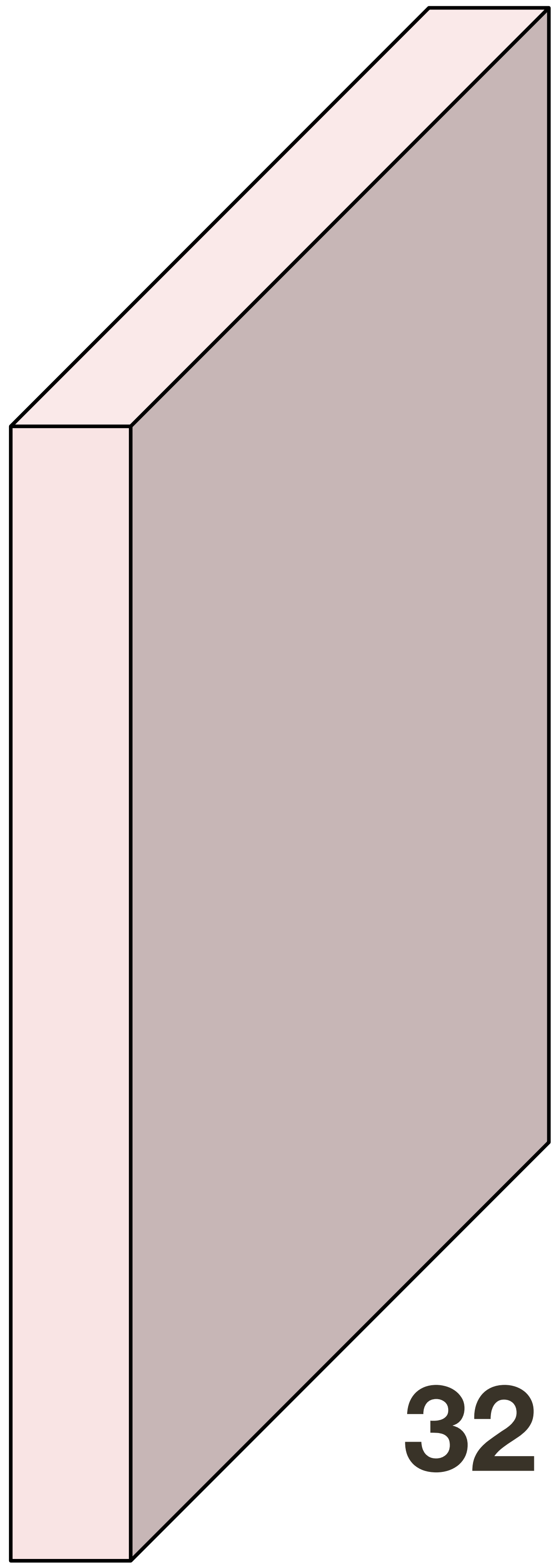

32 height

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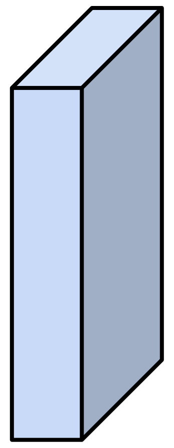
3 depth

Filters always extend the full depth of the input volume

5 x 5 x 3 **filter**



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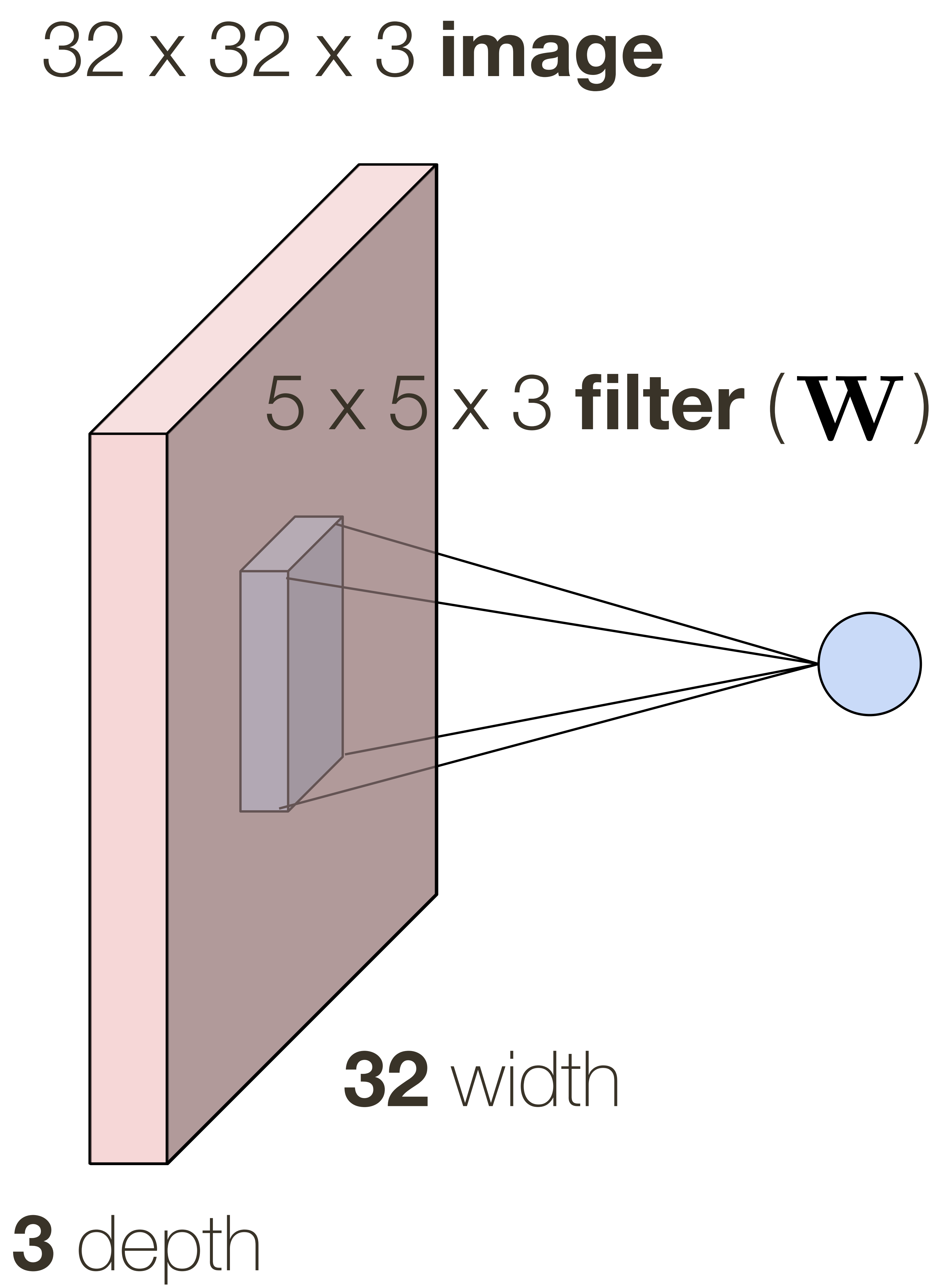
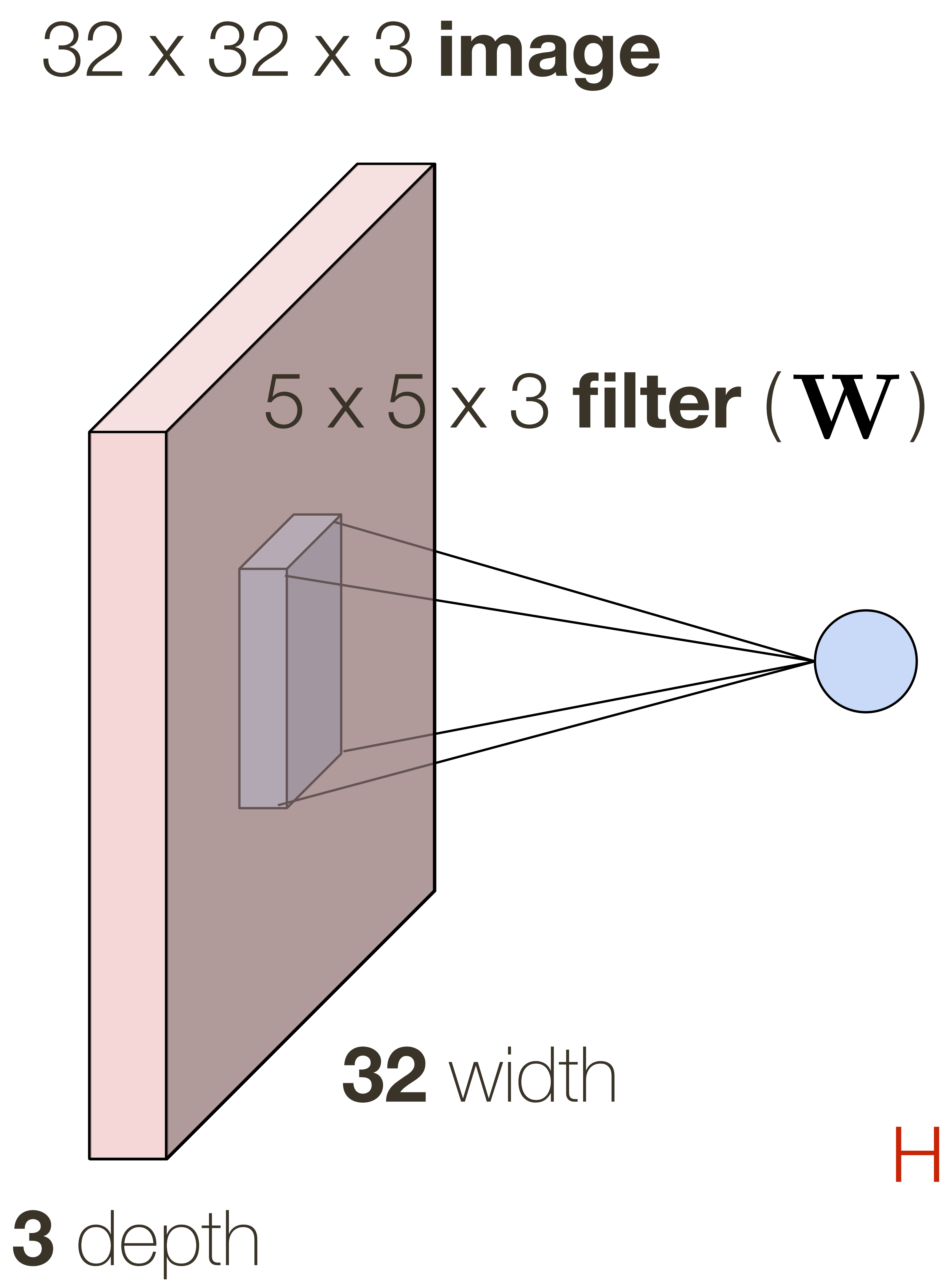


1 number: the result of taking a dot product between the filter and a small 5 x 5 x 3 part of the image

$$\mathbf{W}^T\mathbf{x} + b, \text{where } \mathbf{W}, \mathbf{x} \in \mathbb{R}^{75}$$

Convolutional Layer



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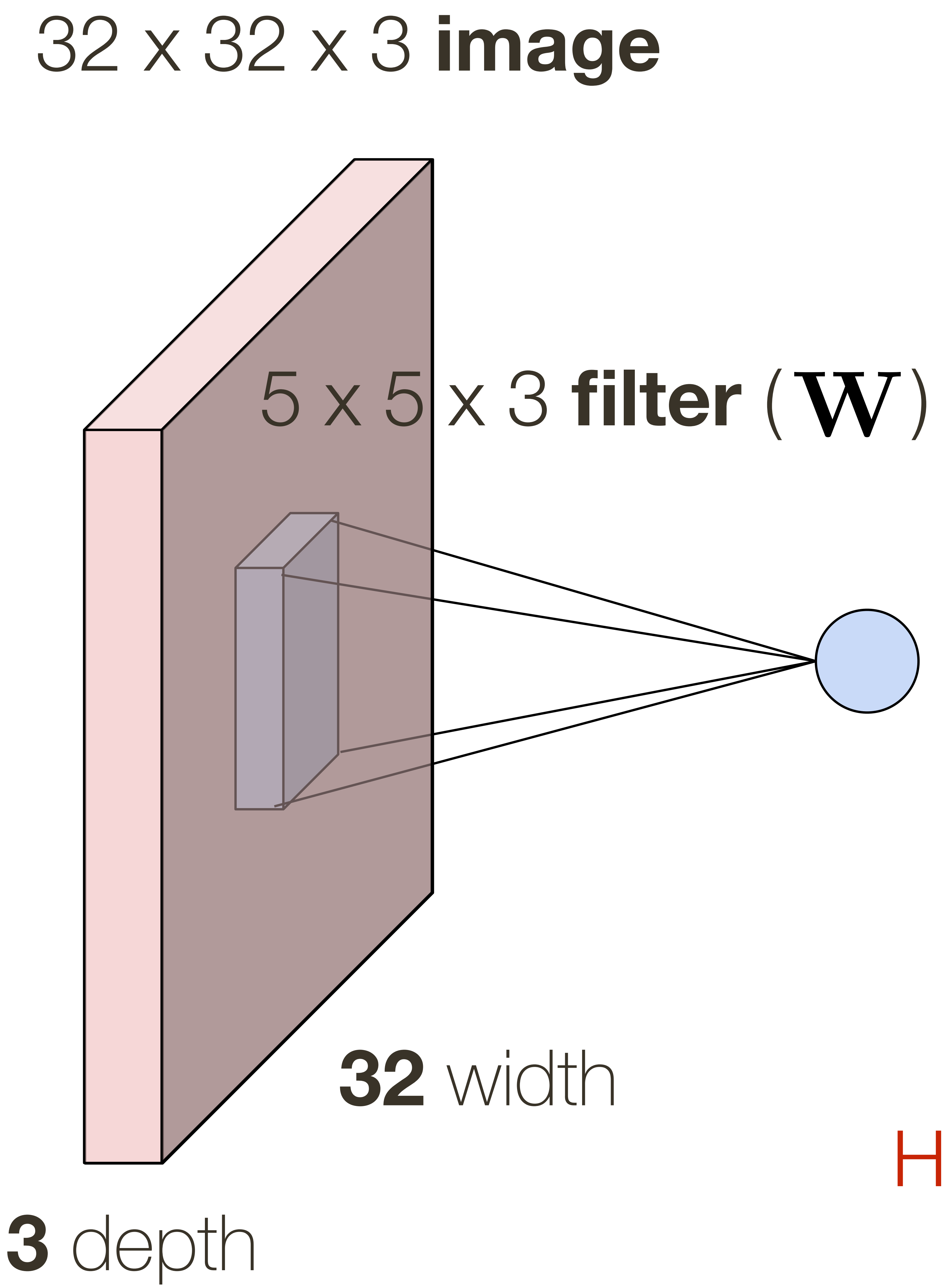
How many **parameters** does the layer have?

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer



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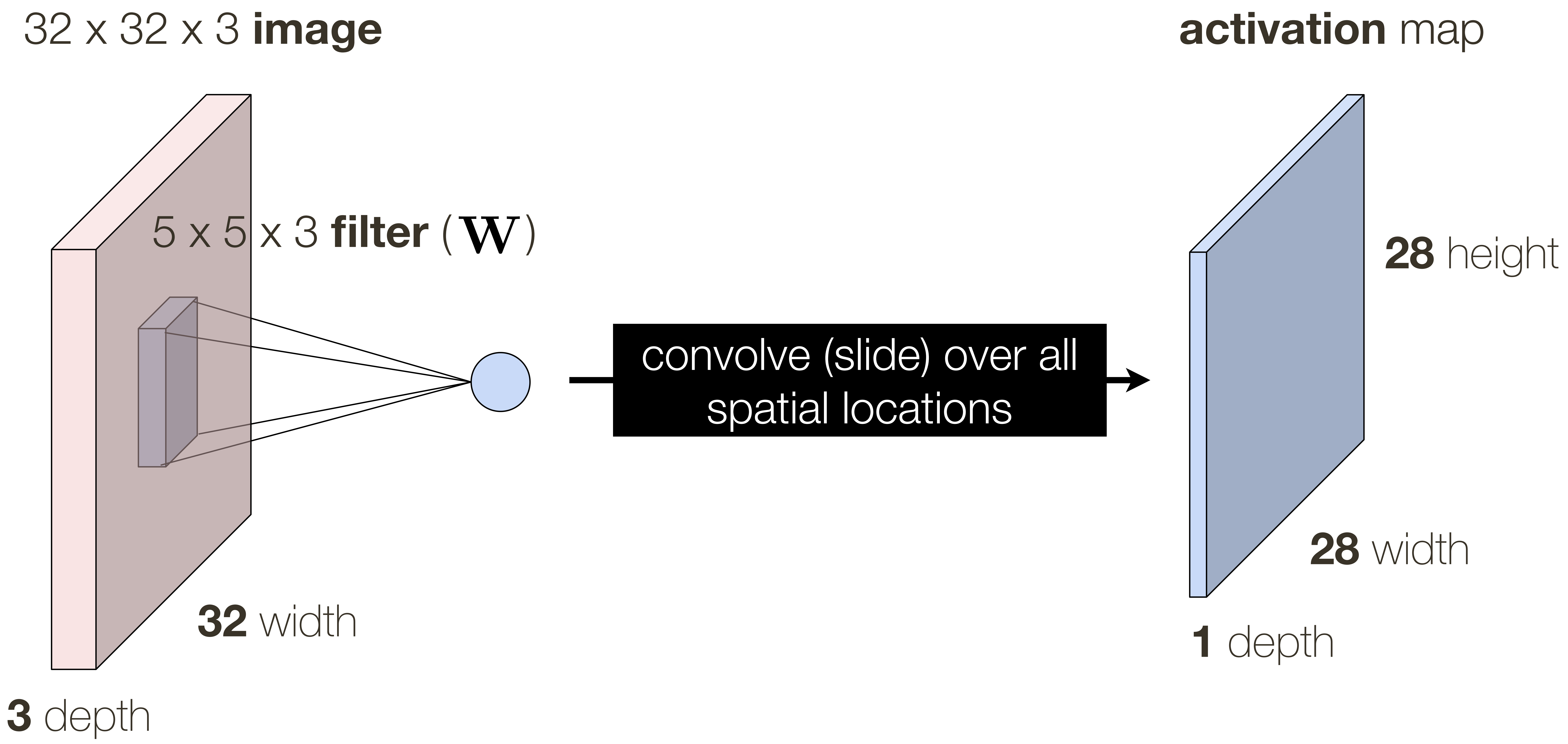
How many **parameters** does the layer have? **76**

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer



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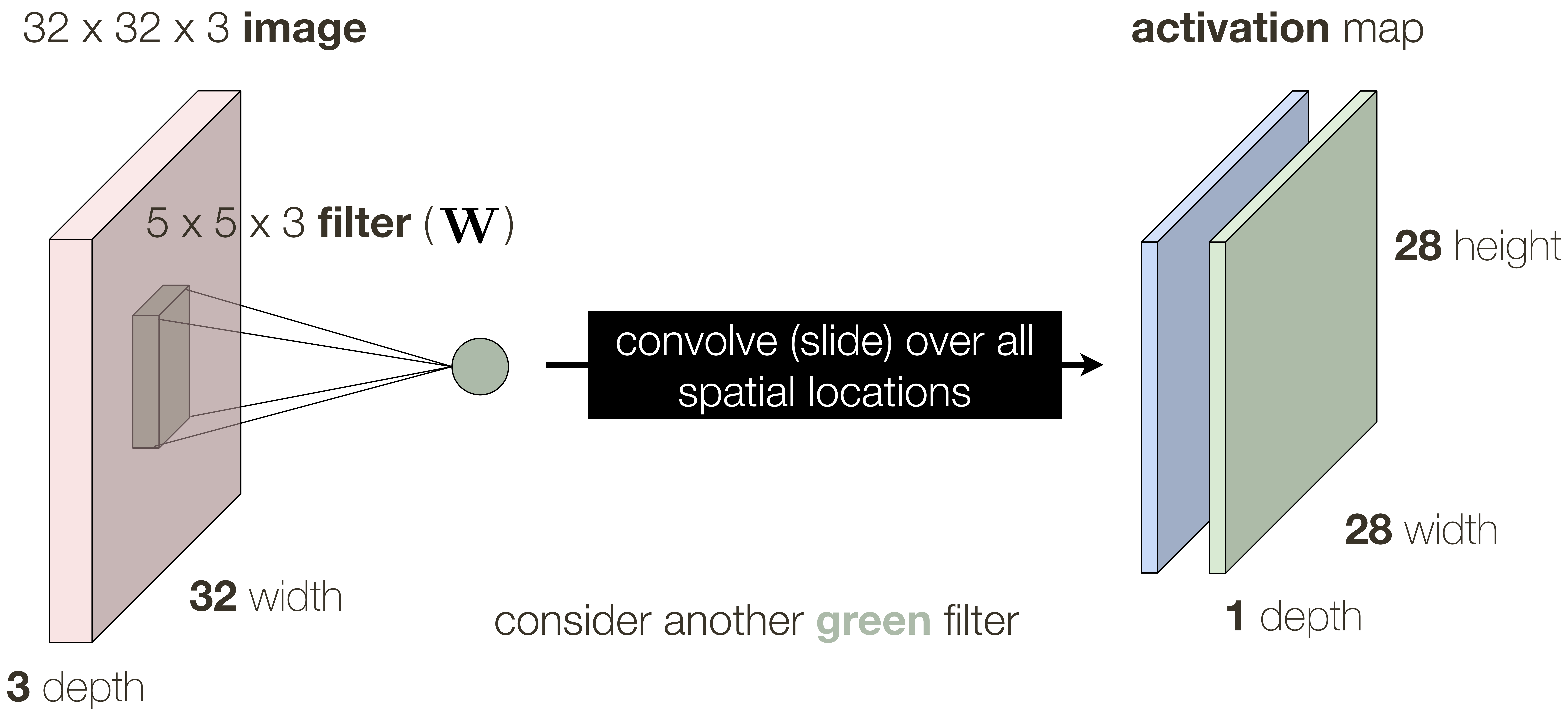
Convolutional Layer

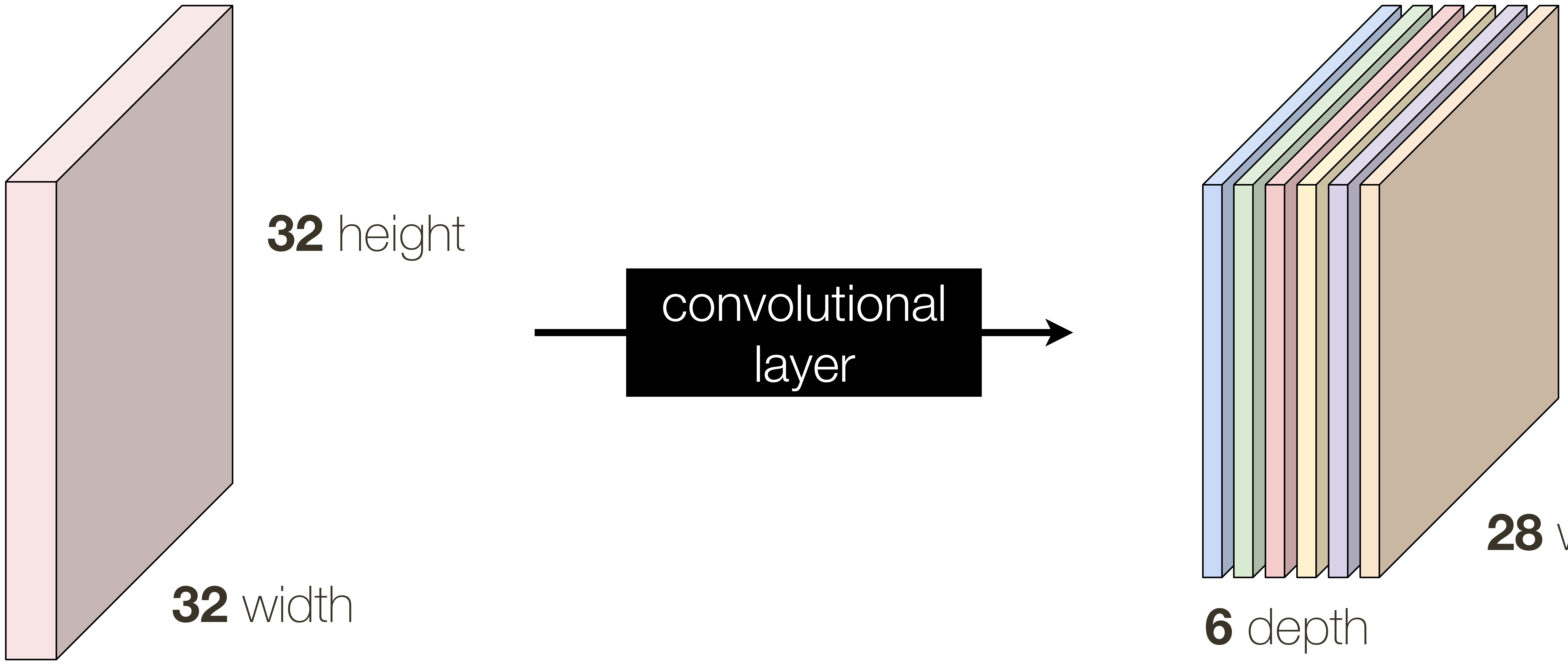


consider another **green** filter

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer

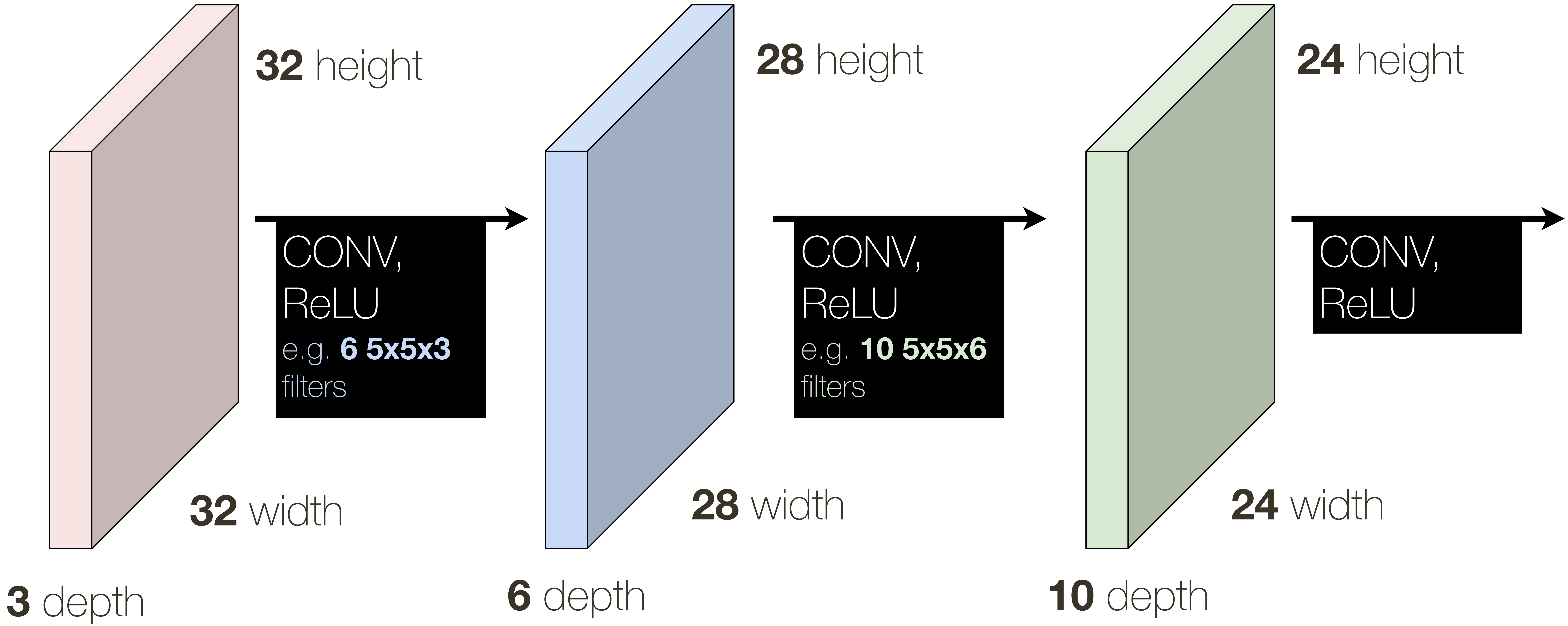
If we have 6 5x5 filter, we'll get 6 separate activation maps: **activation** map



this results in the "new image" of size 28 x 28 x 6!

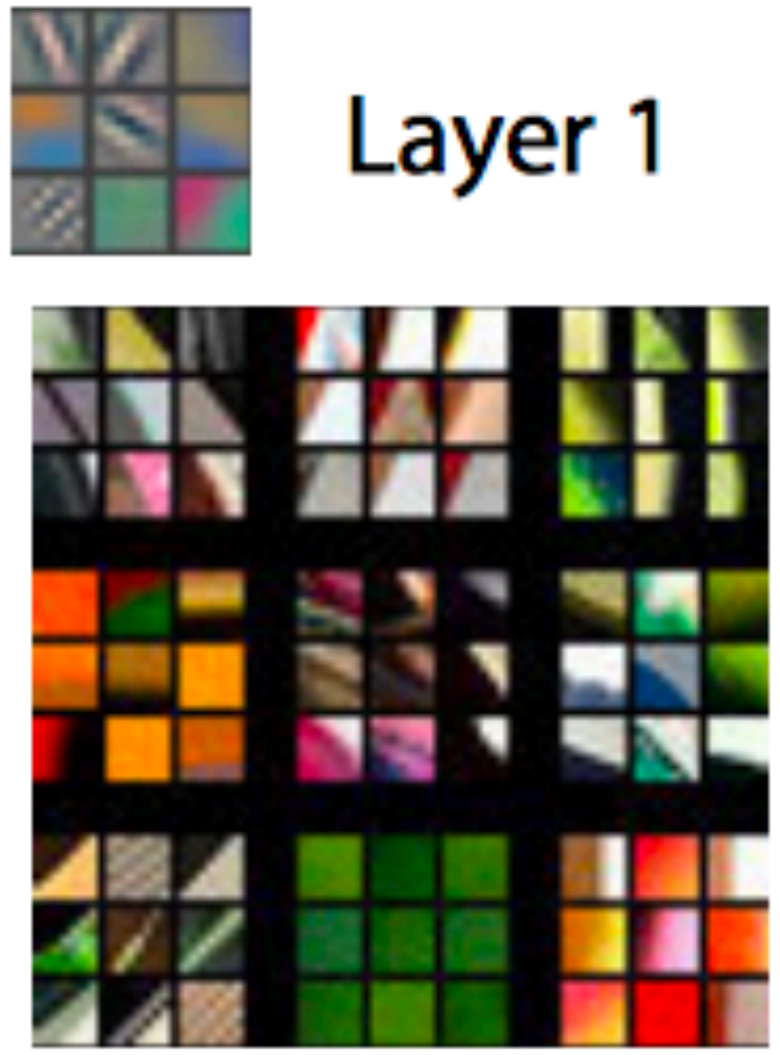
* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

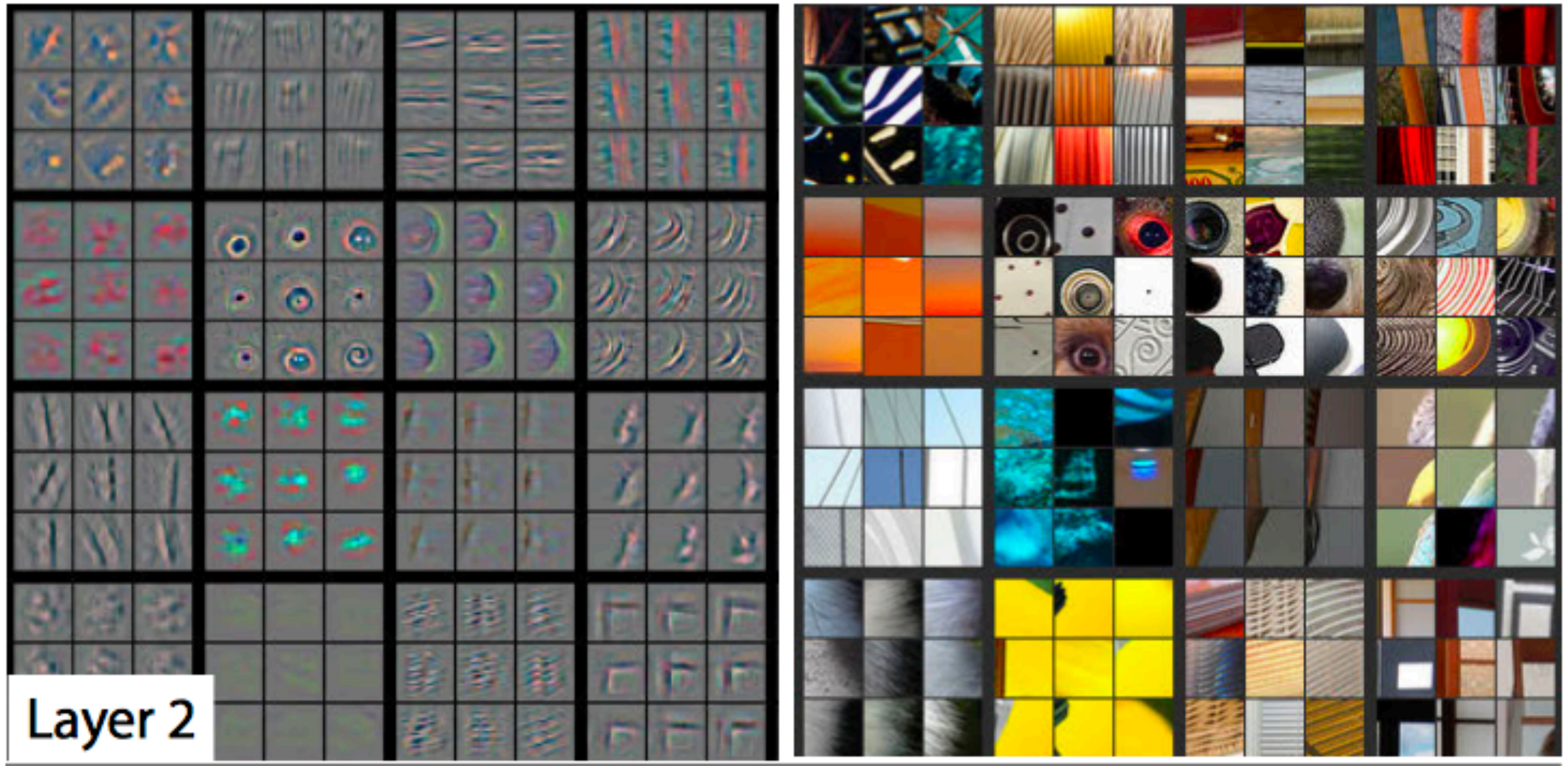
Convolutional Neural Network (ConvNet)



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

What **filters** do networks learn?





[Zeiler and Fergus, 2013]

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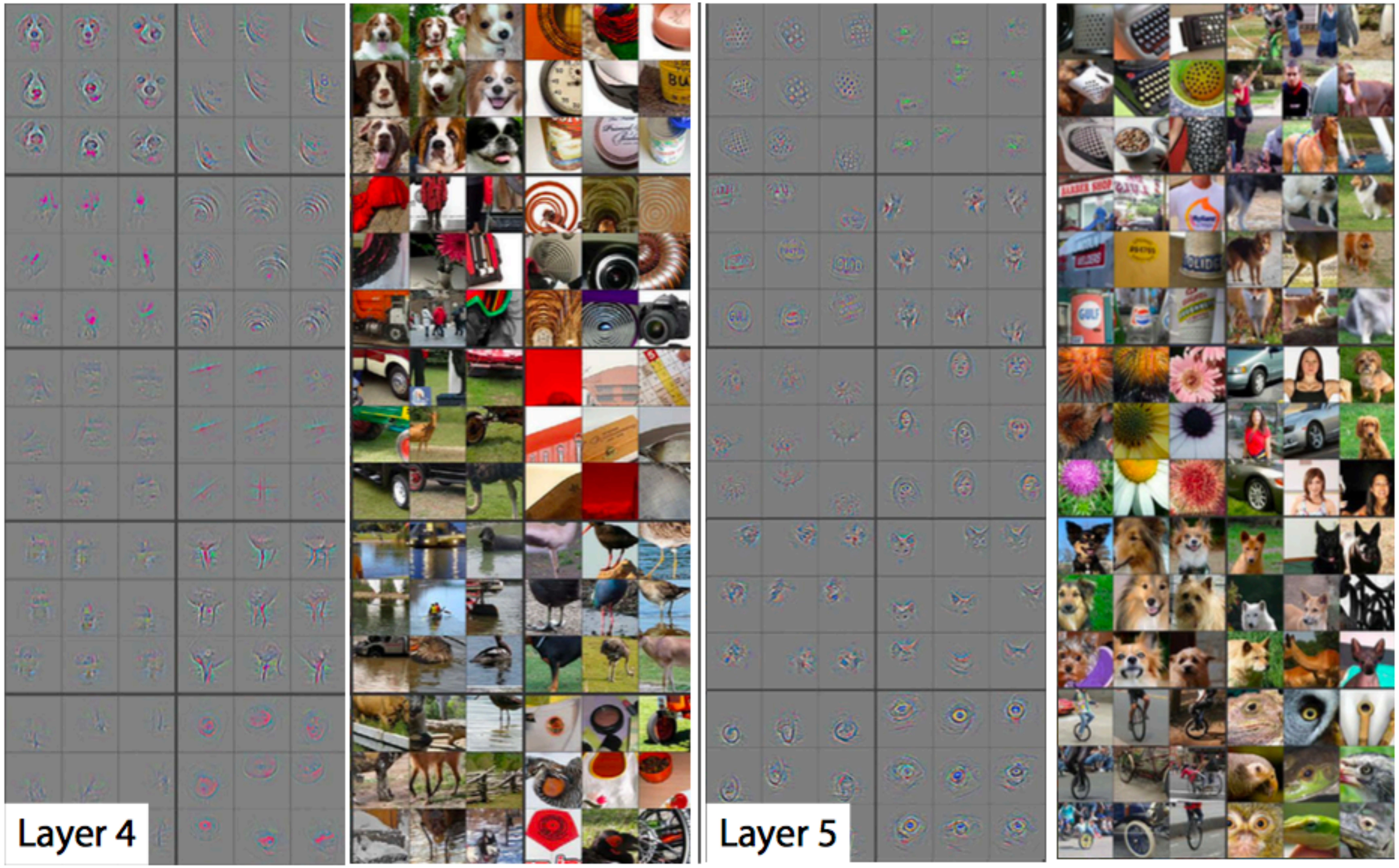
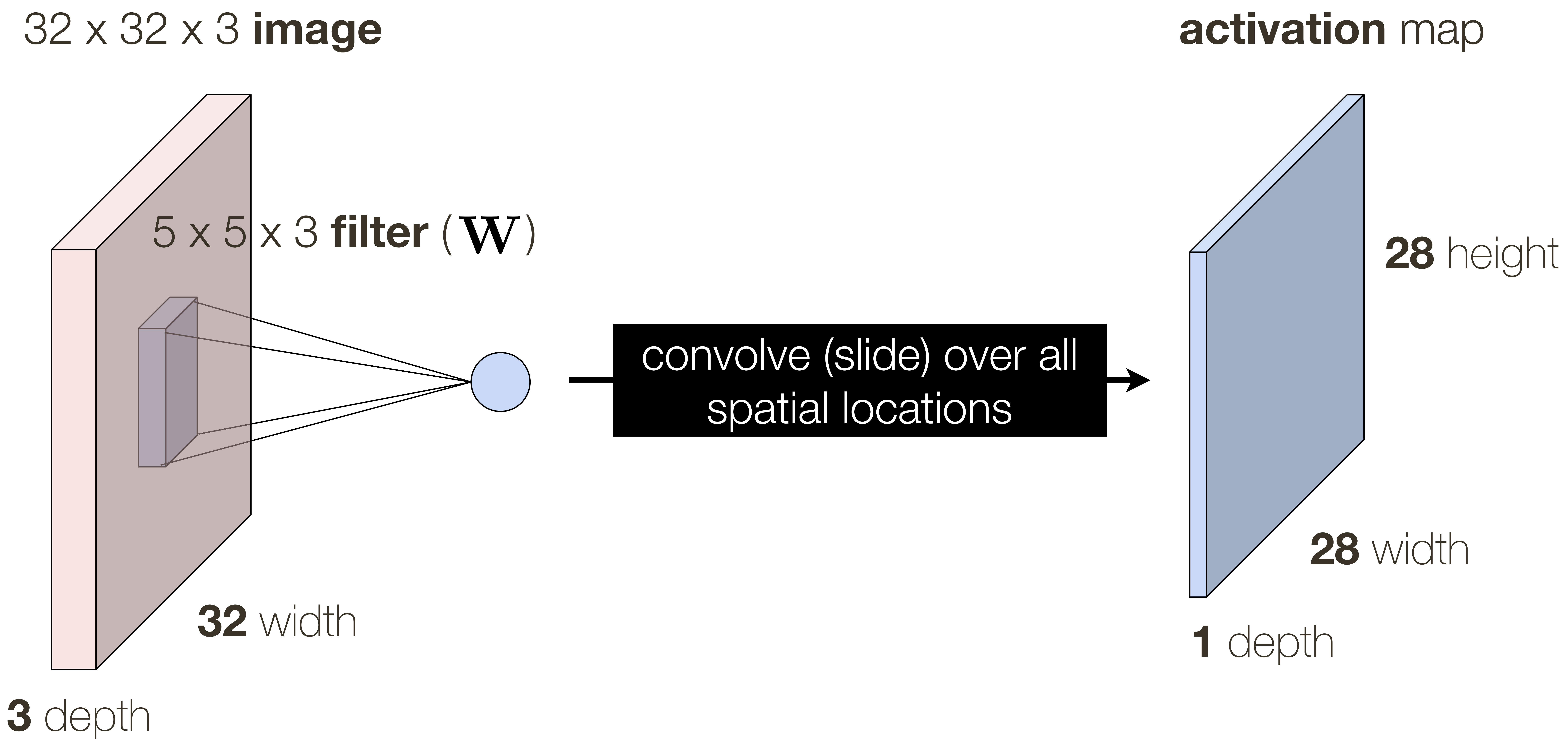


[Zeiler and Fergus, 2013]

Convolutional Layer: Closer Look at **Spatial Dimensions**



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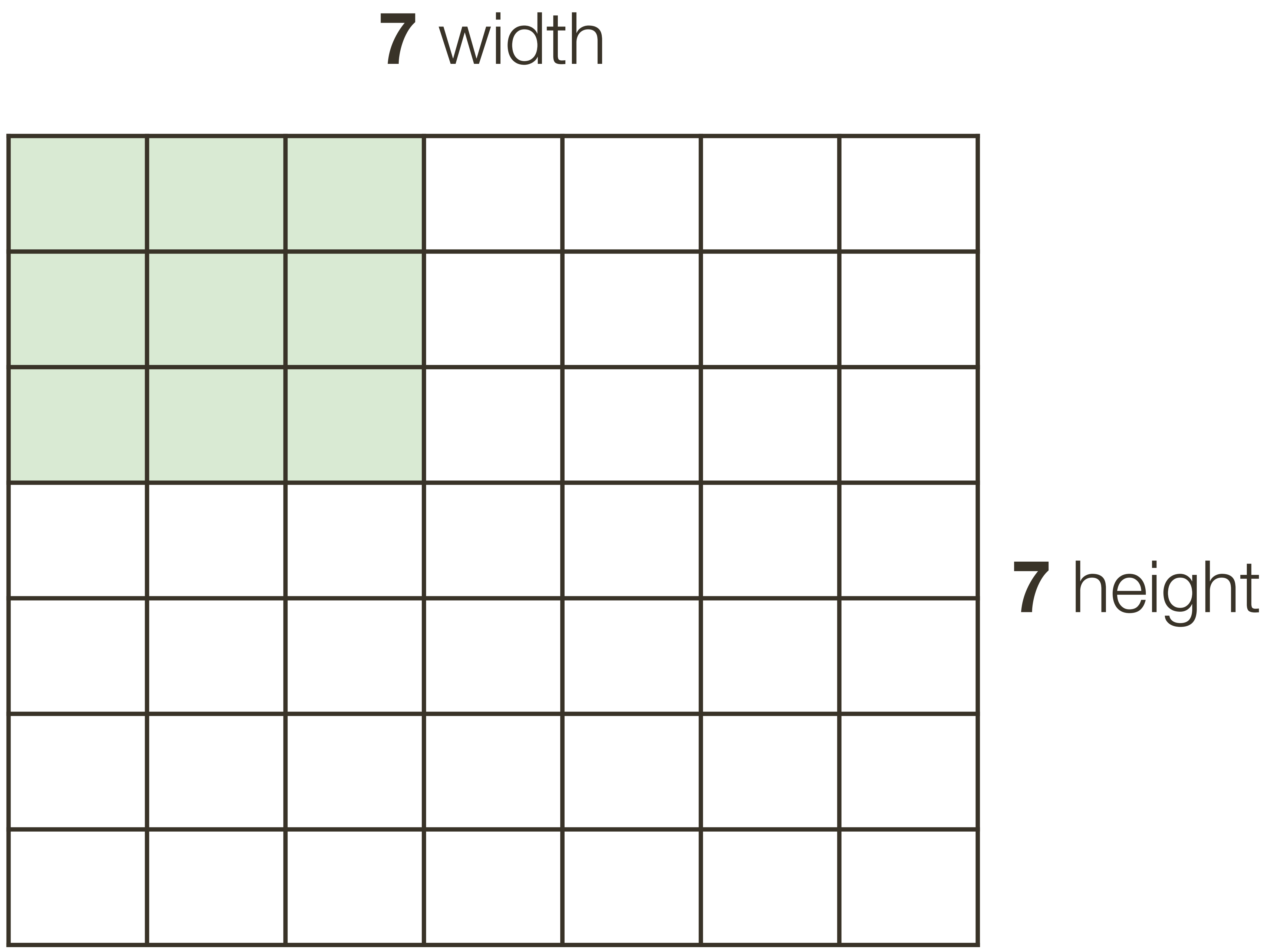
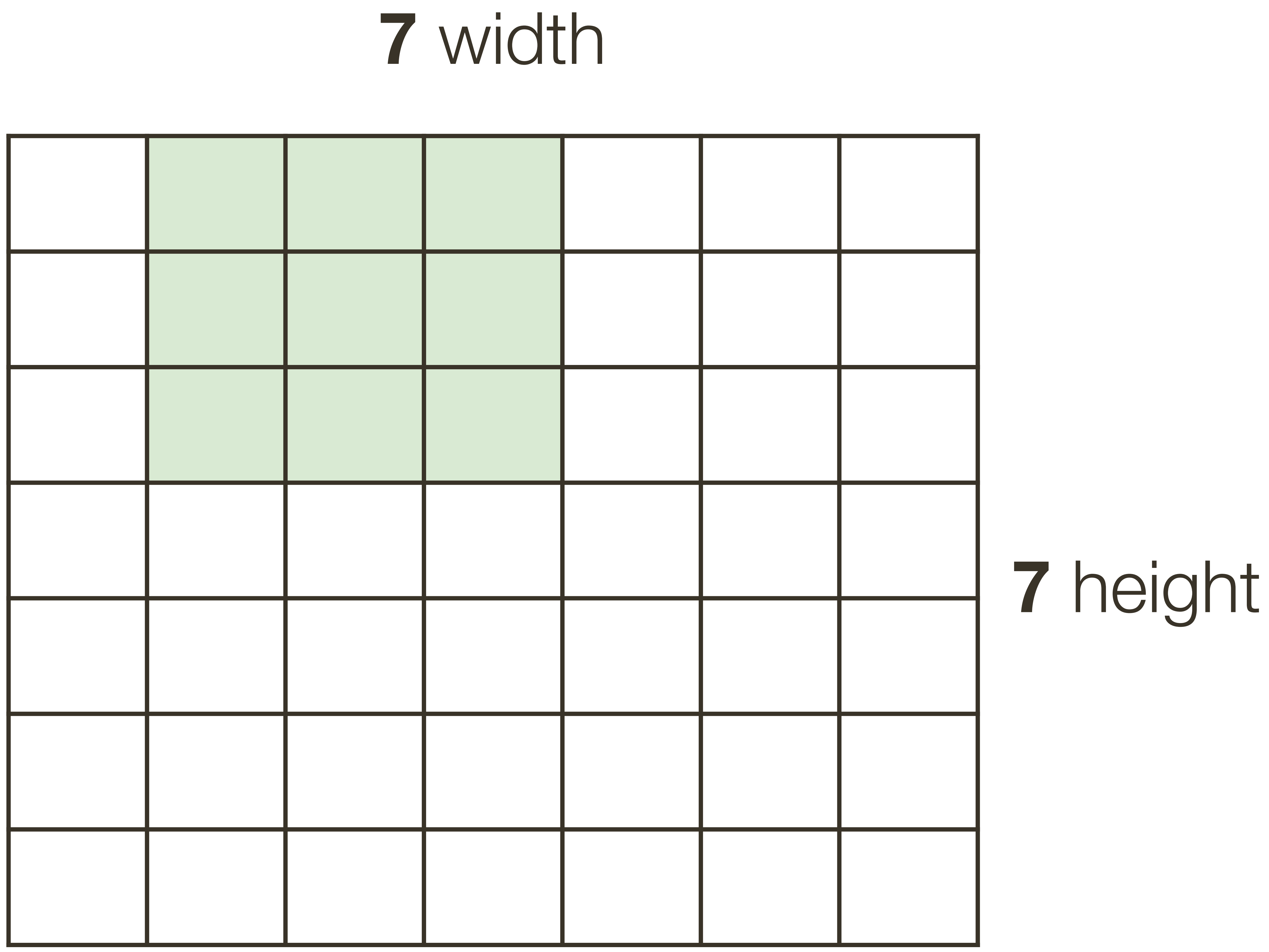


7 x 7 input image (spatially)
3 x 3 filter

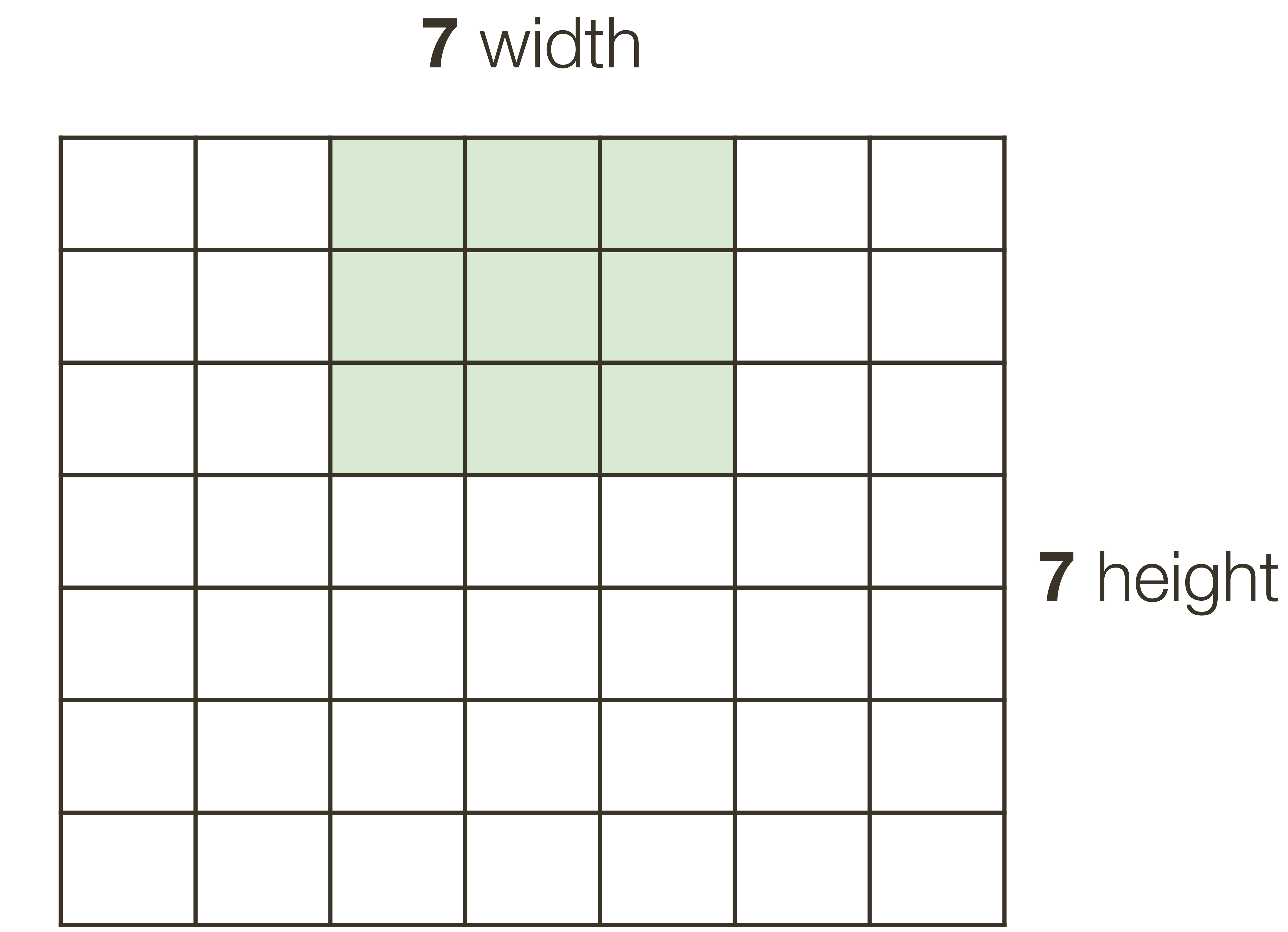
Convolutional Layer: Closer Look at **Spatial Dimensions**



7 x 7 input image (spatially)
3 x 3 filter

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer: Closer Look at **Spatial Dimensions**



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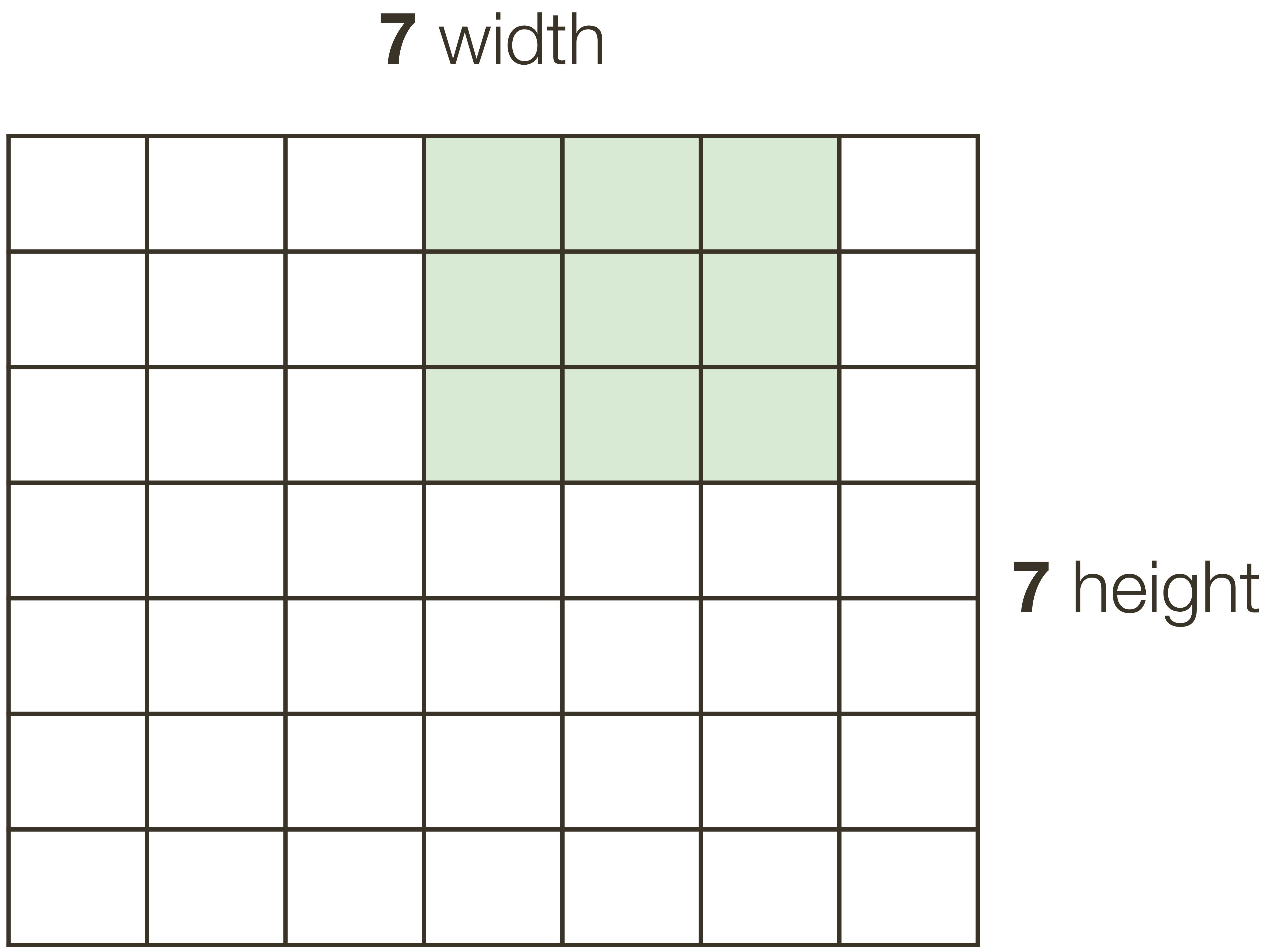

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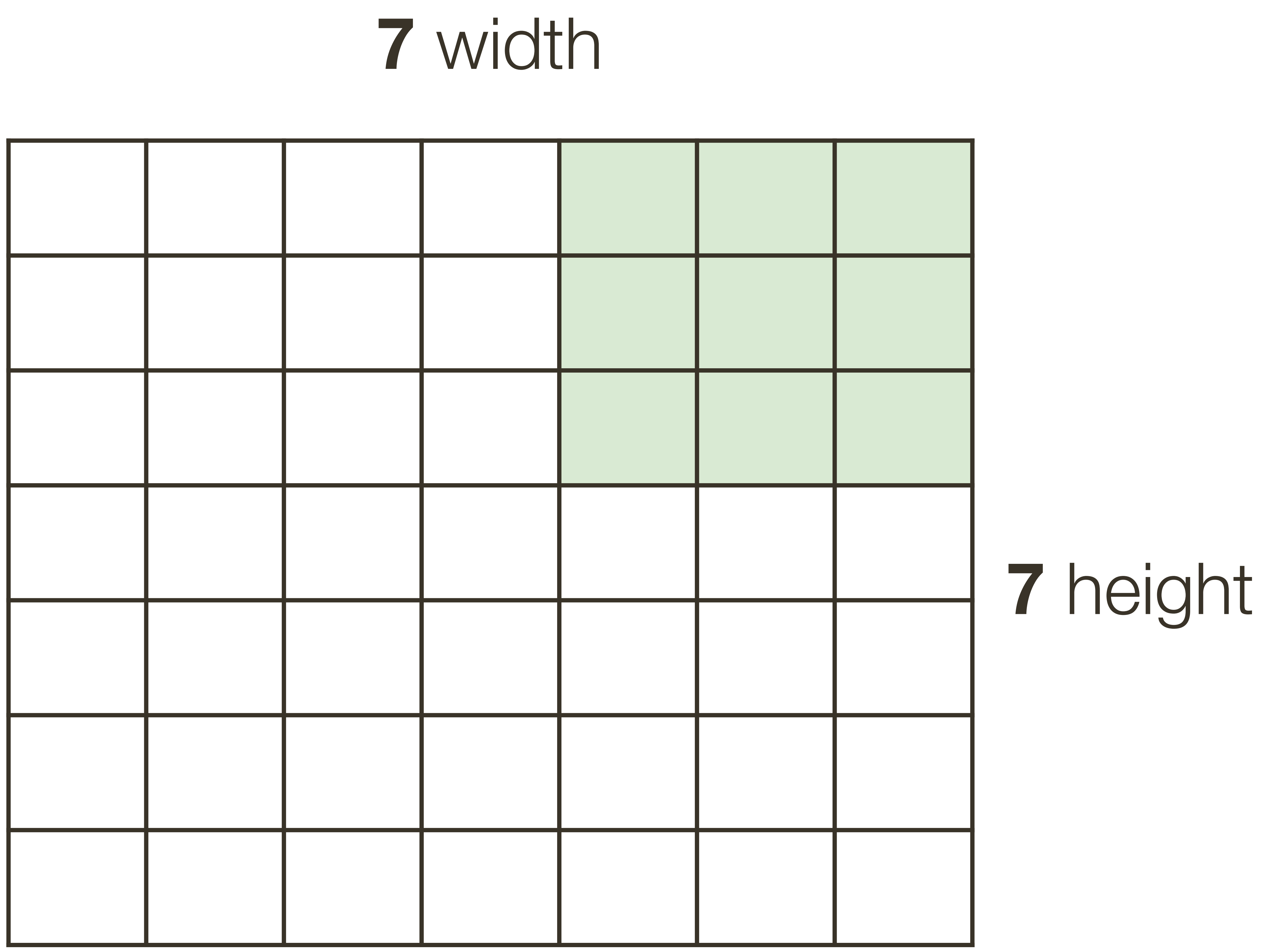

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3 x 3 filter

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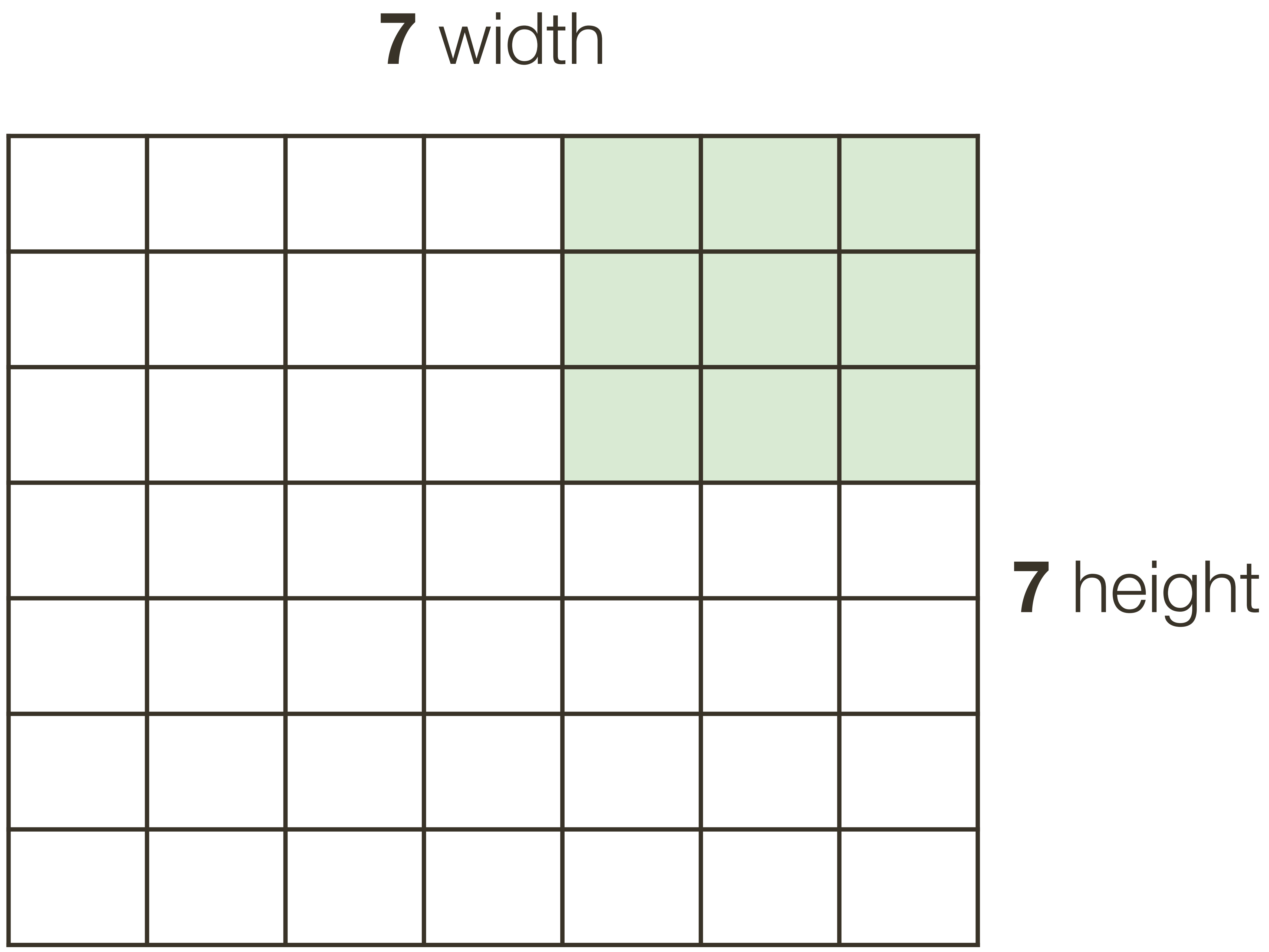
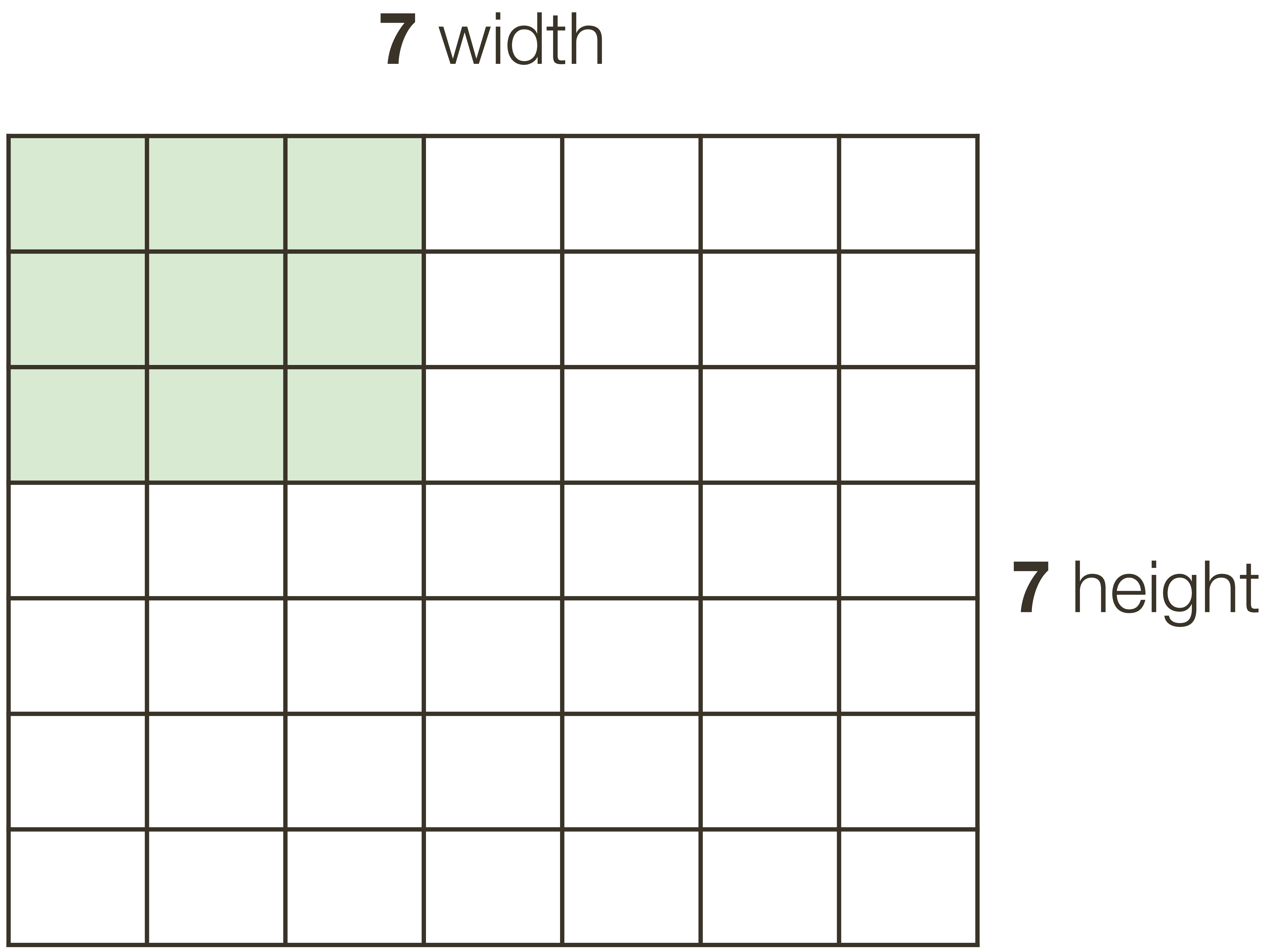


7 x 7 input image (spatially)
3 x 3 filter

=> **5 x 5 output**

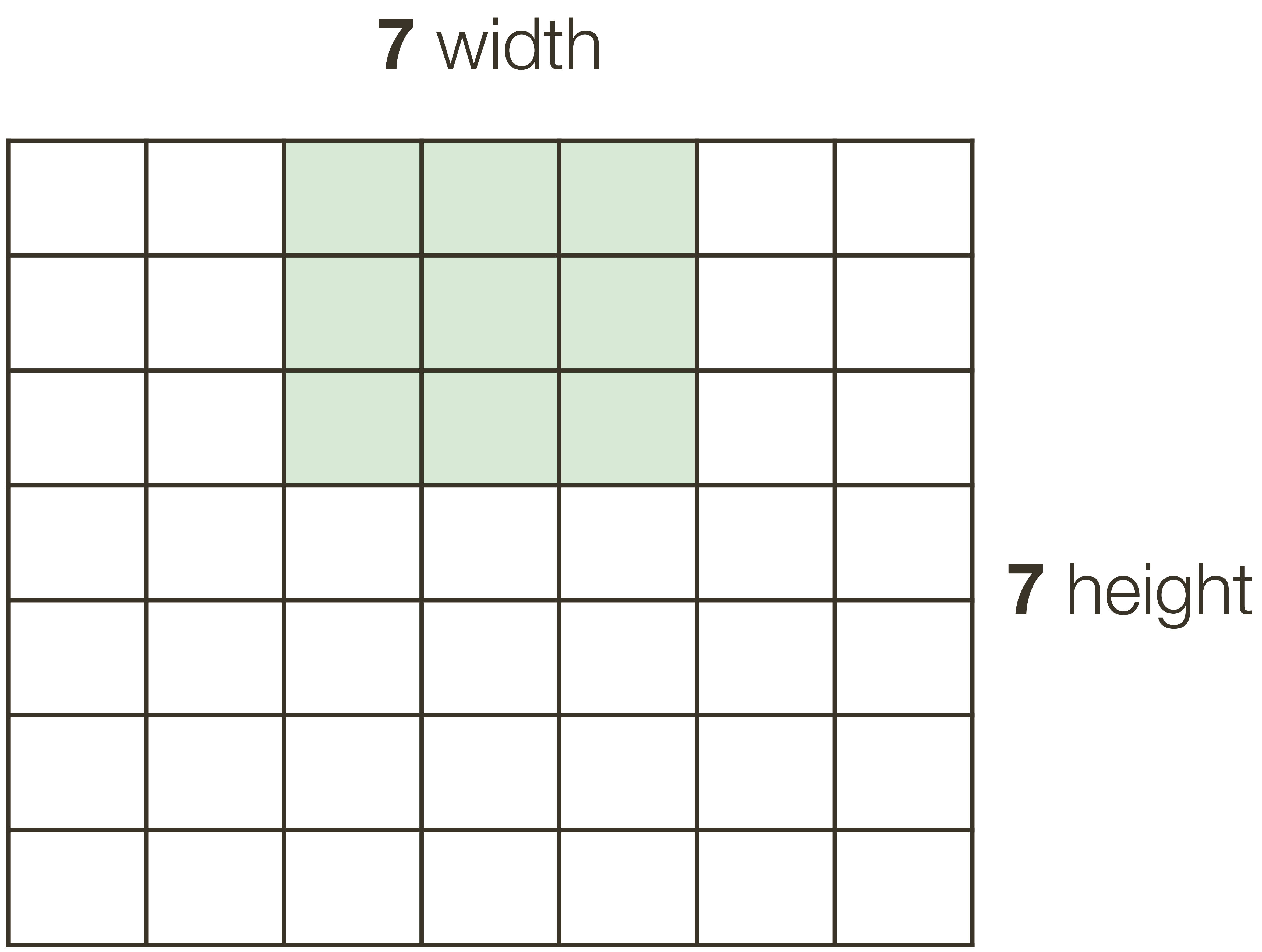
* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer: Closer Look at **Spatial Dimensions**



7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 2**)

Convolutional Layer: Closer Look at **Spatial Dimensions**



7 x 7 input image (spatially)
3 x 3 filter
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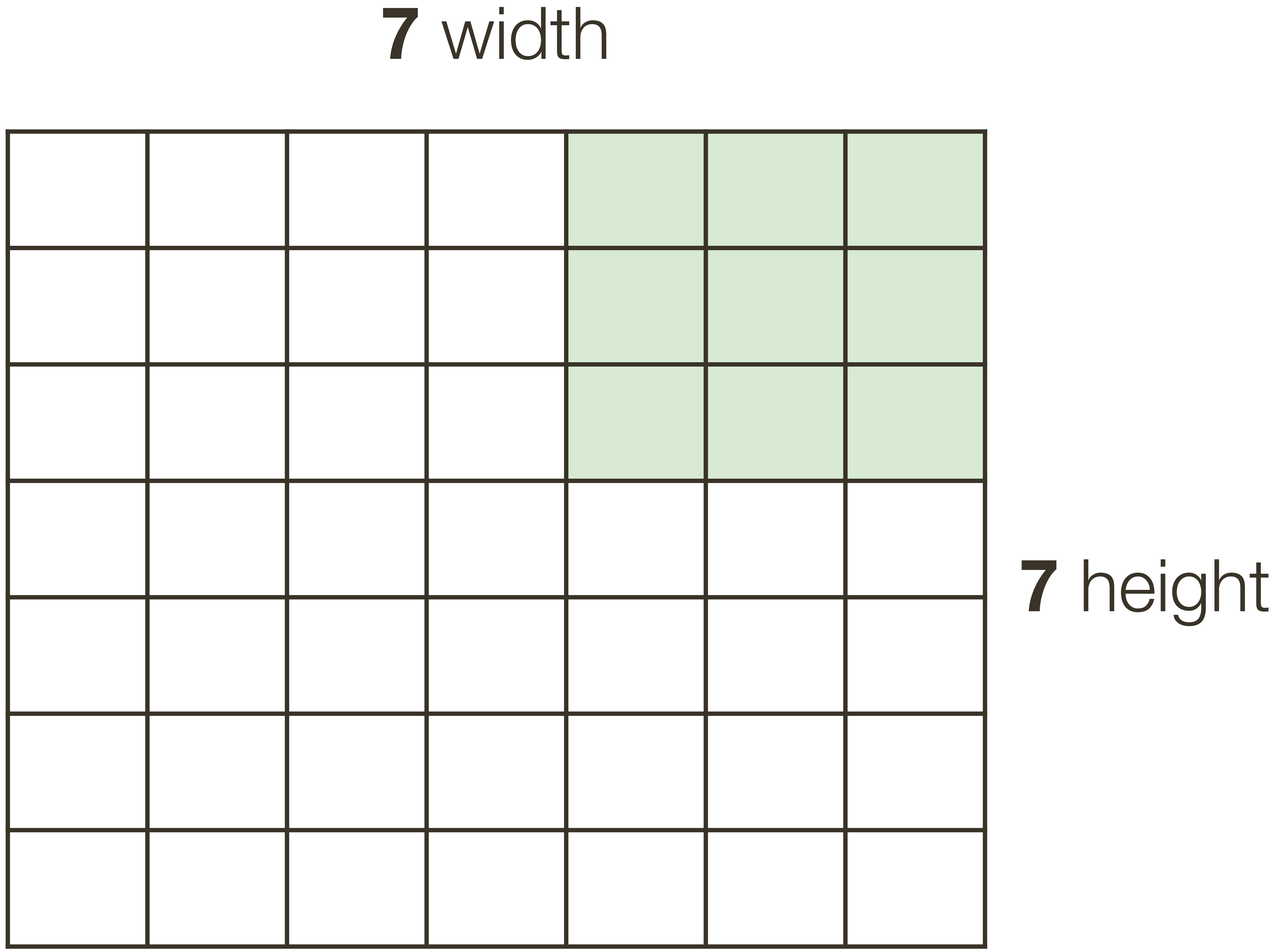
Convolutional Layer: Closer Look at **Spatial Dimensions**



7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 2**)

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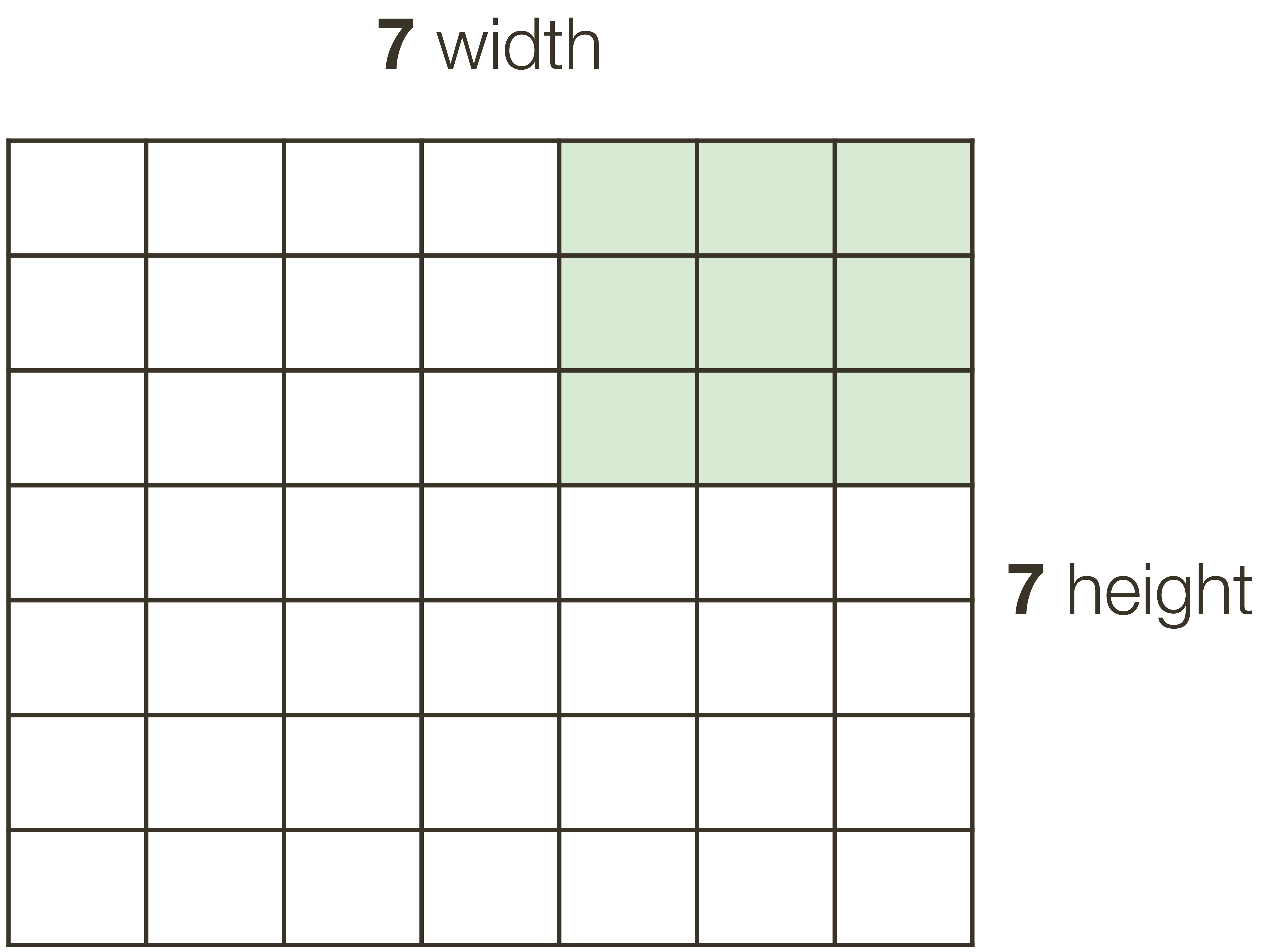
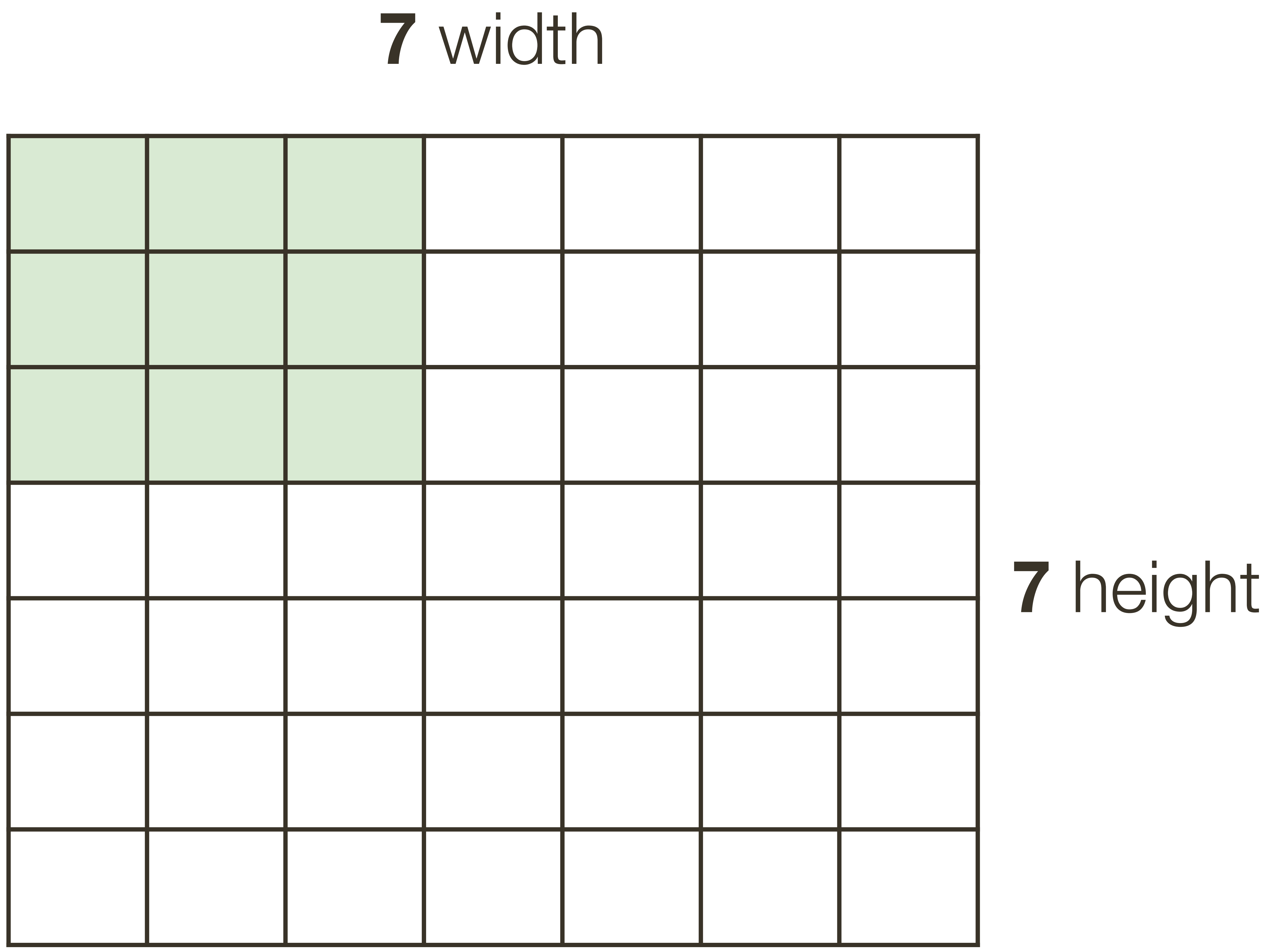
Convolutional Layer: Closer Look at **Spatial Dimensions**



7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 2**)

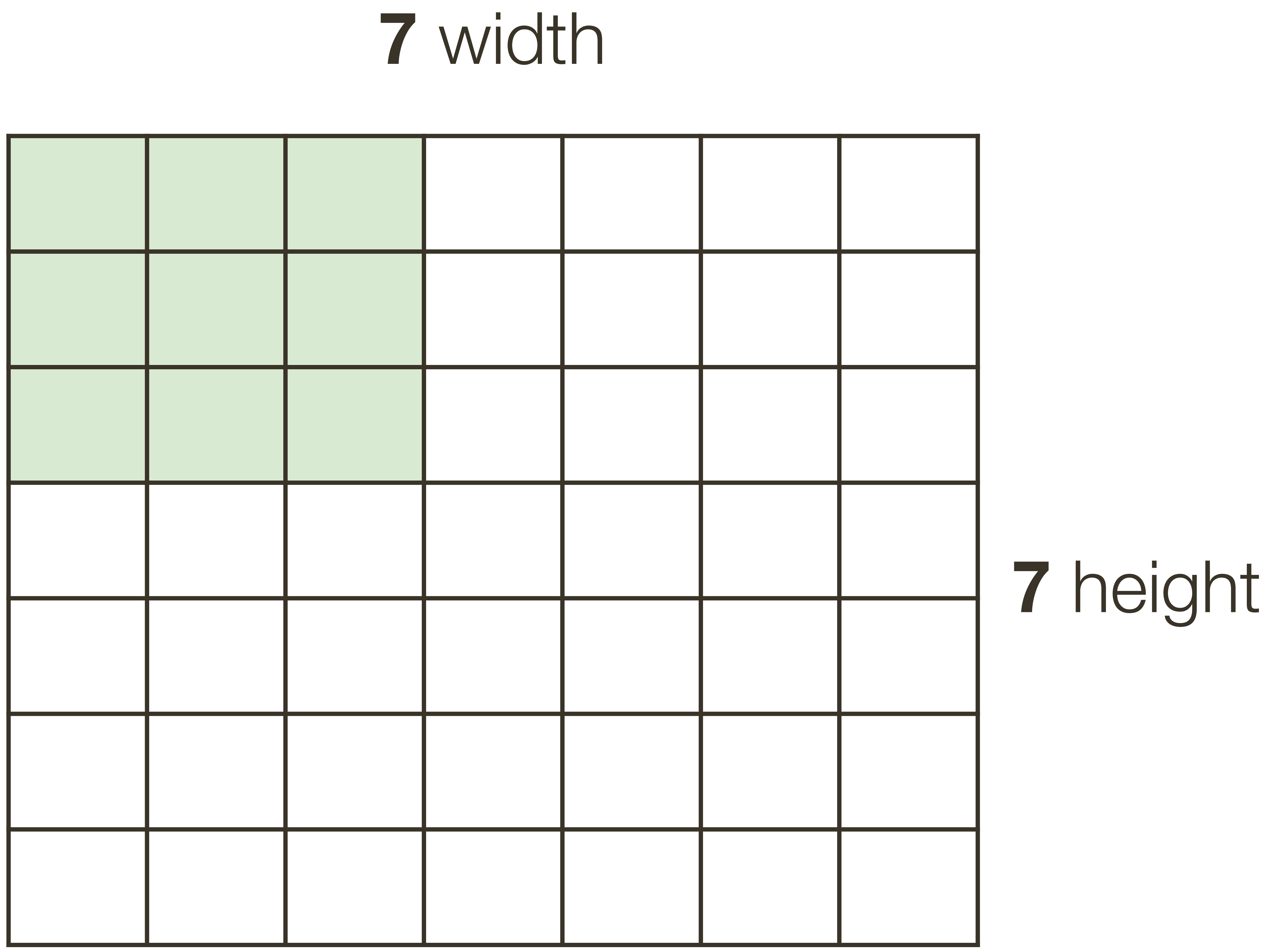
=> **3 x 3 output**

Convolutional Layer: Closer Look at **Spatial Dimensions**



7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 3**)

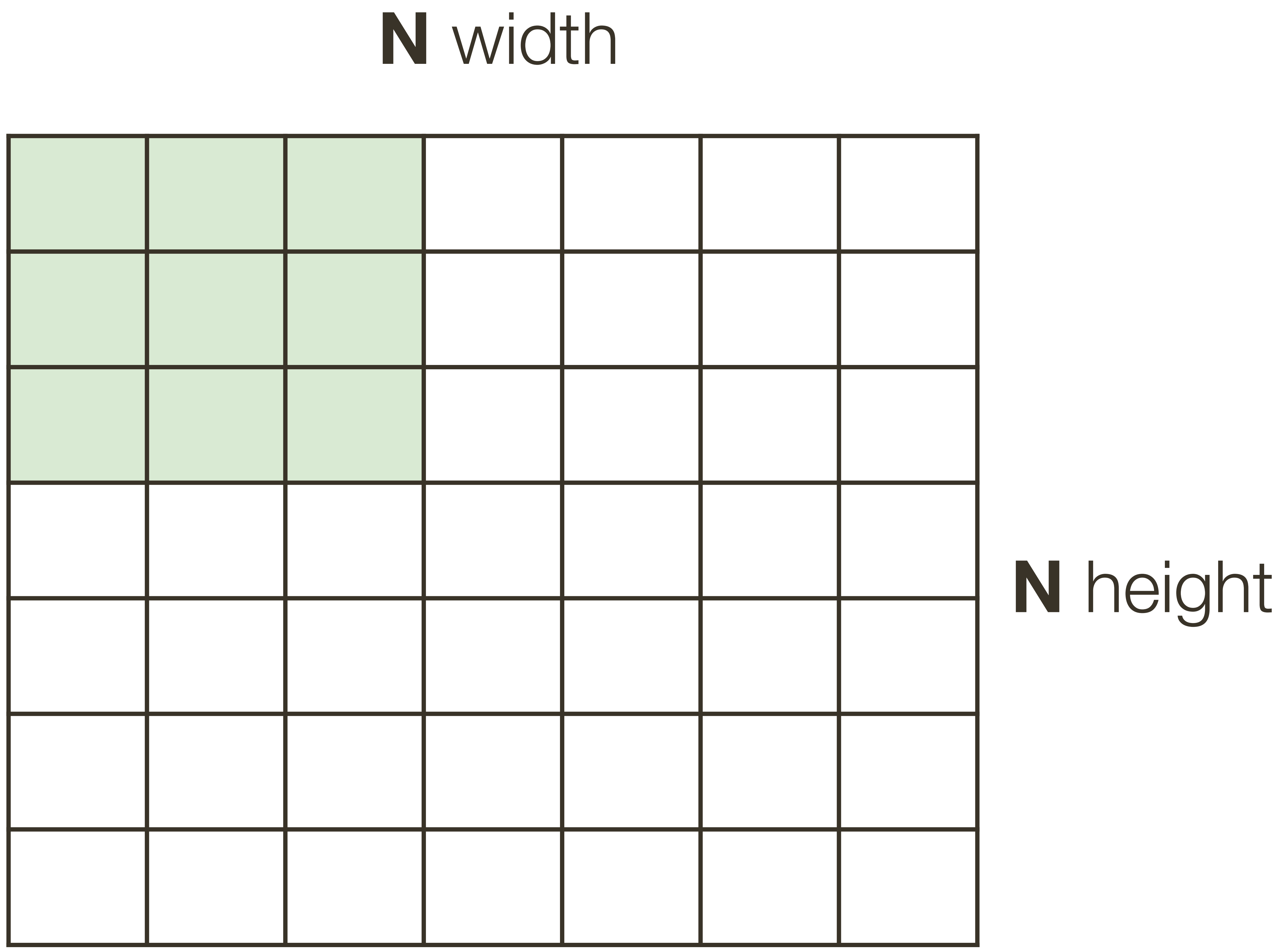
Convolutional Layer: Closer Look at **Spatial Dimensions**



7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 3**)

Does not fit! **Cannot apply** 3 x 3 filter on 7 x 7 image with stride 3

Convolutional Layer: Closer Look at **Spatial Dimensions**

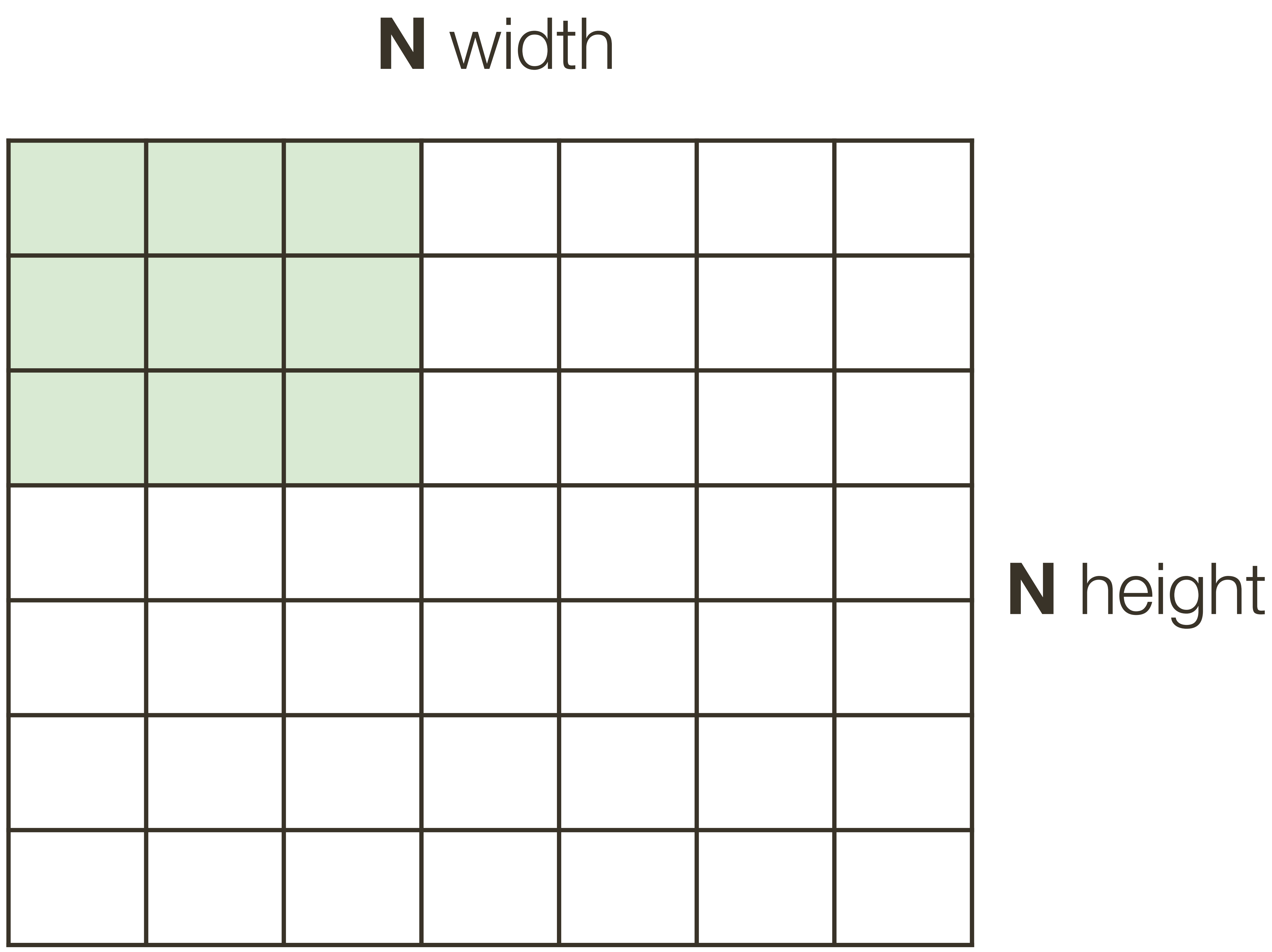


N x N input image (spatially)
F x F filter

Output size: (N-F) / stride + 1

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer: Closer Look at **Spatial Dimensions**



N x N input image (spatially)
F x F filter

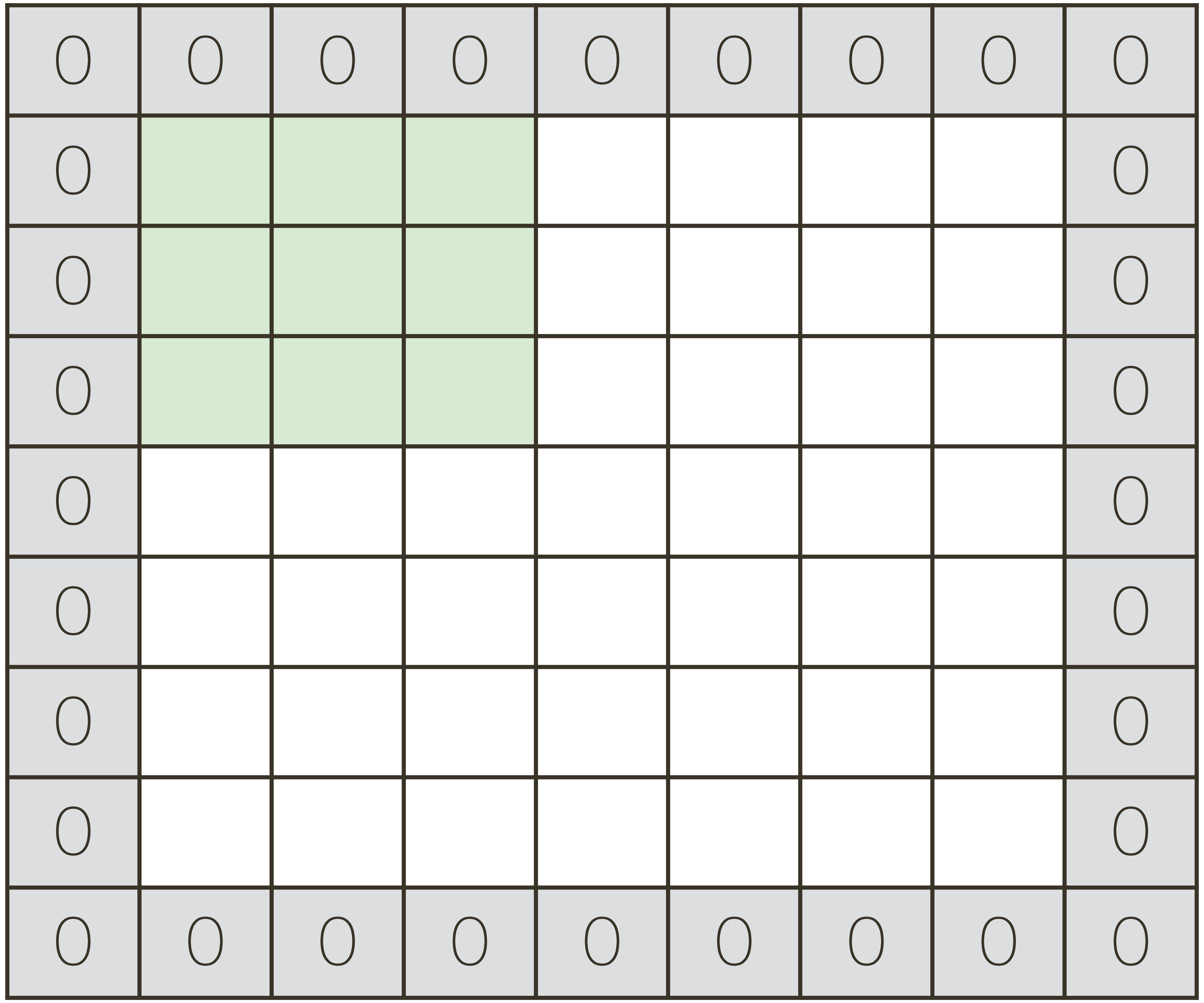
Output size: (N-F) / stride + 1

Example: N = 7, F = 3

stride 1 => (7-3)/1+1 = 5
stride 2 => (7-3)/2+1 = 3
stride 3 => (7-3)/3+1 = **2.33**

Convolutional Layer: **Border padding**

7 width



7 height

5 x 5 input image (spatially)
3 x 3 filter
(applied with **stride 1**)

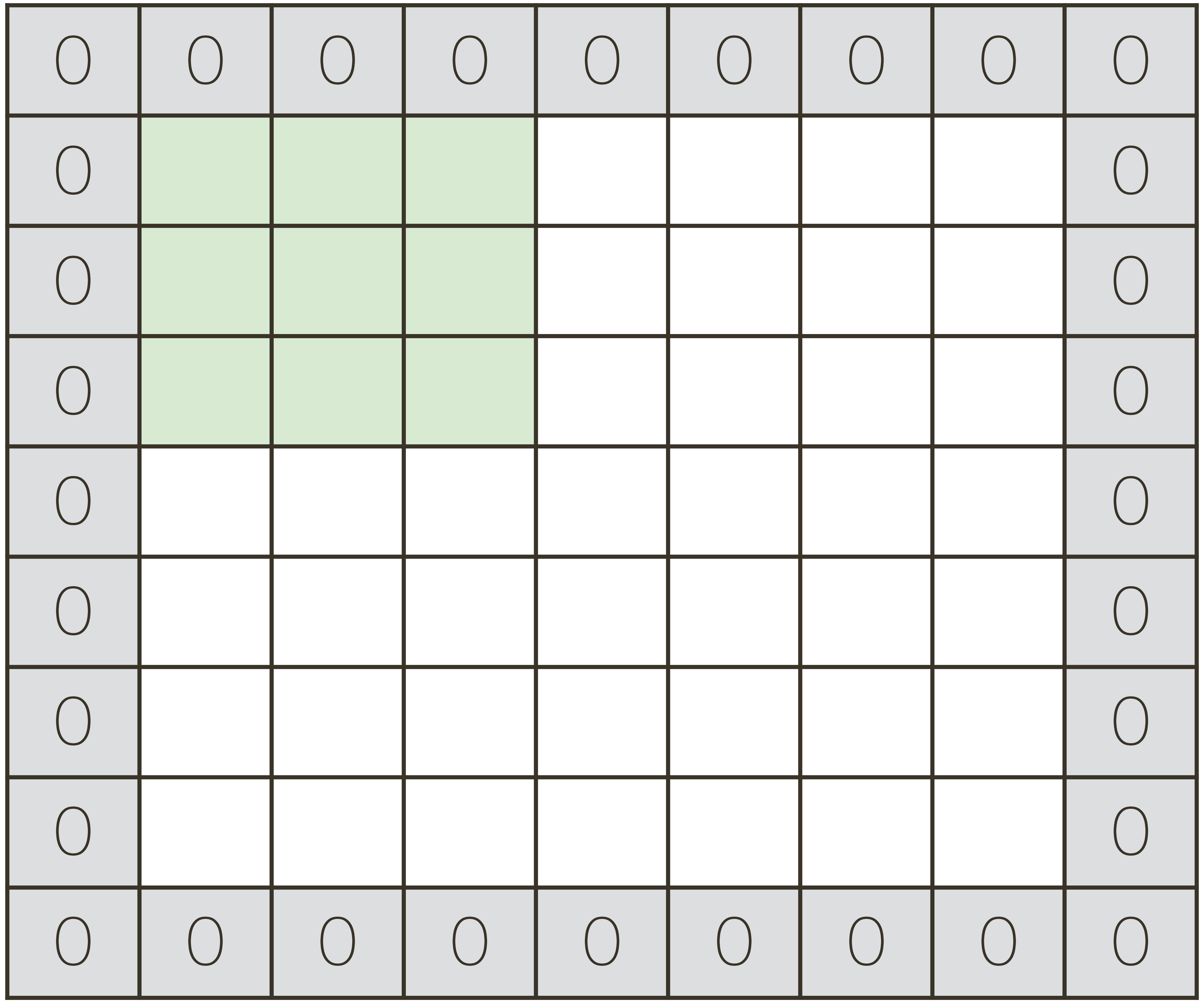
pad with 1 pixel border

Output size: 7 x 7

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Layer: **Border padding**

7 width



7 height

5 x 5 input image (spatially)
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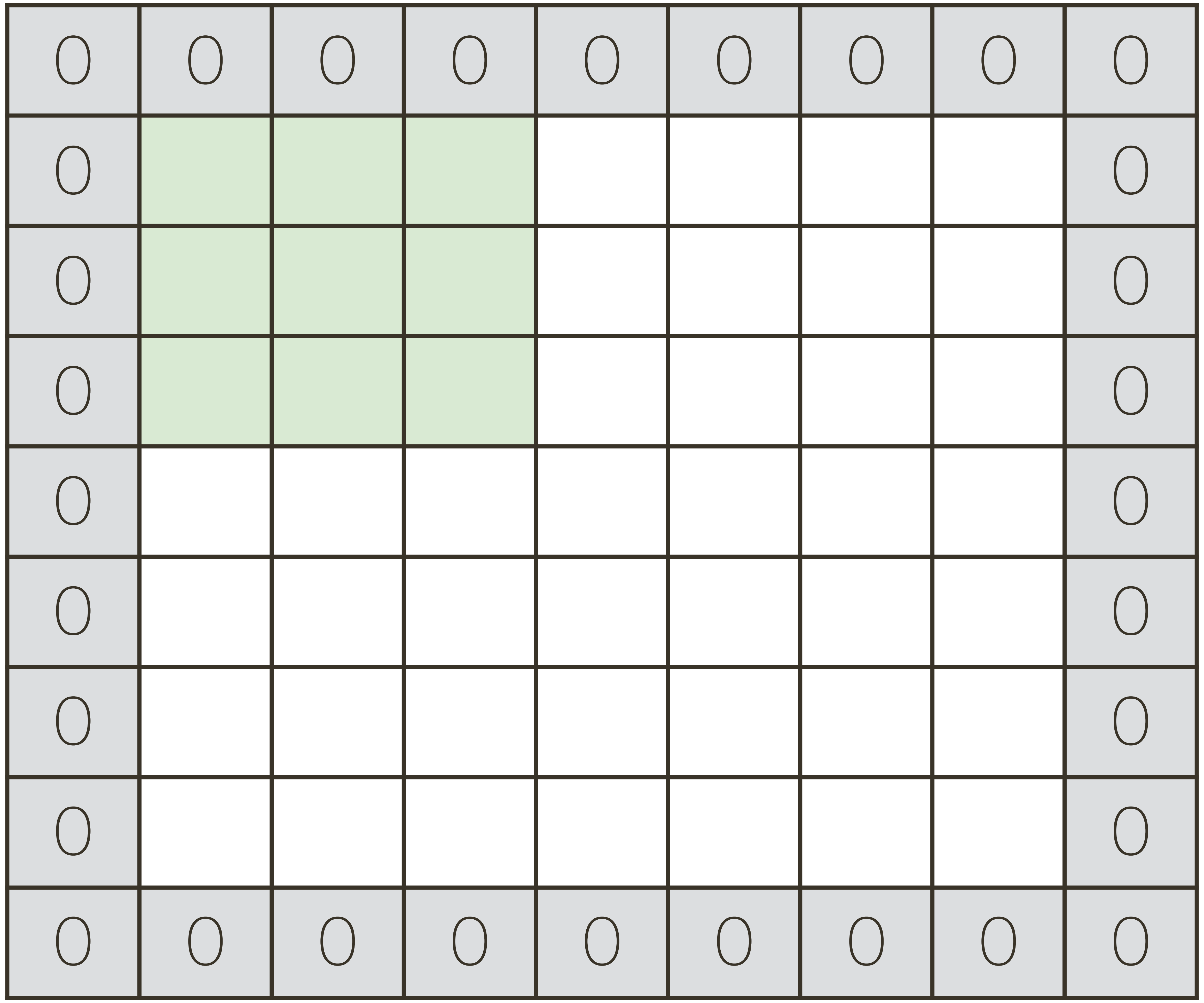
(applied with **stride 3**)

pad with 1 pixel border

Convolutional Layer: **Border padding**

7 width



7 height

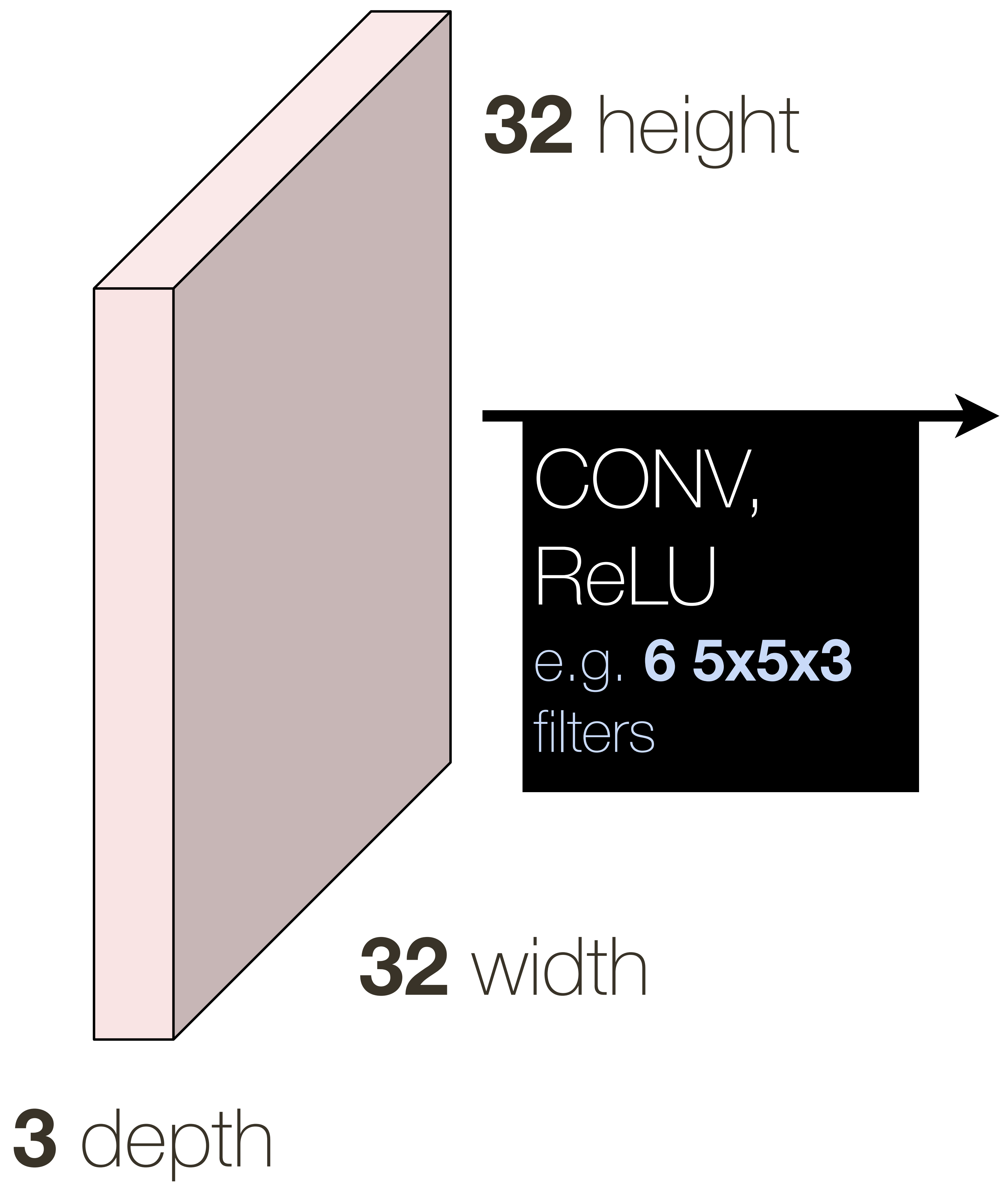
5 x 5 input image (spatially)
3 x 3 filter
(applied with **stride 3**)

pad with 1 pixel border

Example: N = 7, F = 3

stride 1 => (9-3)/1+1 = 7
stride 2 => (9-3)/2+1 = 4
stride 3 => (9-3)/3+1 = **3**

Convolutional Neural Network (ConvNet)



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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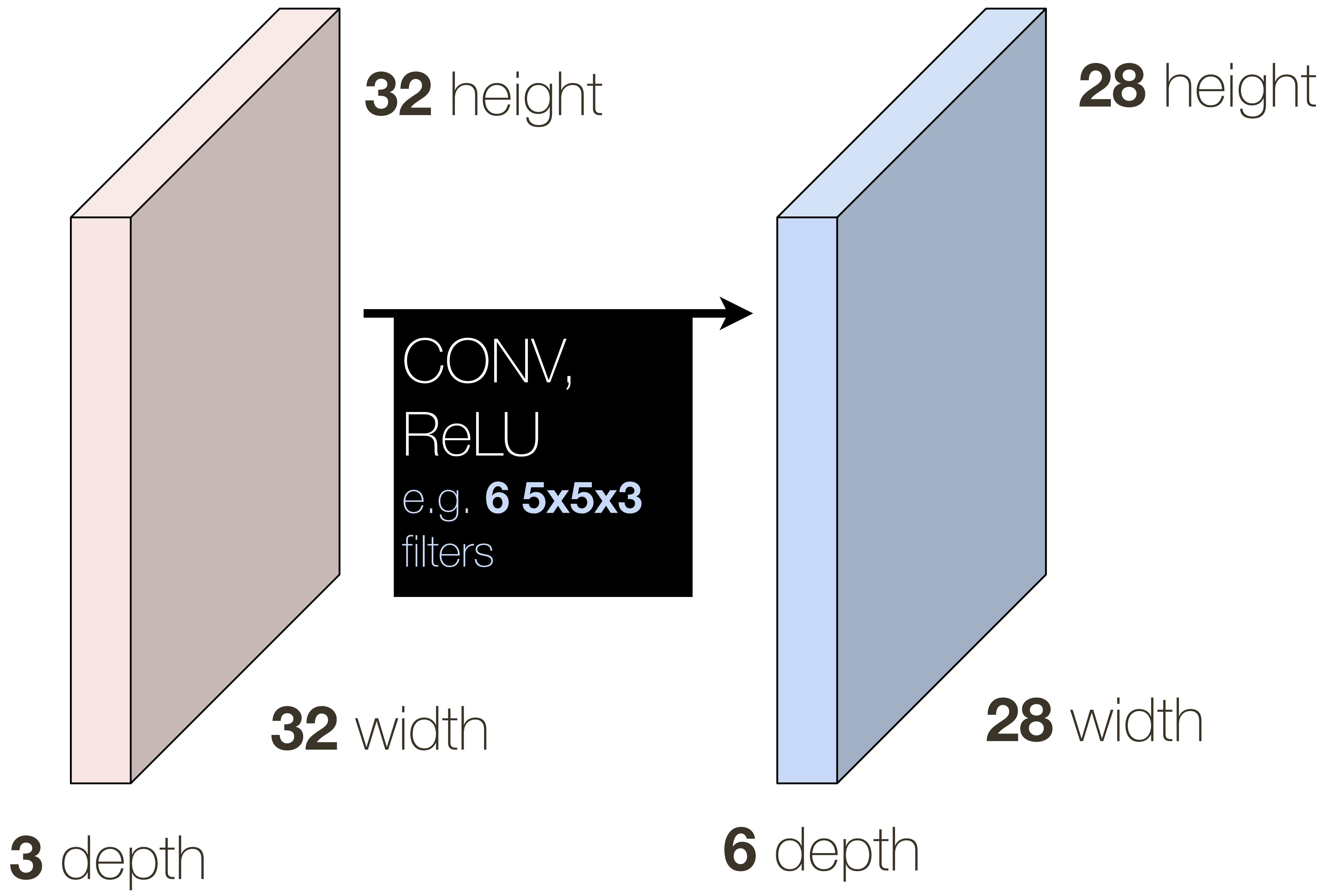

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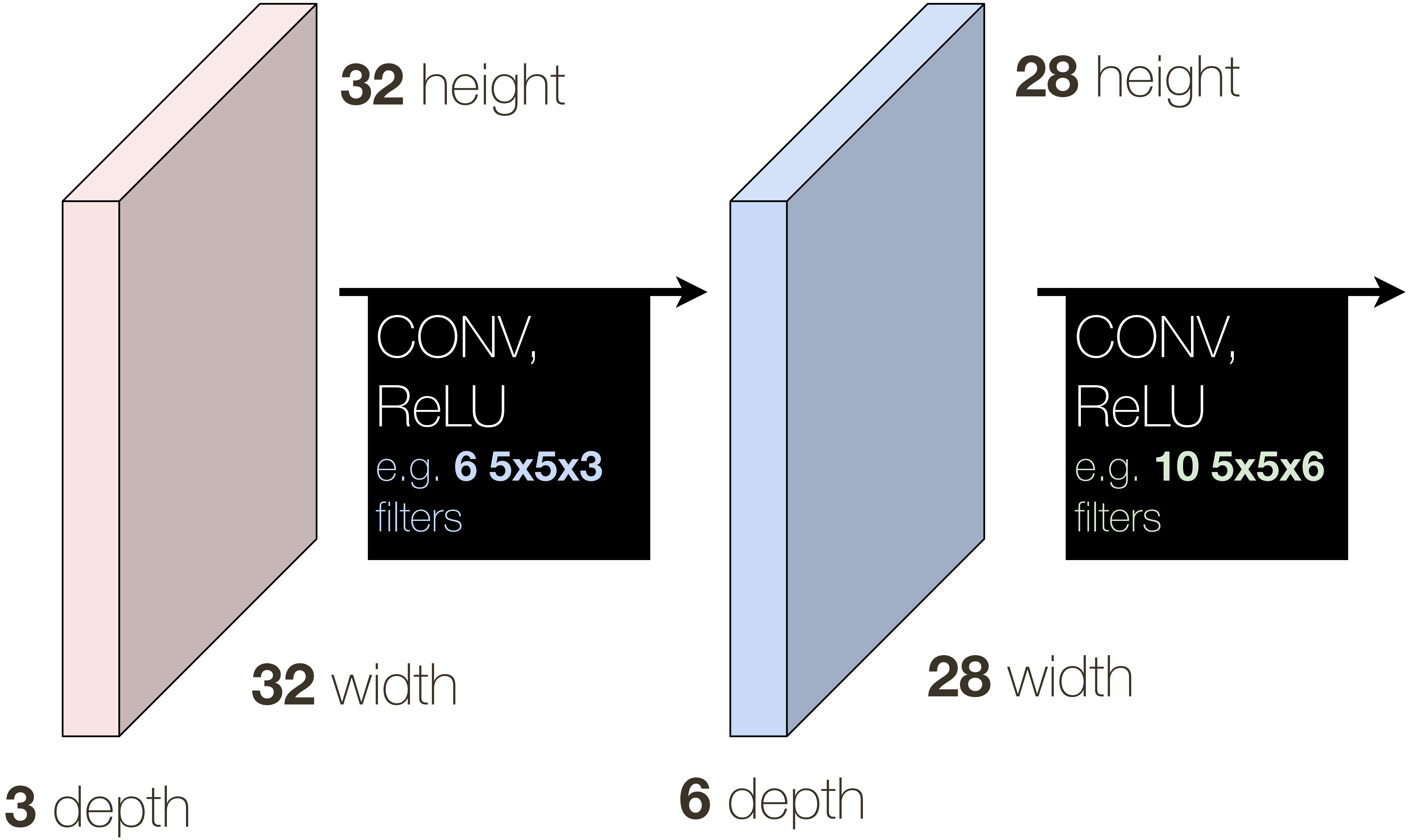

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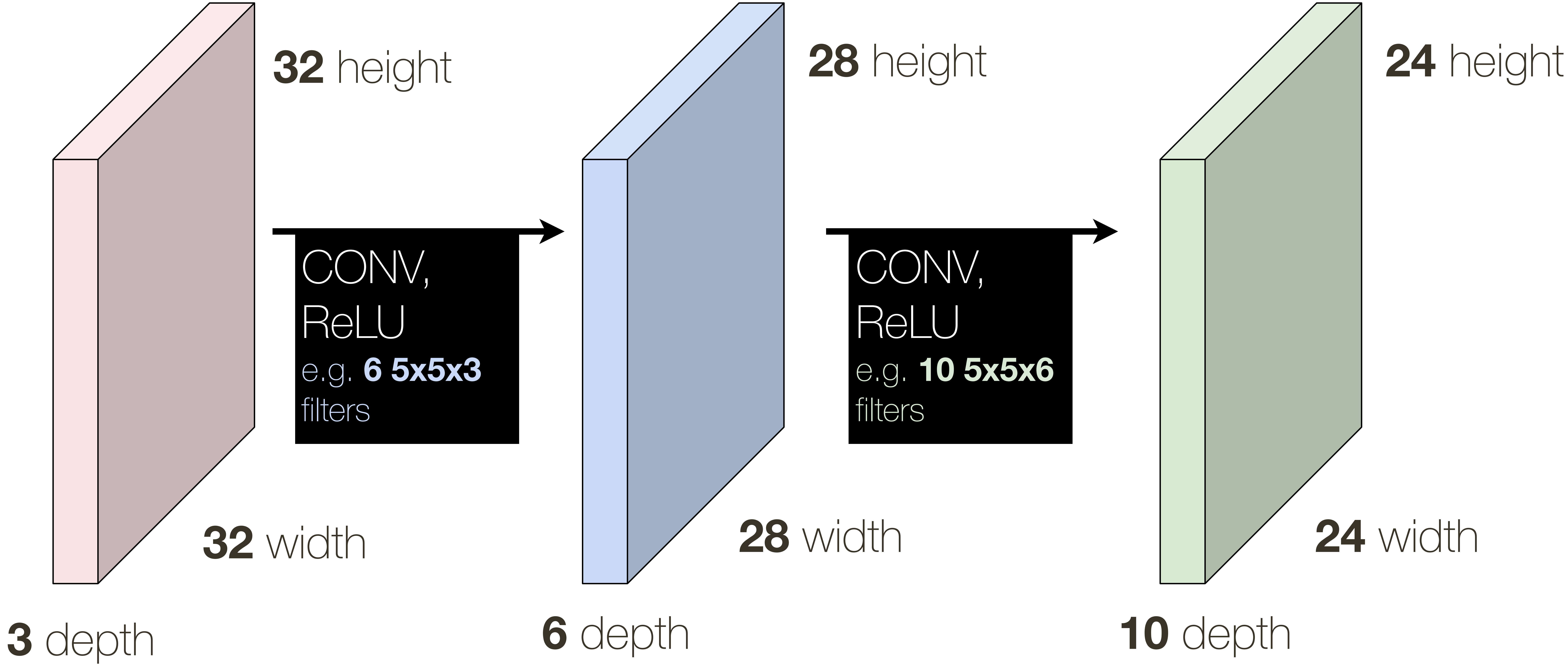

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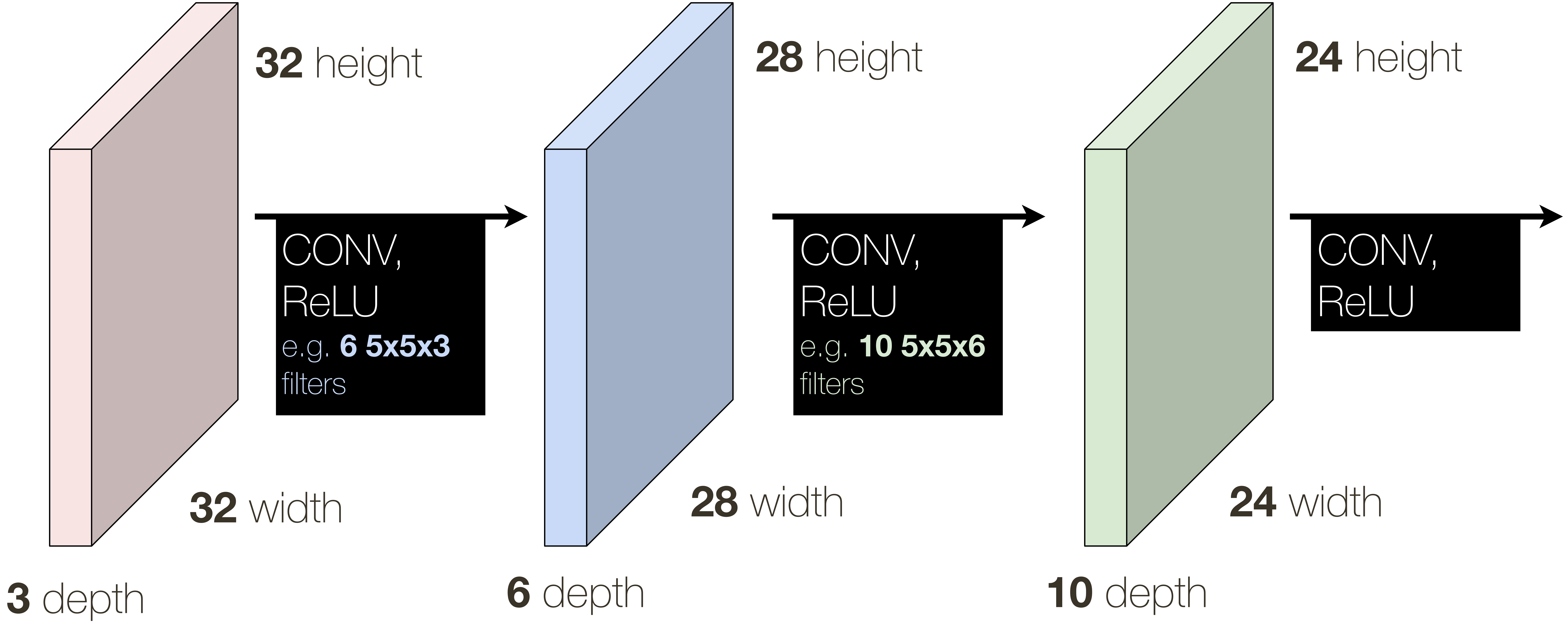
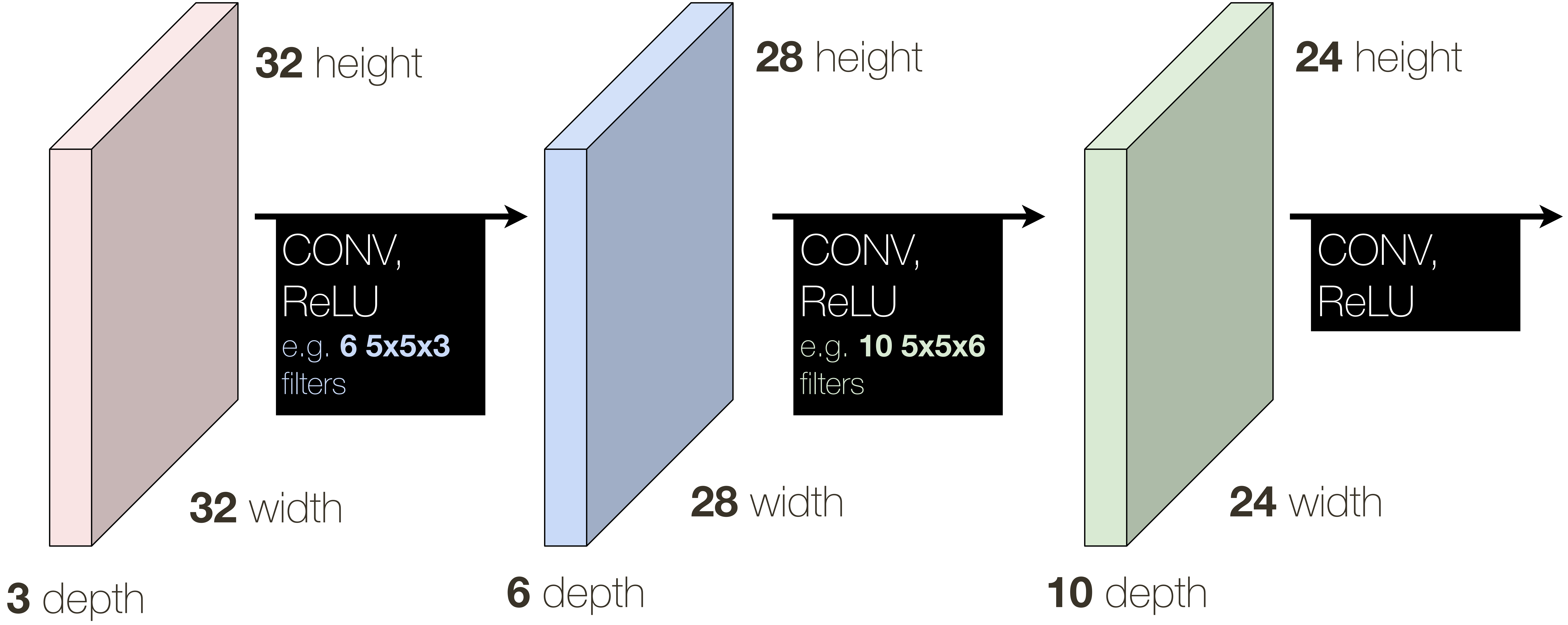


Convolutional Neural Network (ConvNet)

With padding we can achieve no shrinking (32 -> 28 -> 24); shrinking quickly (which happens with larger filters) doesn't work well in practice



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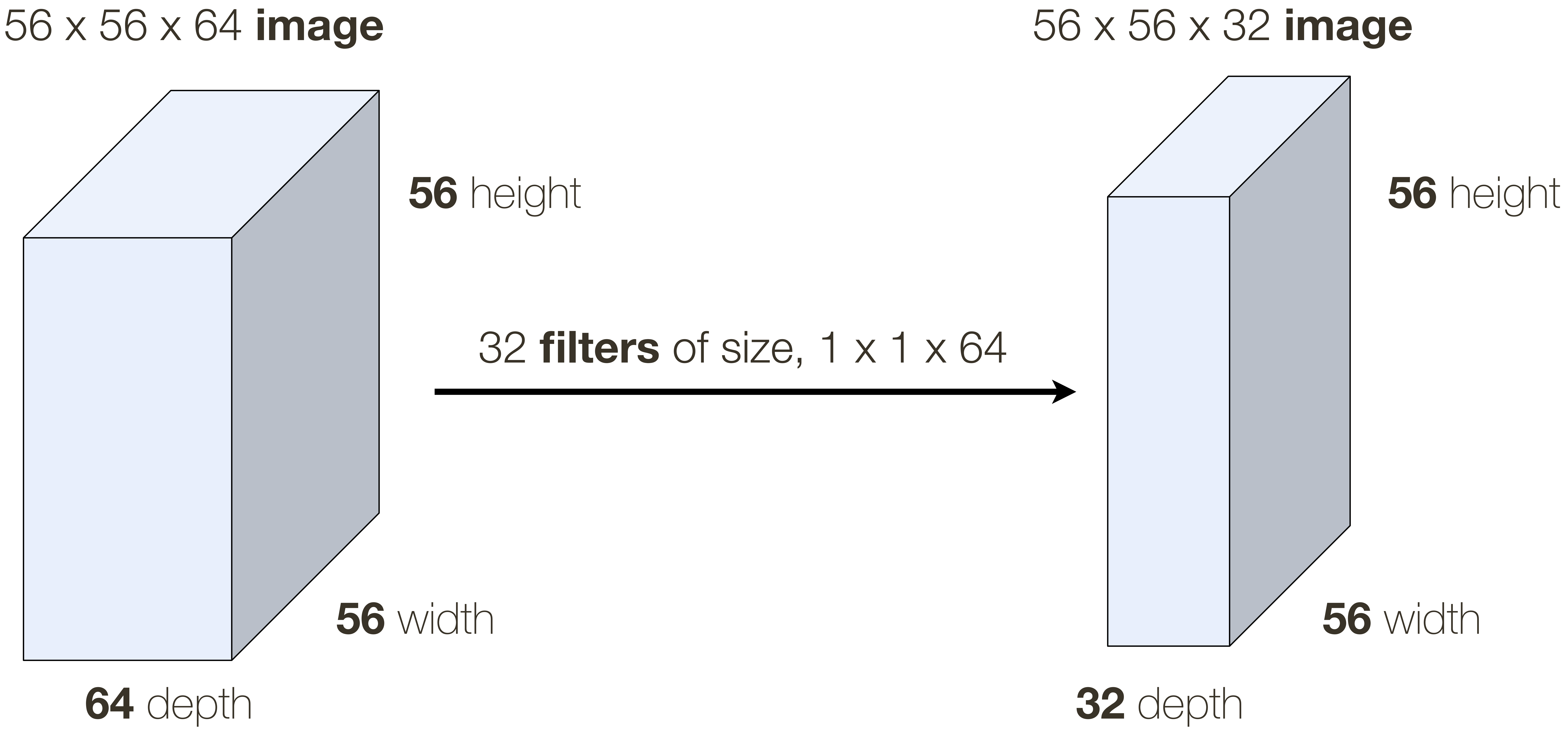
Convolutional Layer: **1x1 convolutions**



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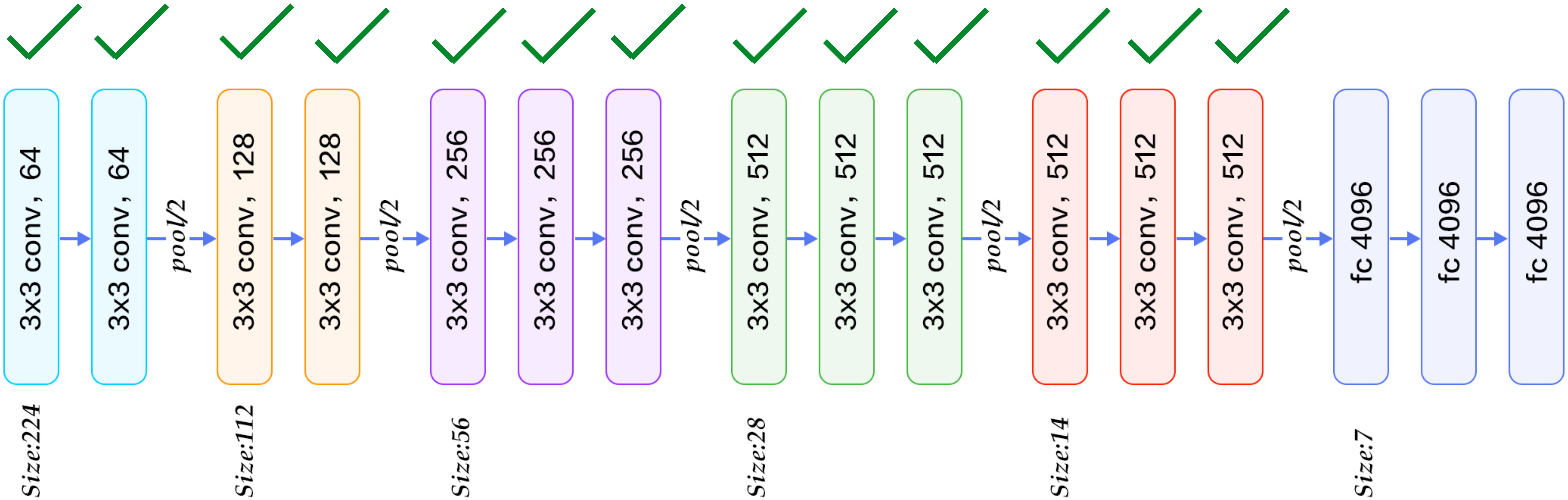
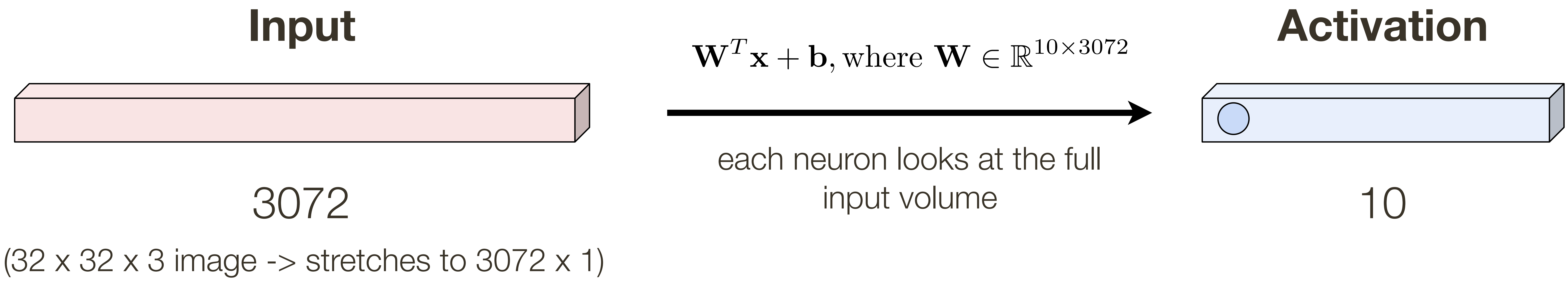
Convolutional Neural Networks

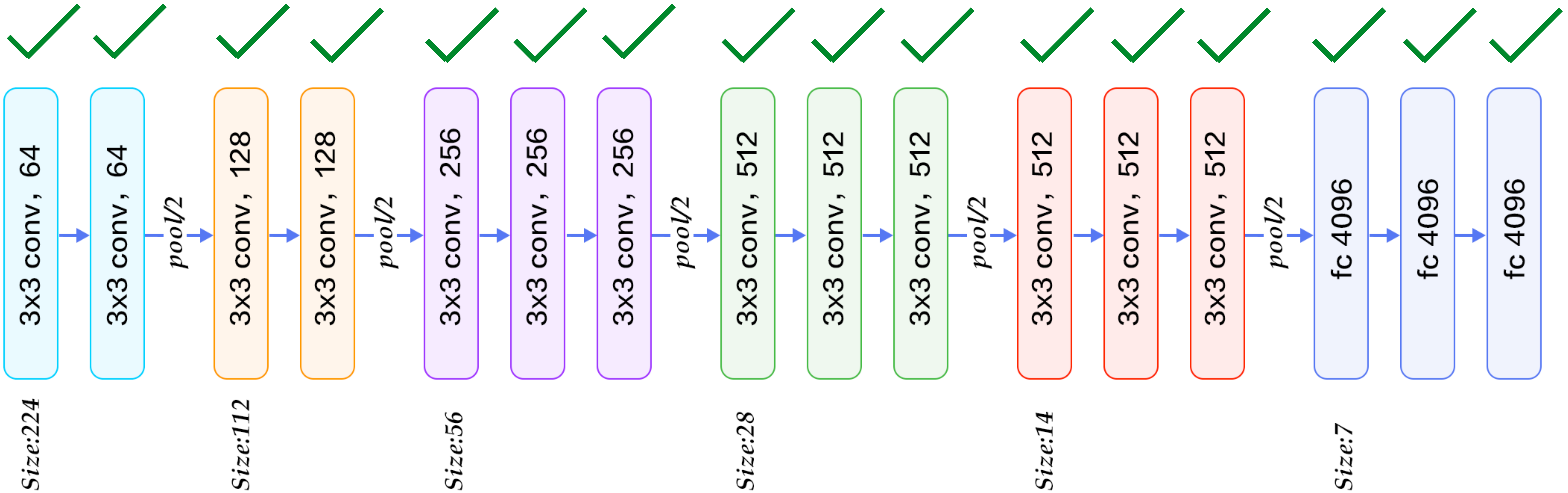


VGG-16 Network

CNNs: Reminder Fully Connected Layers

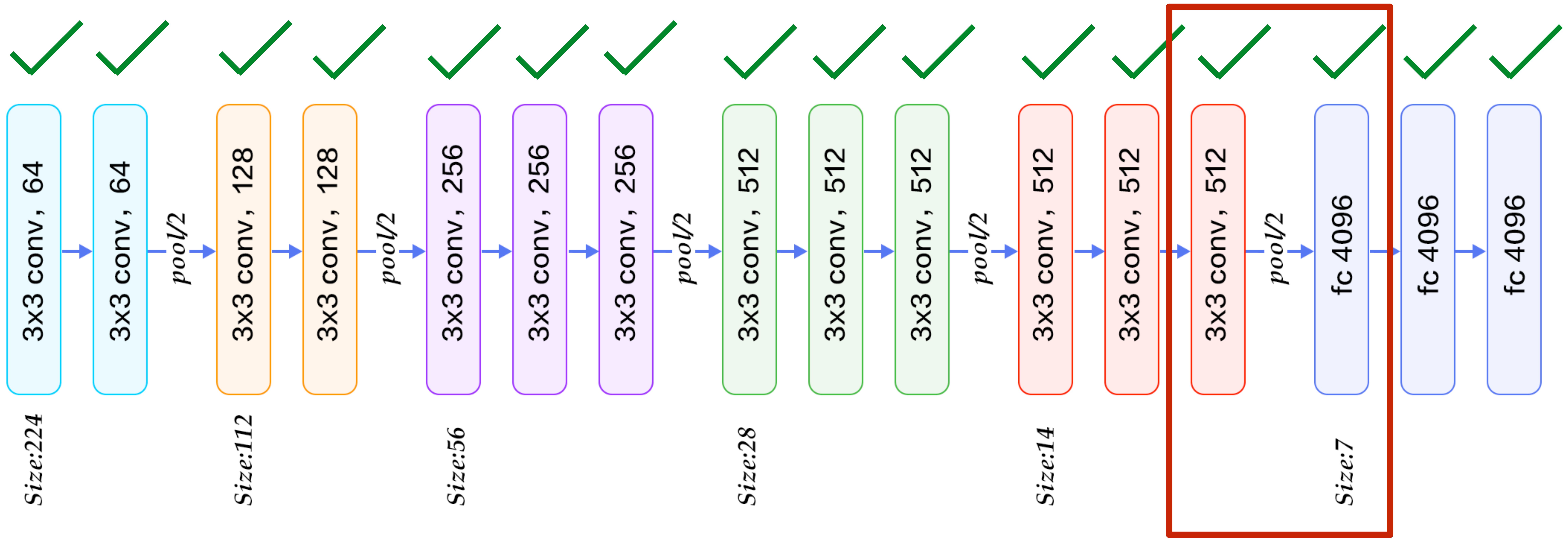


Convolutional Neural Networks



VGG-16 Network

Convolutional Neural Networks



VGG-16 Network

CNNs: Reminder Fully Connected Layers

Input

$$\mathbf{W}^T\mathbf{x} + \mathbf{b}, \text{ where } \mathbf{W} \in \mathbb{R}^{25,088 \times 4,096}$$

Activation

25,088

(7 x 7 x 512 image -> stretches to 25,088 x 1)

each neuron looks at the full
input volume

4,096

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25,088

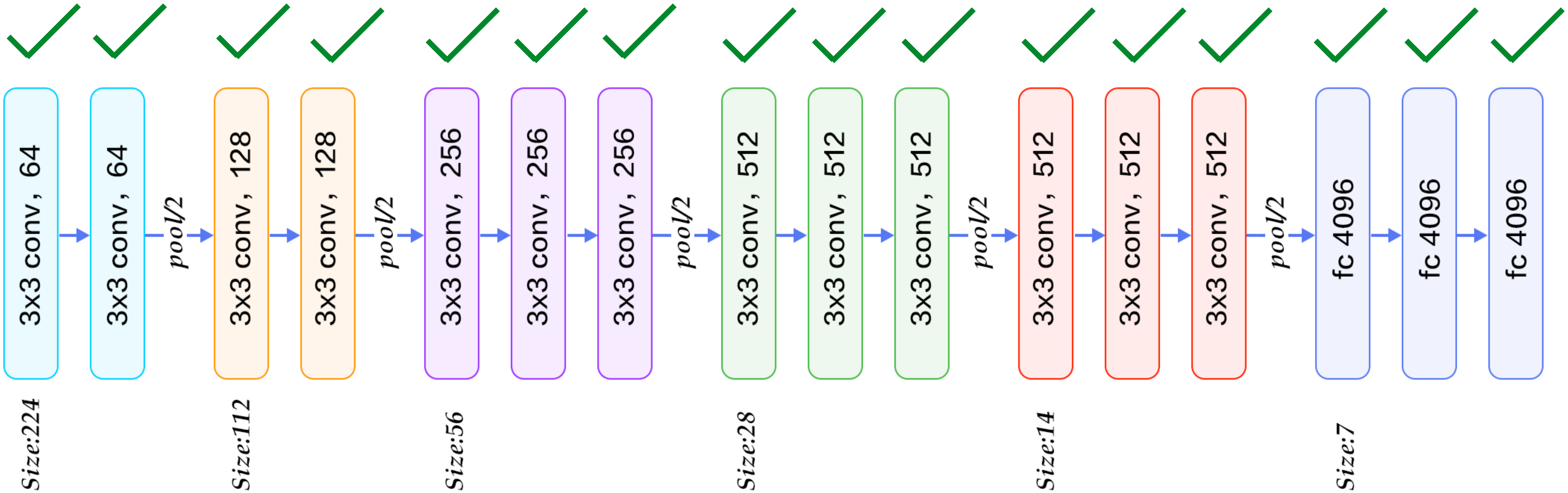
(7 x 7 x 512 image -> stretches to 25,088 x 1)

4,096

102,760,448 parameters!

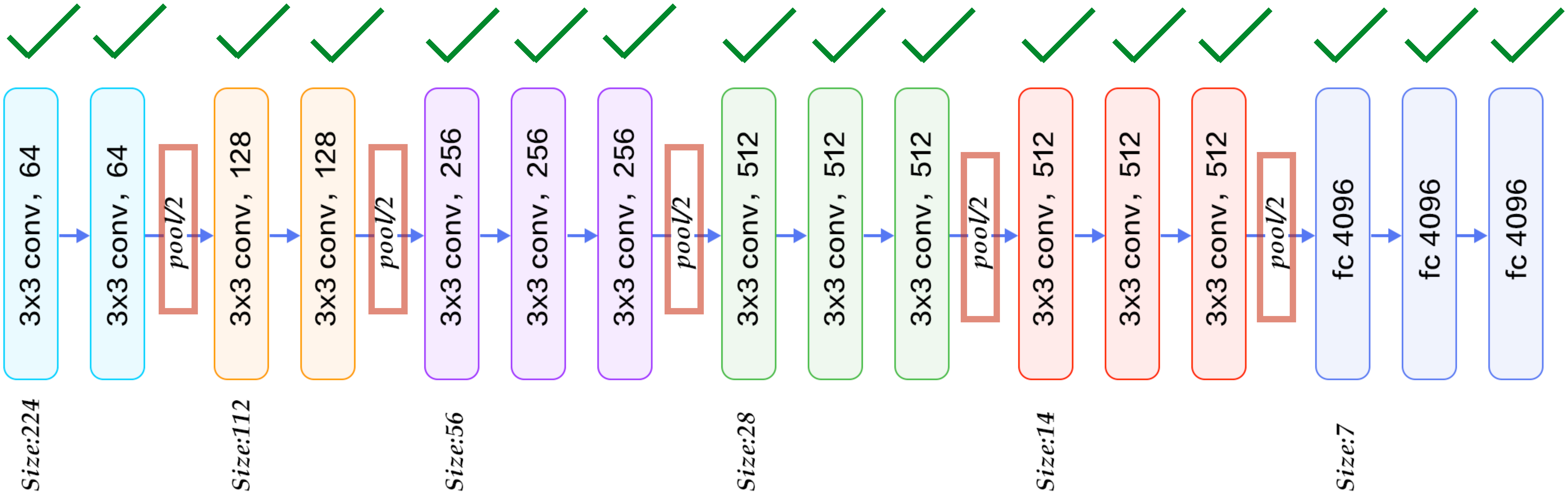
* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Neural Networks



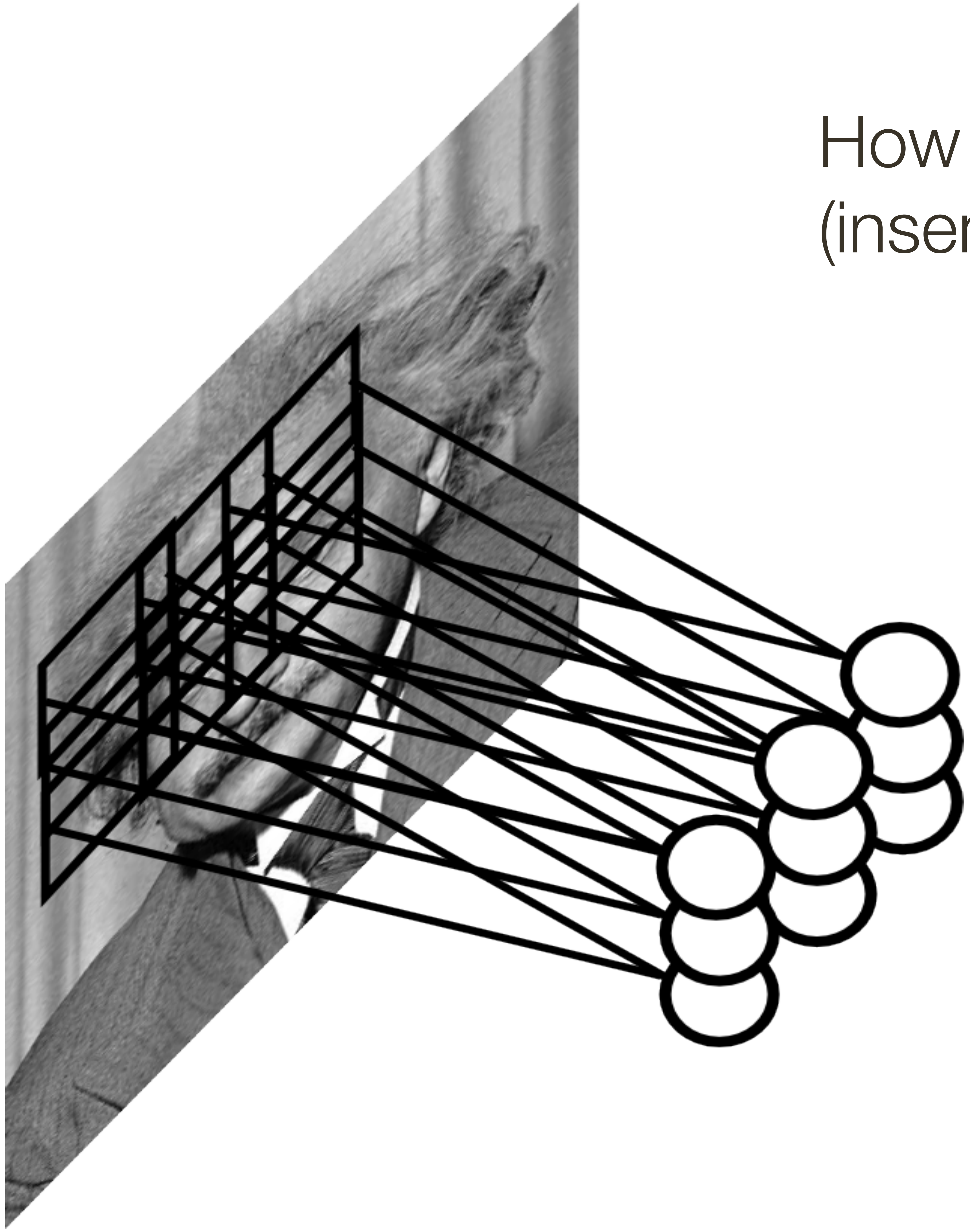
VGG-16 Network

Convolutional Neural Networks



VGG-16 Network

Pooling Layer



Let us assume the filter is an “eye” detector

How can we make detection spatially invariant (insensitive to position of the eye in the image)

* slide from Marc’Aurelio Renzato

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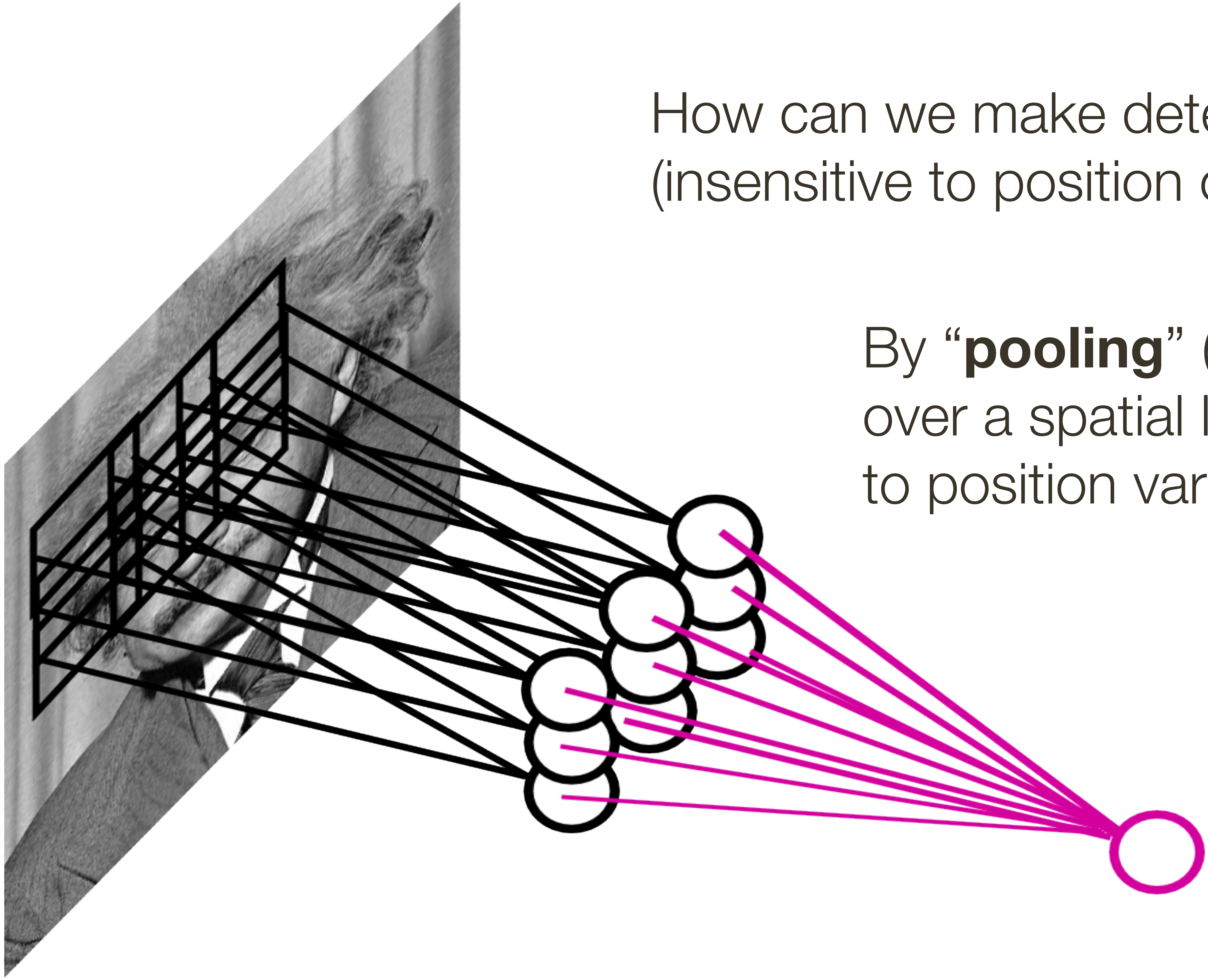

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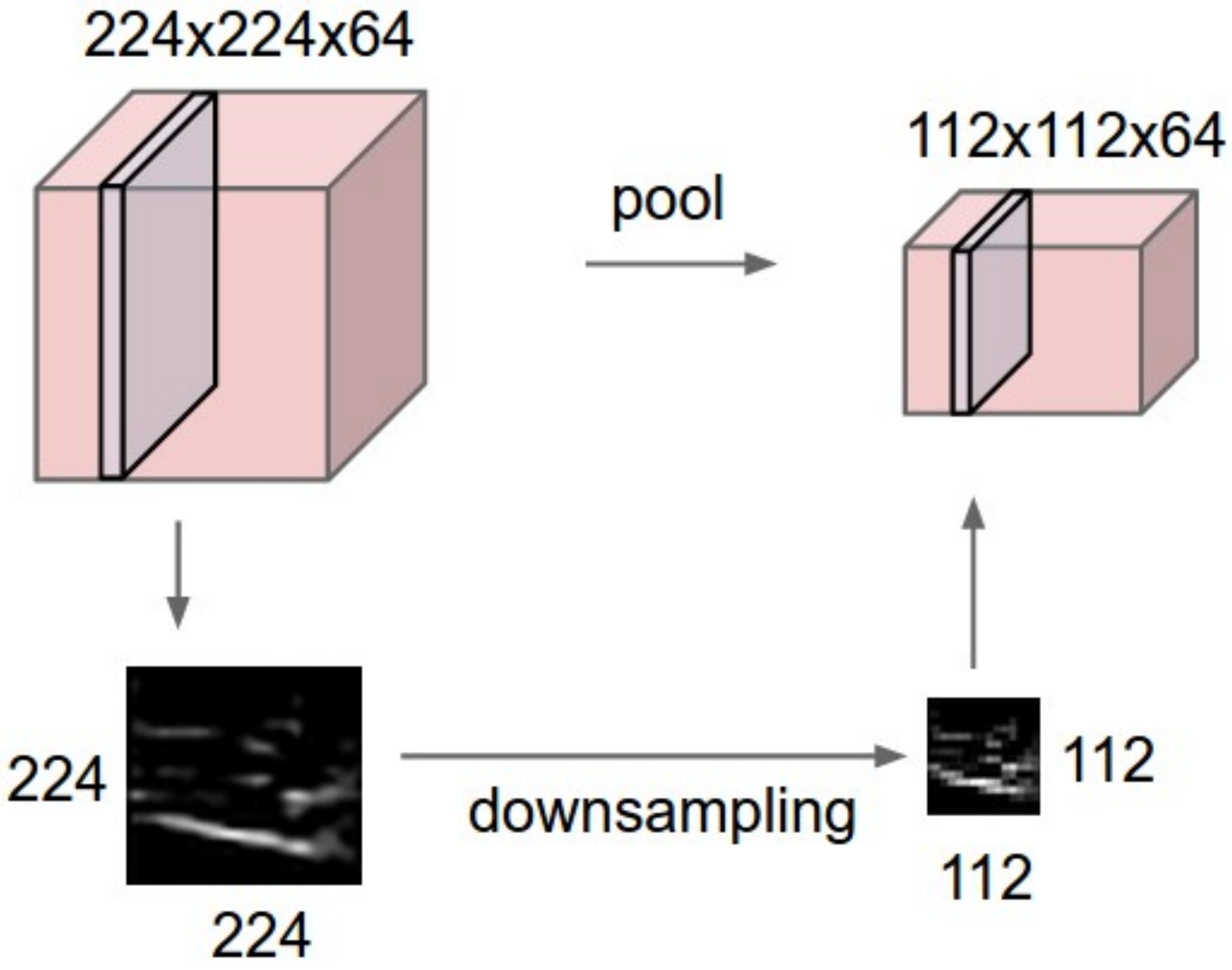
How can we make detection spatially invariant (insensitive to position of the eye in the image)

By “**pooling**” (e.g., taking a max) response over a spatial locations we gain robustness to position variations

* slide from Marc’Aurelio Renzato

Pooling Layer

- Makes representation smaller, more manageable and spatially invariant
- Operates over each activation map independently



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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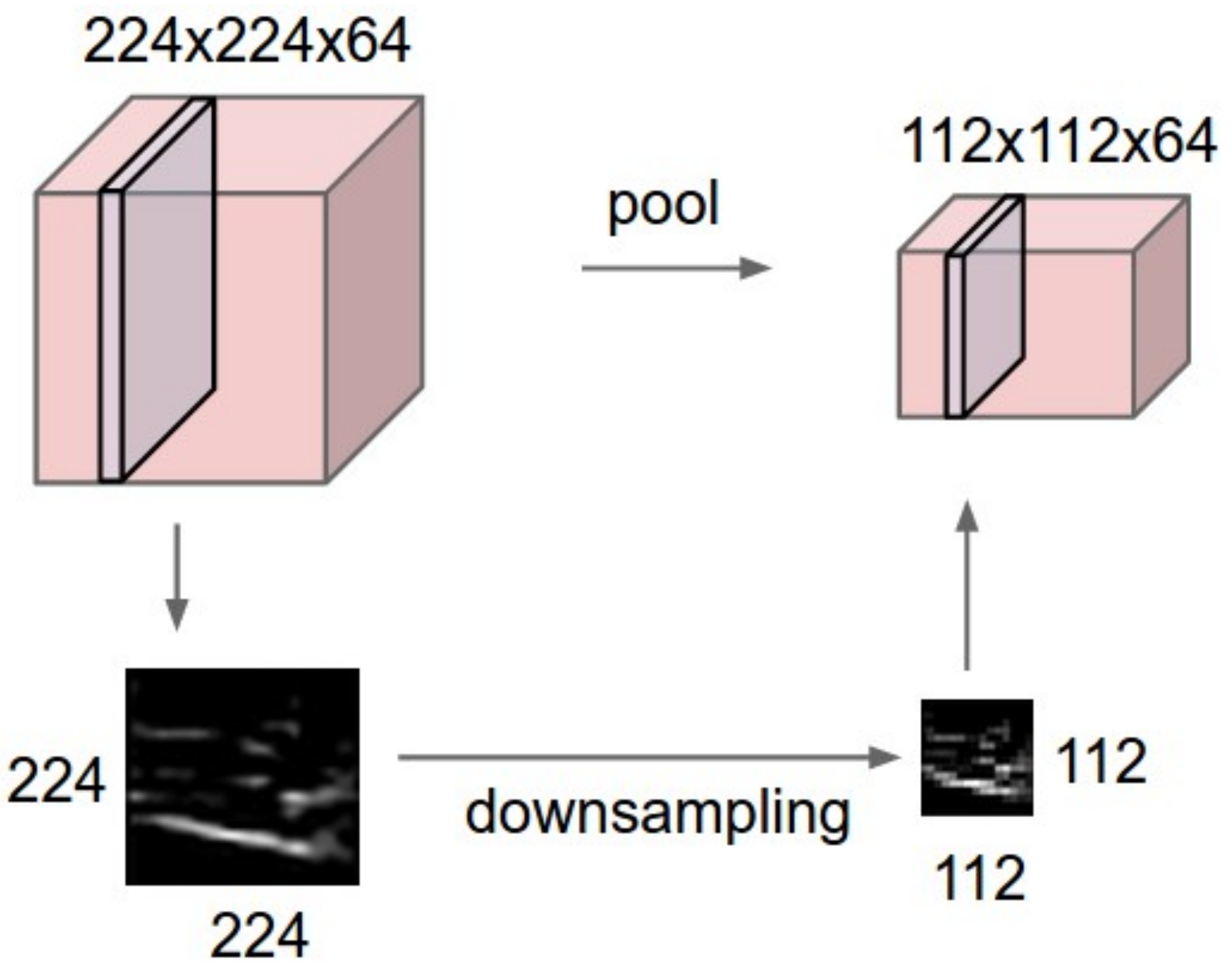

How many **parameters**?

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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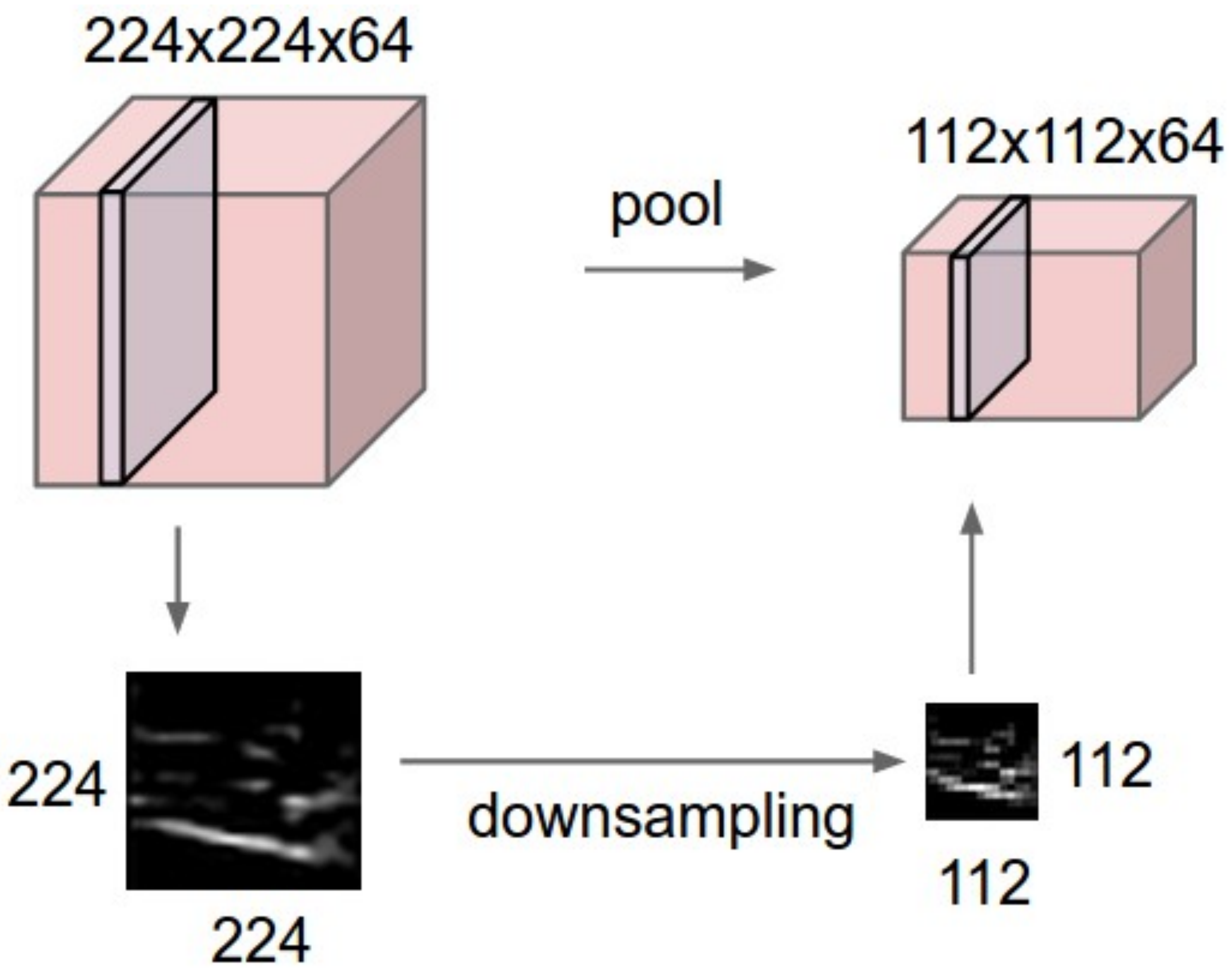


How many **parameters**?

None!

Max **Pooling**

activation map

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

max pool with 2 x 2 filter
and stride of 2

6	8
3	4

Average **Pooling**

activation map

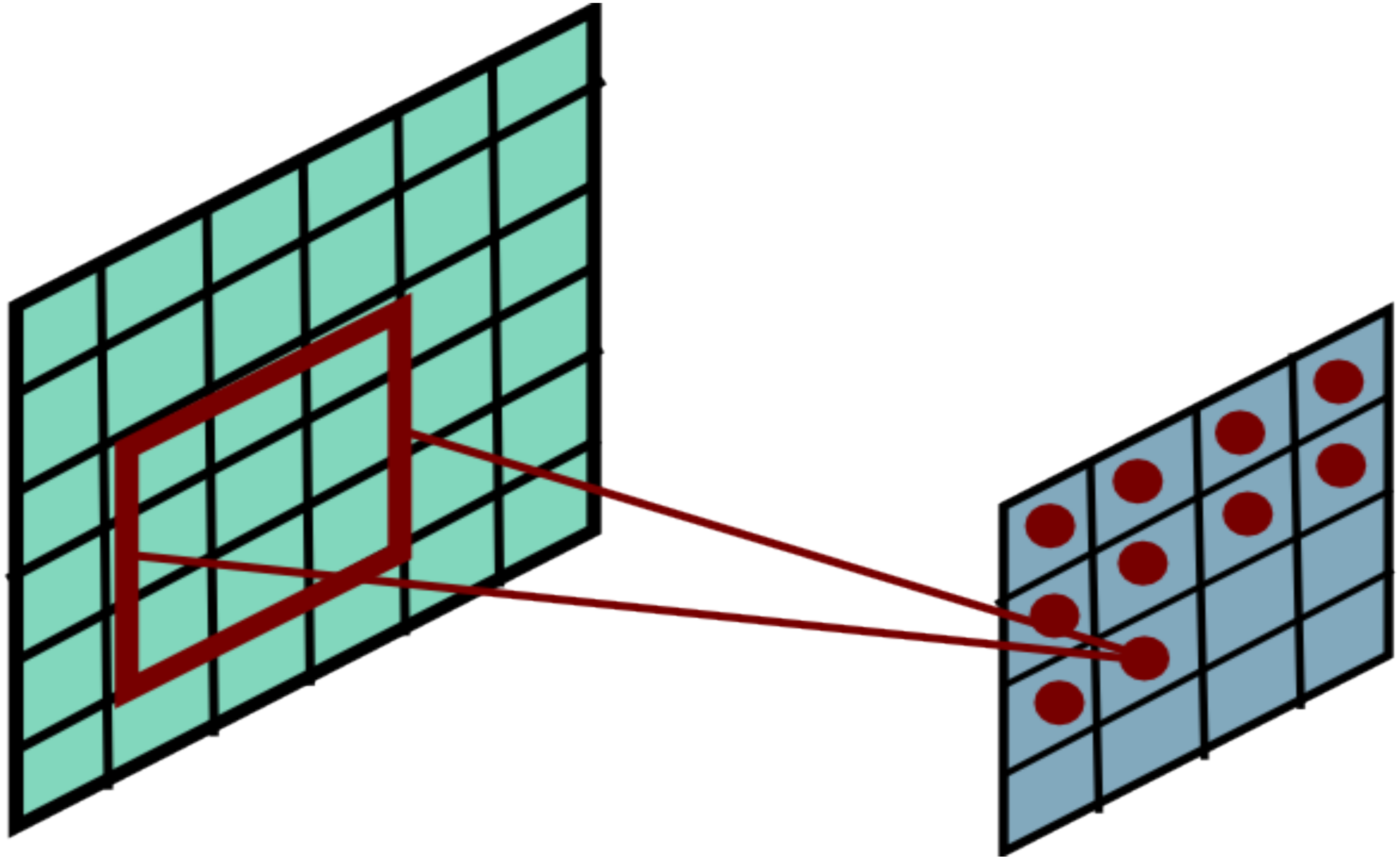
1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

avg pool with 2 x 2 filter
and stride of 2

3.25	5.25
2	2

Pooling Layer **Receptive Field**

If convolutional filters have size KxK and stride 1, and pooling layer has pools of size PxP, then each unit in the pooling layer depends upon a patch (at the input of the preceding conv. layer) of size: **(P+K-1)x(P+K-1)**



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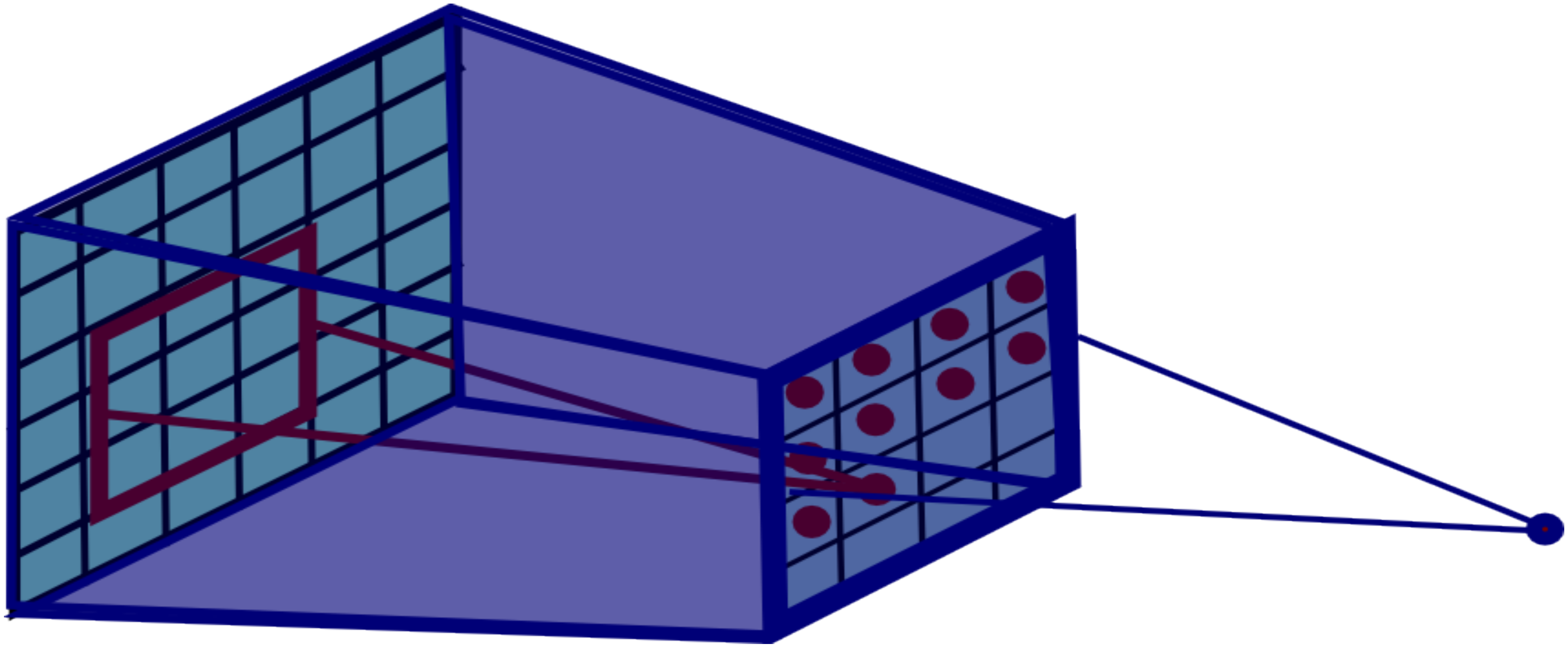

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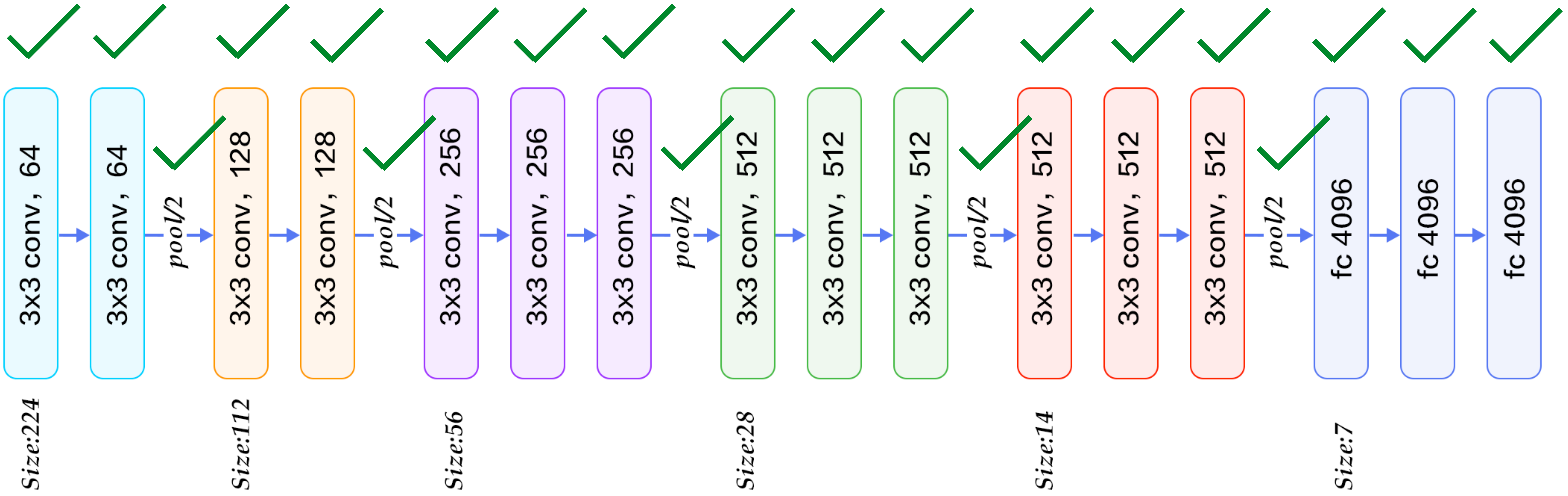
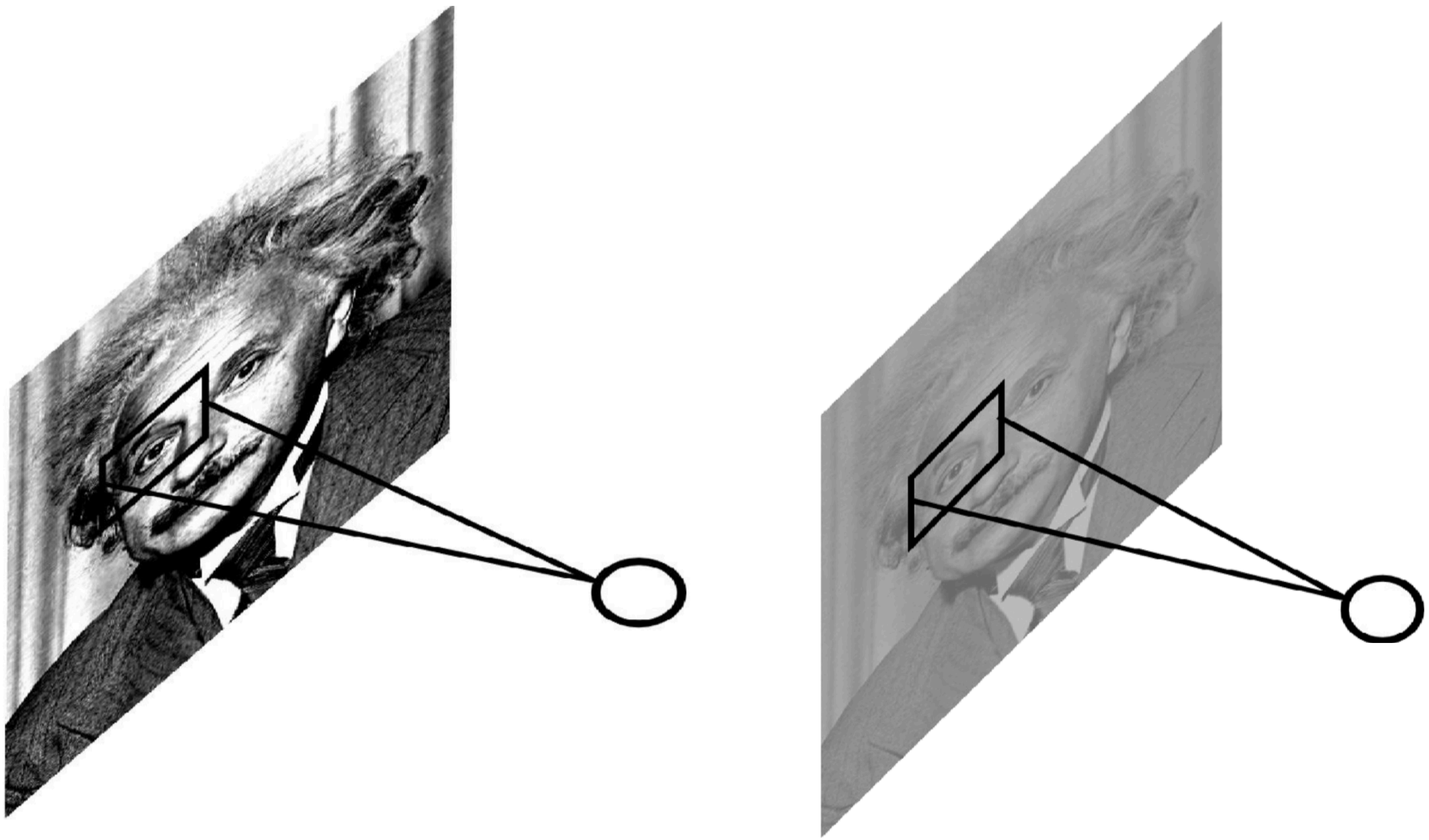
Convolutional Neural Networks



VGG-16 Network

Local **Contrast Normalization** Layer

ensures response is the same in both case (details omitted, no longer popular)



* images from Marc'Aurelio Renzato

Improving **Single Model**

Regularization

- L2, L1
- Dropout / Inverted Dropout
- Data augmentation

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L2 Regularization: Learn a more (dense) distributed representation

$$R(\mathbf{W}) = ||\mathbf{W}||_2 = \sum_i \sum_j \mathbf{W}_{i,j}^2$$

L1 Regularization: Learn a sparse representation (few non-zero wight elements)

$$R(\mathbf{W}) = ||\mathbf{W}||_1 = \sum_i \sum_j |\mathbf{W}_{i,j}|$$

Improving **Single Model**

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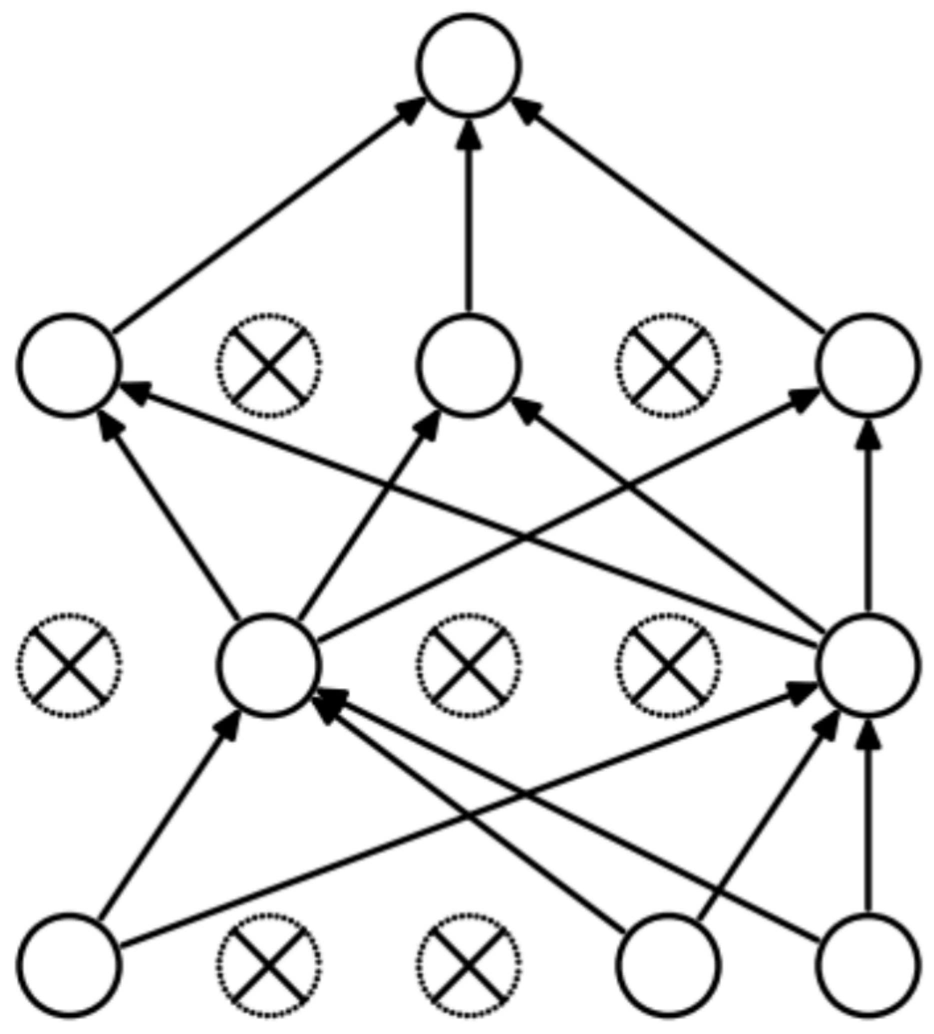

Dropout

L2 Regularization: Learn a more (dense) distributed representation

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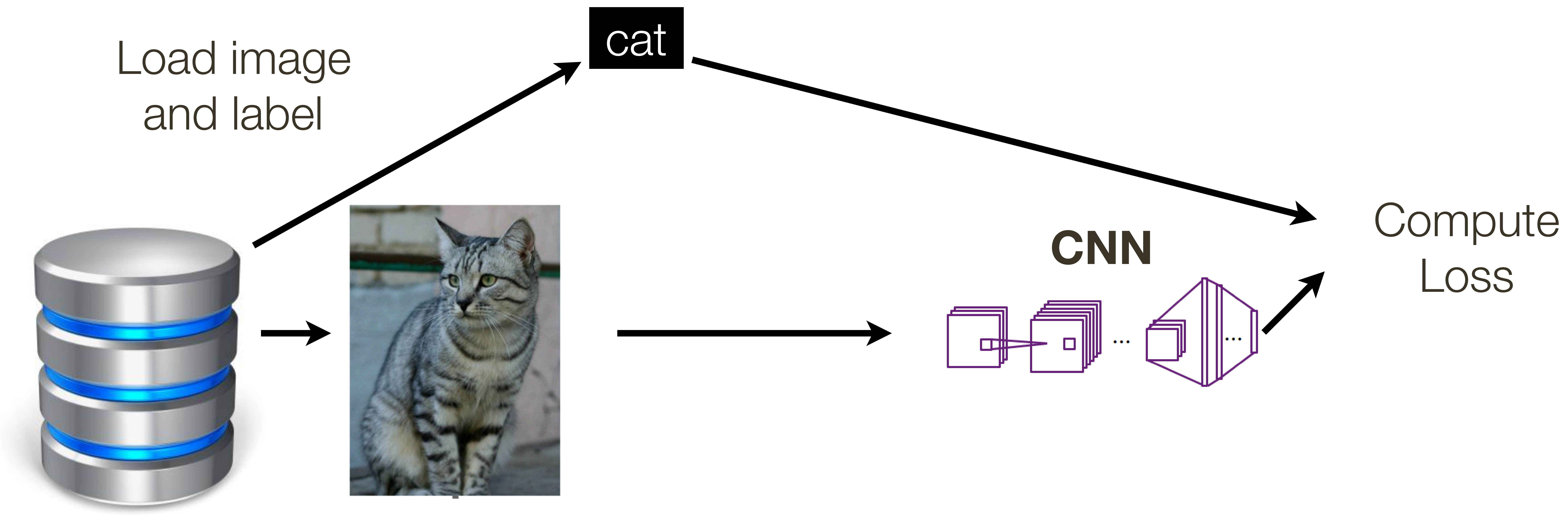
Regularization: Data Augmentation



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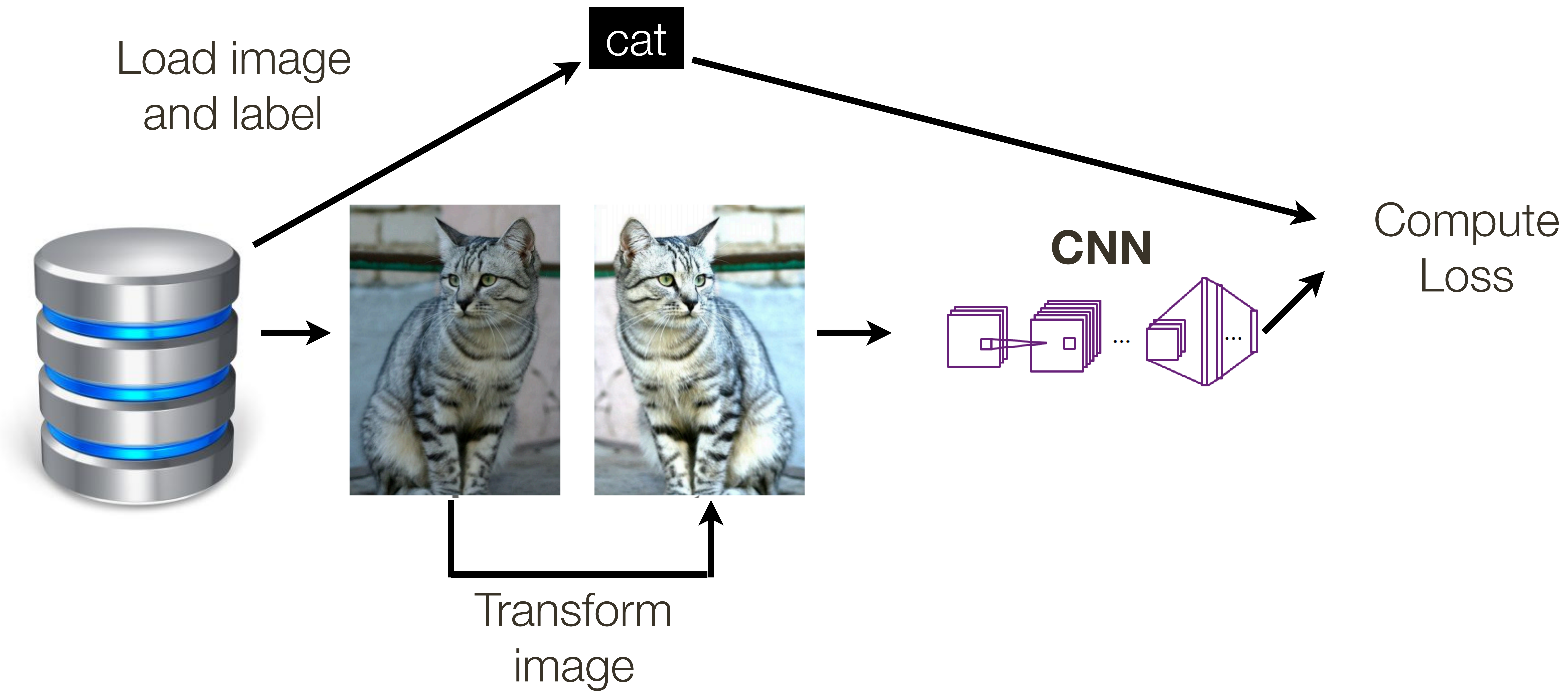

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Regularization: Data Augmentation

Horizontal flips

Random crops & scales

Color Jitter

Regularization: Data Augmentation

Horizontal flips | Random crops & scales | Color Jitter

→

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Regularization: Data Augmentation

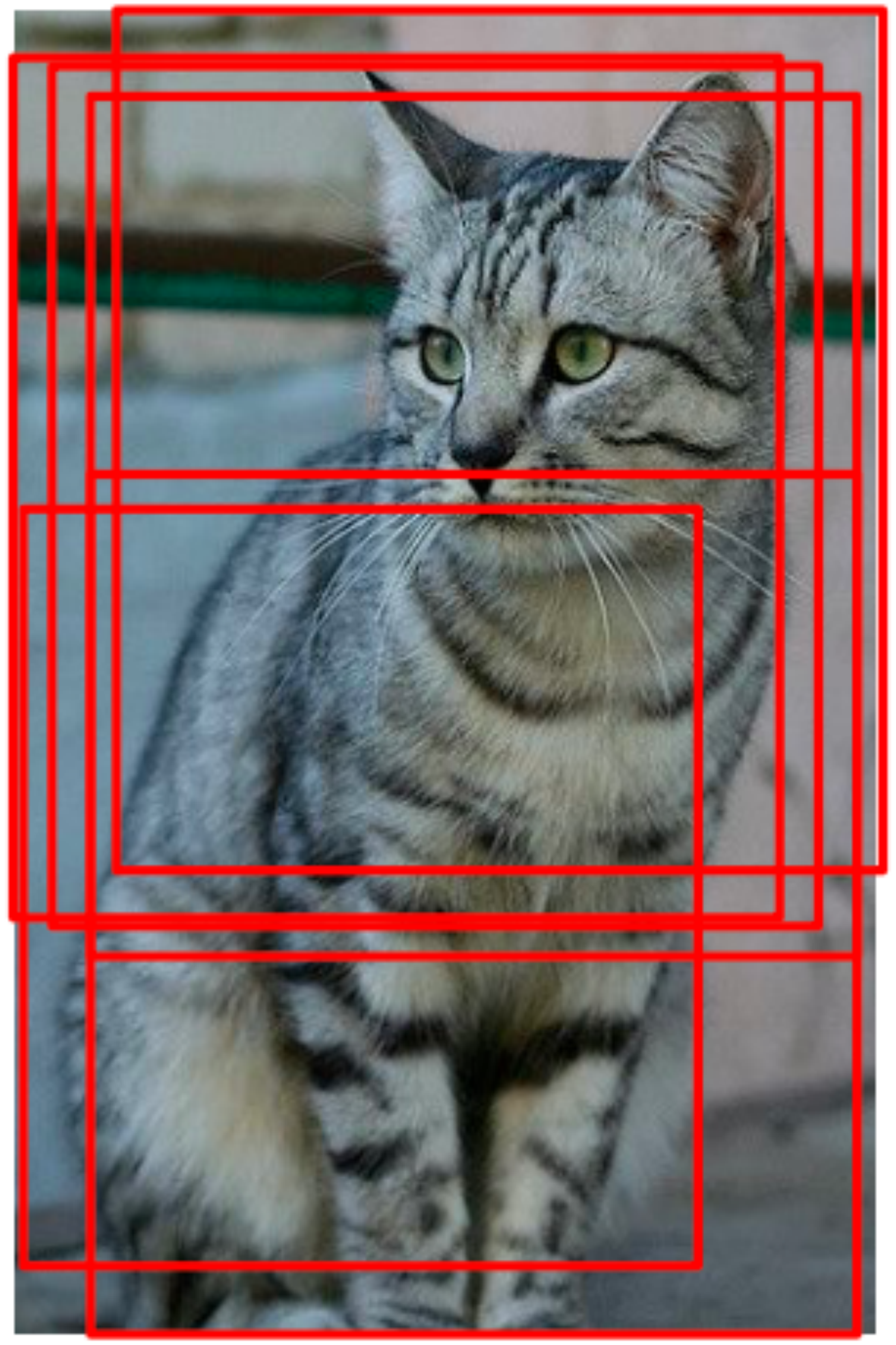
Horizontal flips | **Random crops & scales** | Color Jitter

Training: sample random crops and scales
e.g., ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short size = L
3. Sample random 224x224 patch

Testing: average a fix set of crops
e.g., ResNet:

1. Resize image to 5 scales (224, 256, 384, 480, 640)
2. For each image use 10 224x224 crops: 4 corners + center, + flips



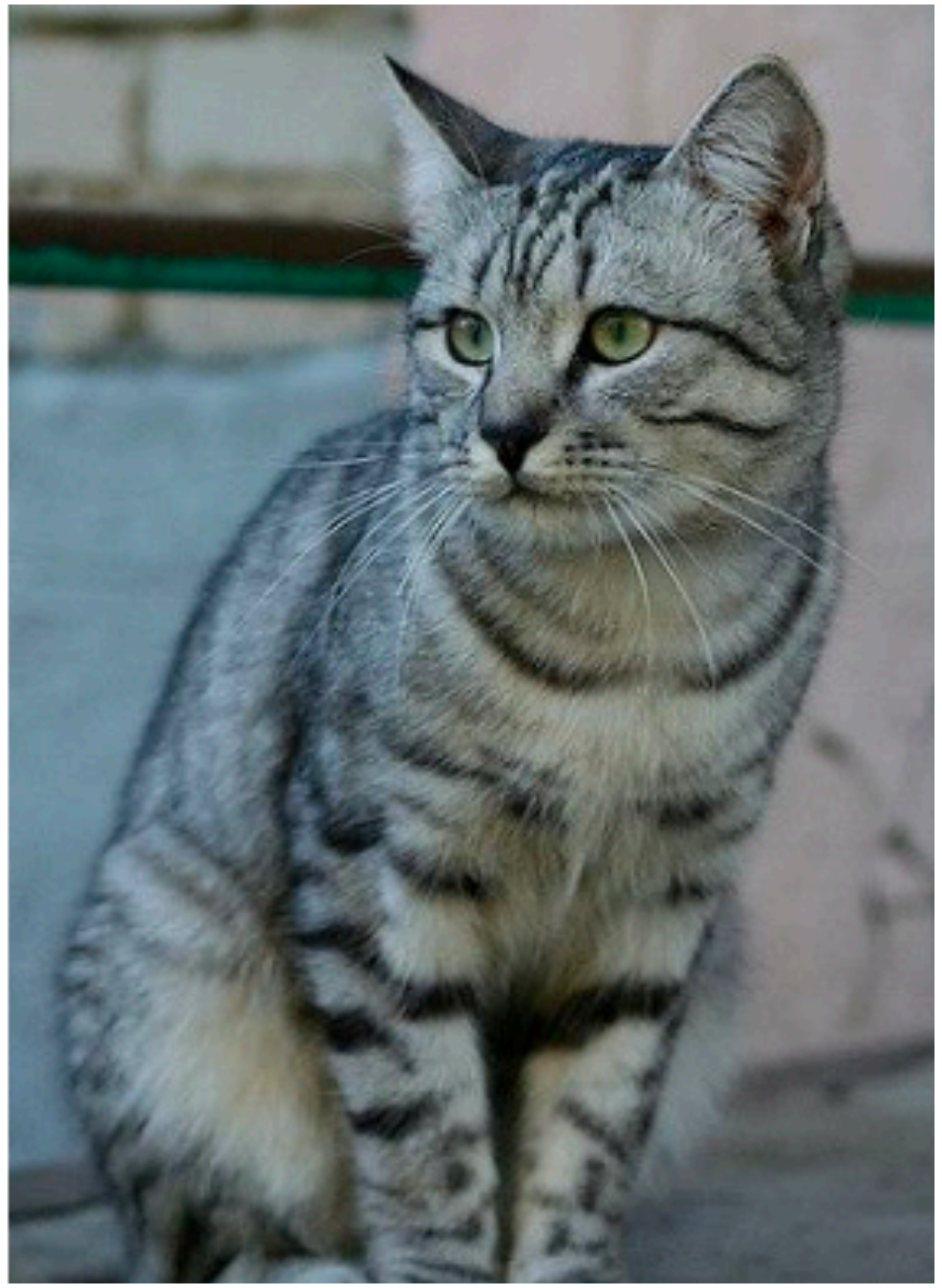
Regularization: Data Augmentation

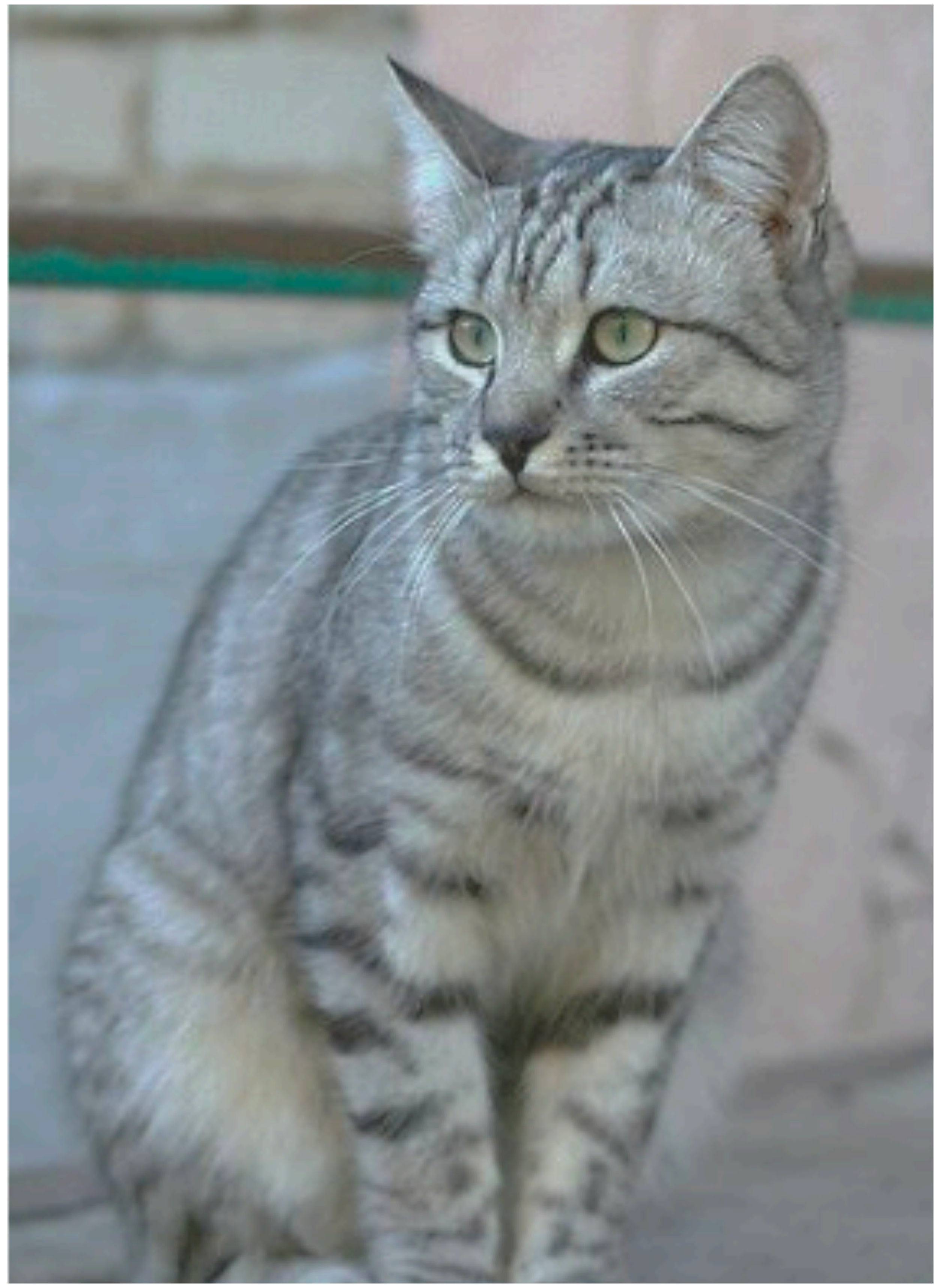
Horizontal flips

Random crops & scales

Color Jitter

Random perturbations in contrast and brightness





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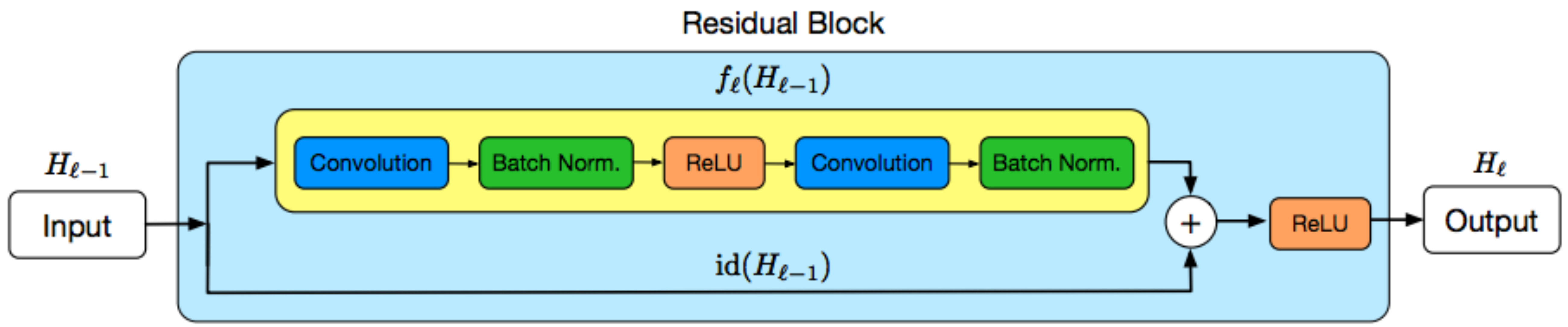
Regularization: Stochastic Depth

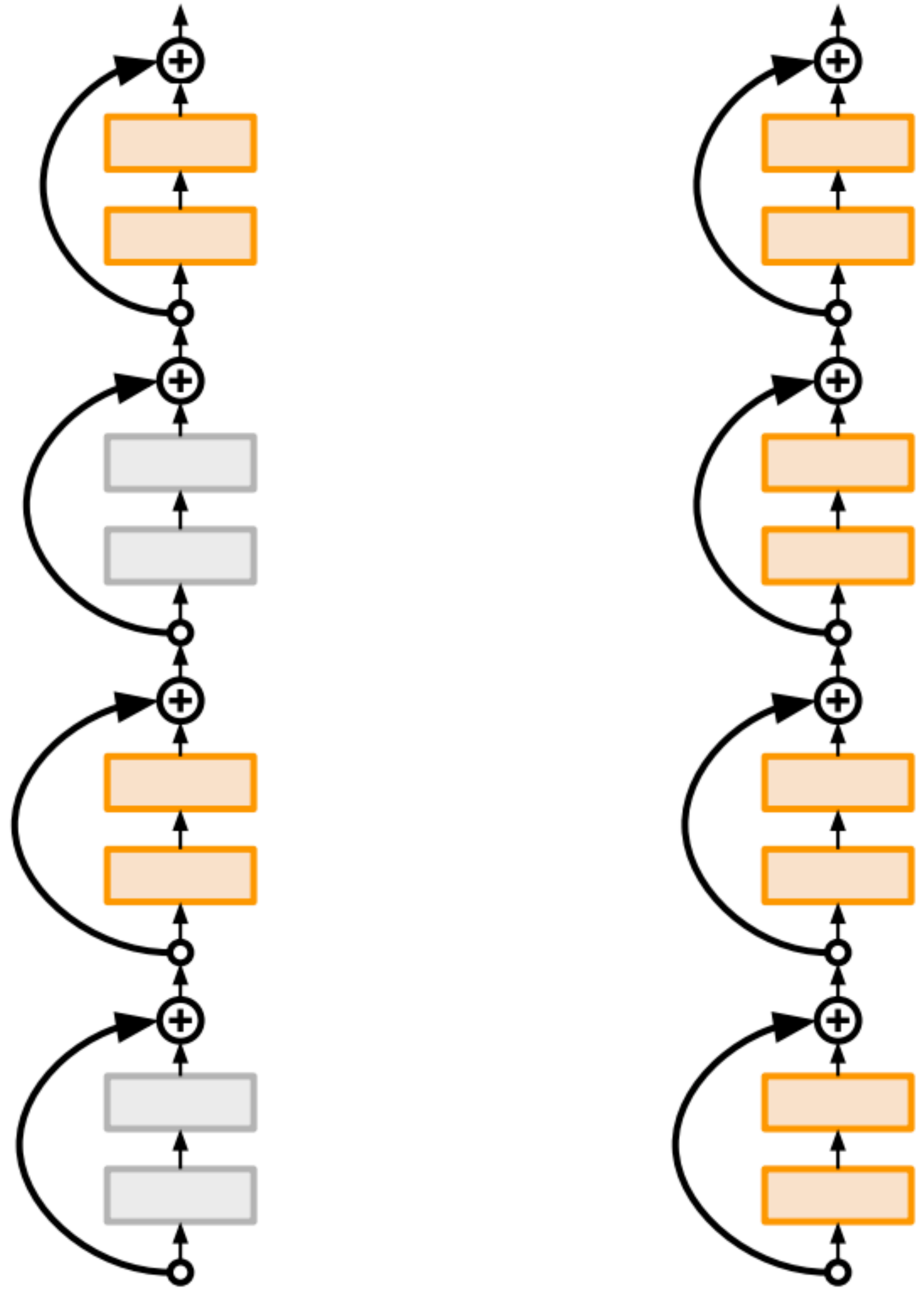
[Huang et al., ECCV 2016]

Effectively "dropout" but for layers

Stochastically with some probability **turn off some layer** (for each batch)

Effectively trains a collection of neural networks





* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Transfer Learning with CNNs

Common “Wisdom”: You need a lot of data to train a CNN

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Solution: Transfer learning — taking a model trained on the task that has lots of data and adopting it to the task that may not

Transfer Learning with CNNs

Common "Wisdom": You need a lot of data to train a CNN

Solution: Transfer learning — taking a model trained on the task that has lots of data and adopting it to the task that may not

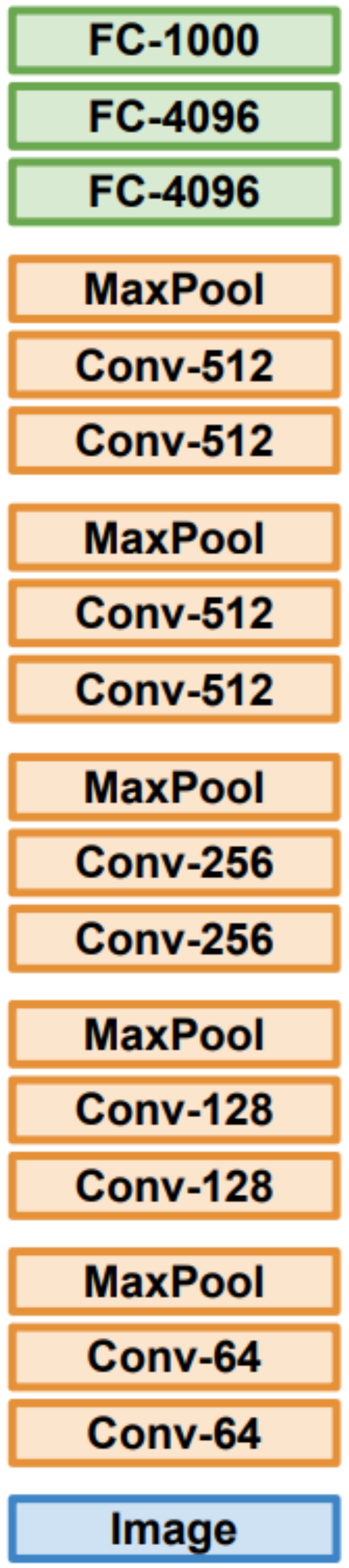
This strategy is PERVASIVE.

* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Transfer Learning with CNNs

[Yosinski et al., NIPS 2014]
[Donahue et al., ICML 2014]
[Razavian et al., CVPR Workshop 2014]

Train on **ImageNet**



Transfer Learning with CNNs

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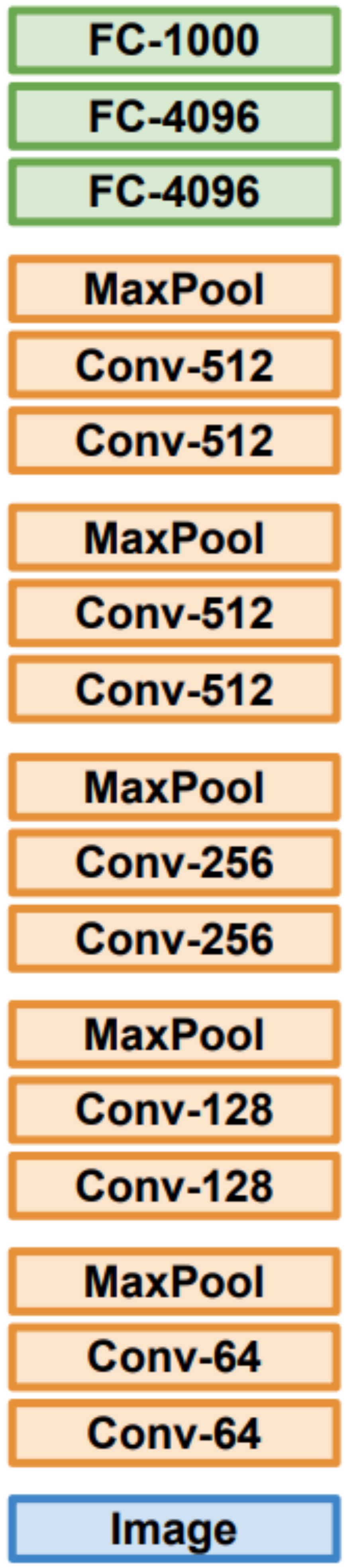
[Razavian et al., CVPR Workshop 2014]

Train on **ImageNet**



Why on **ImageNet**?

Transfer Learning with CNNs

[Yosinski et al., NIPS 2014]
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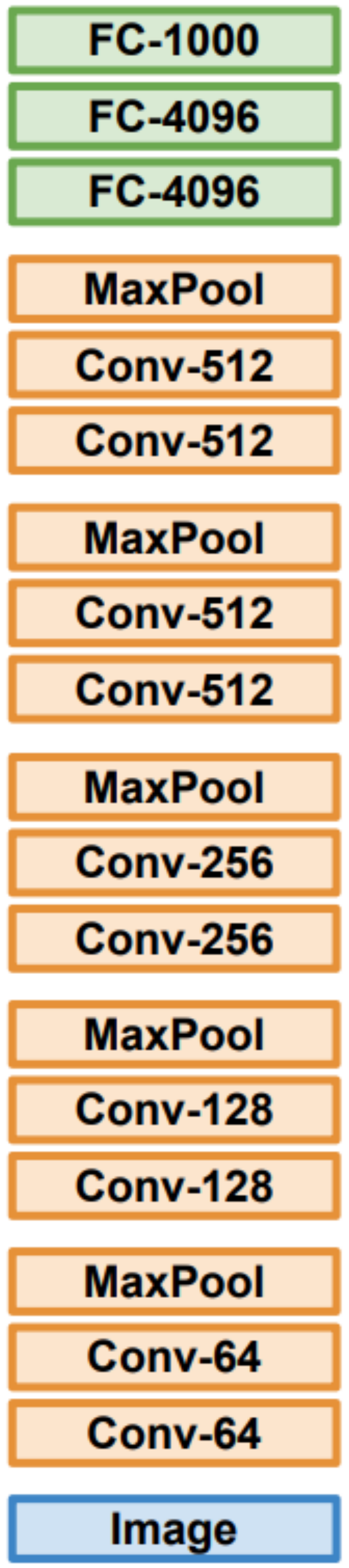

Why on **ImageNet**?

- Convenience, lots of **data**
- We know how to **train these well**

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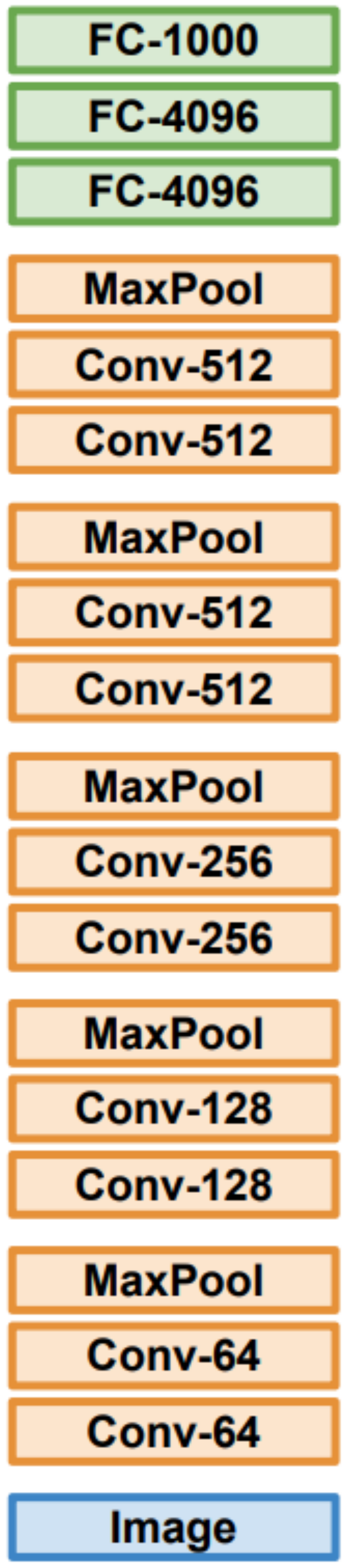

Why on **ImageNet**?

- Convenience, lots of **data**
- We know how to **train these well**

However, for some tasks we would need to start with something else (e.g., videos for optical flow)

Transfer Learning with CNNs

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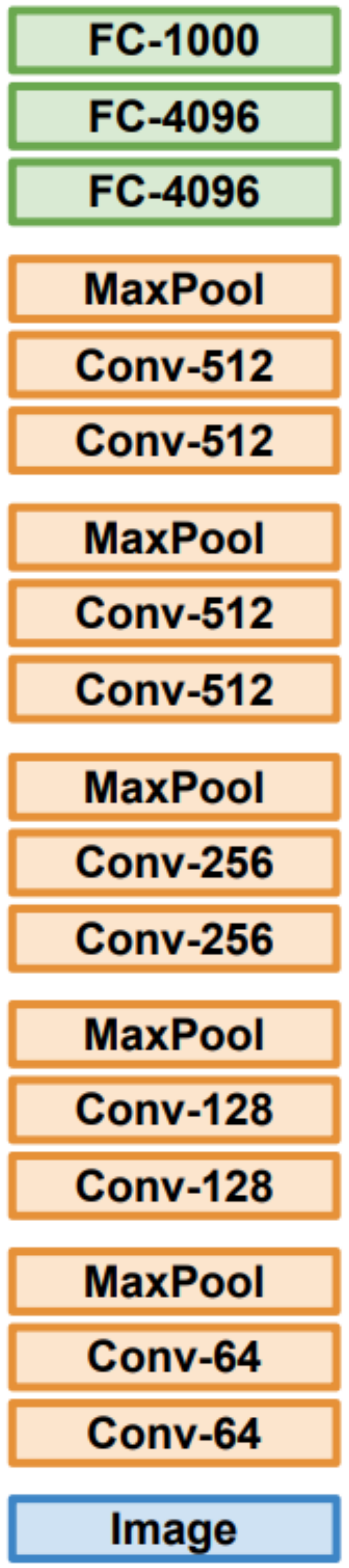

Small dataset with C classes

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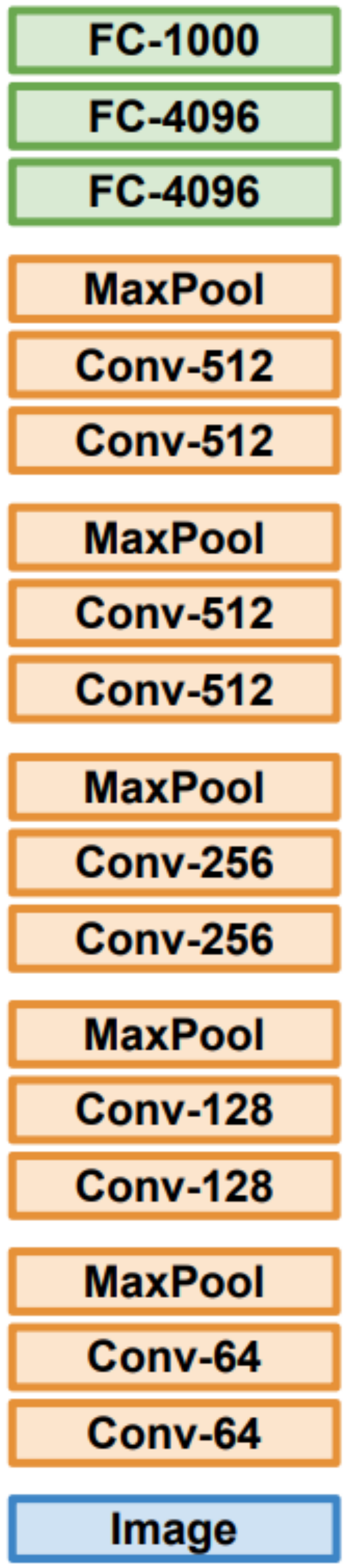

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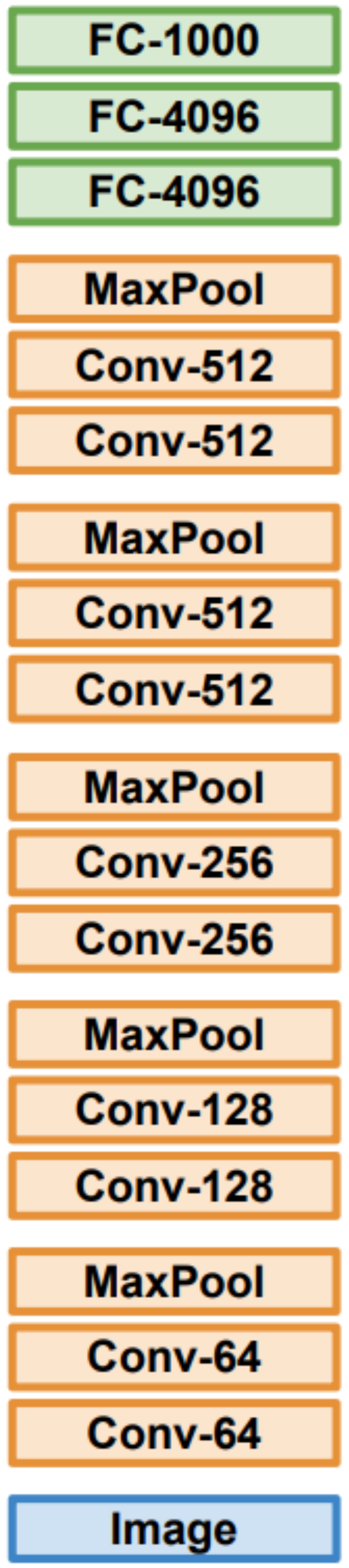

* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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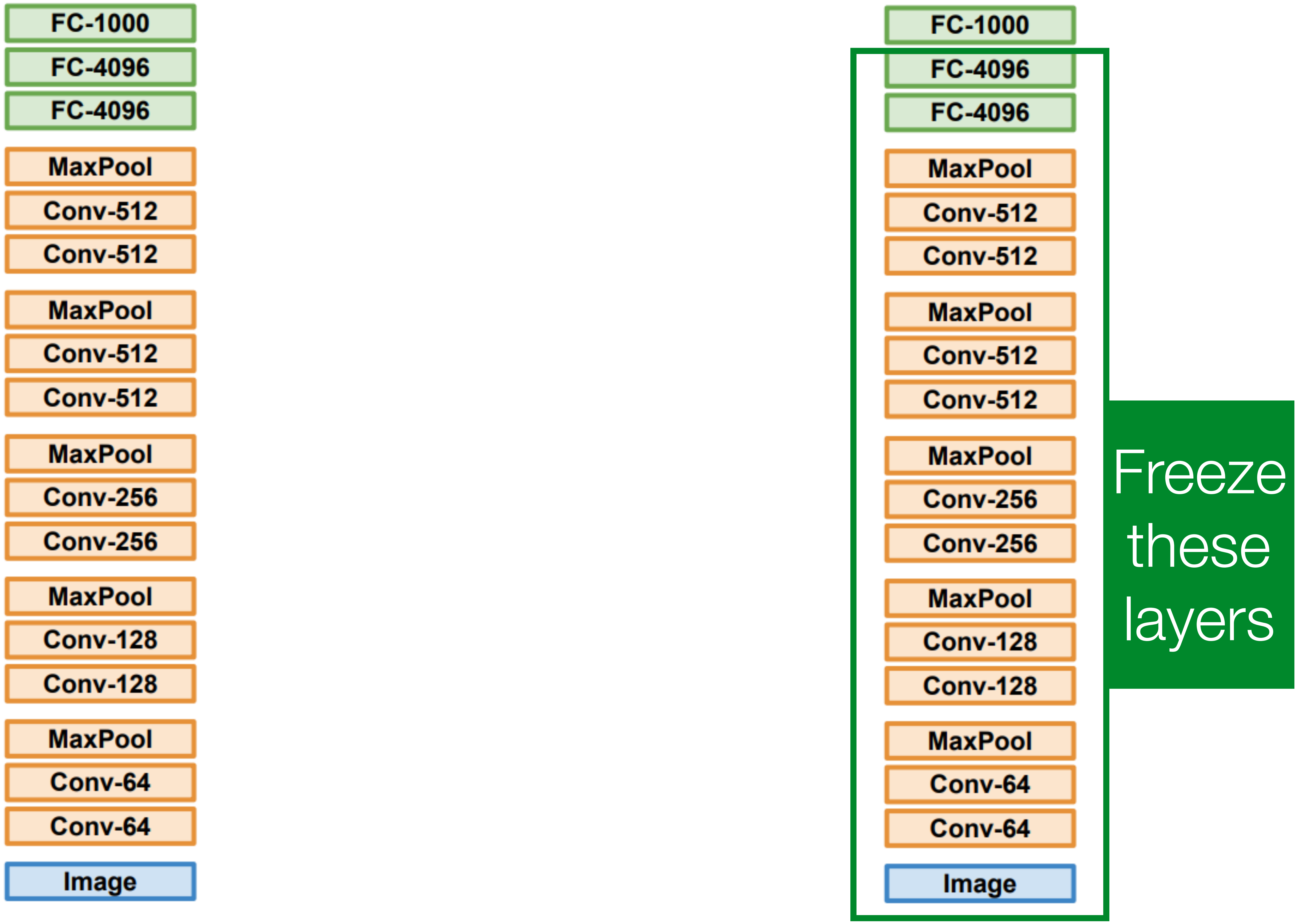

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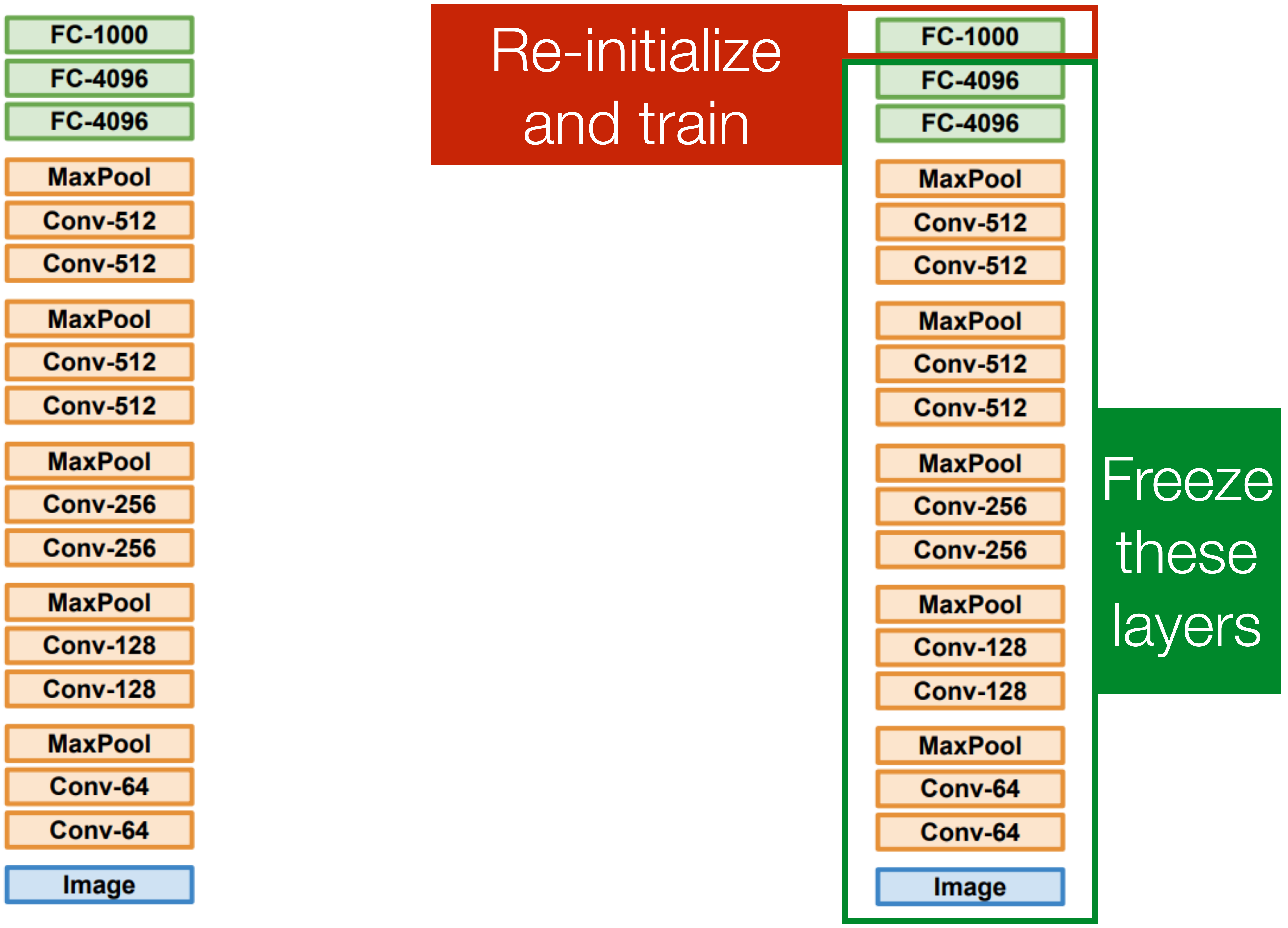

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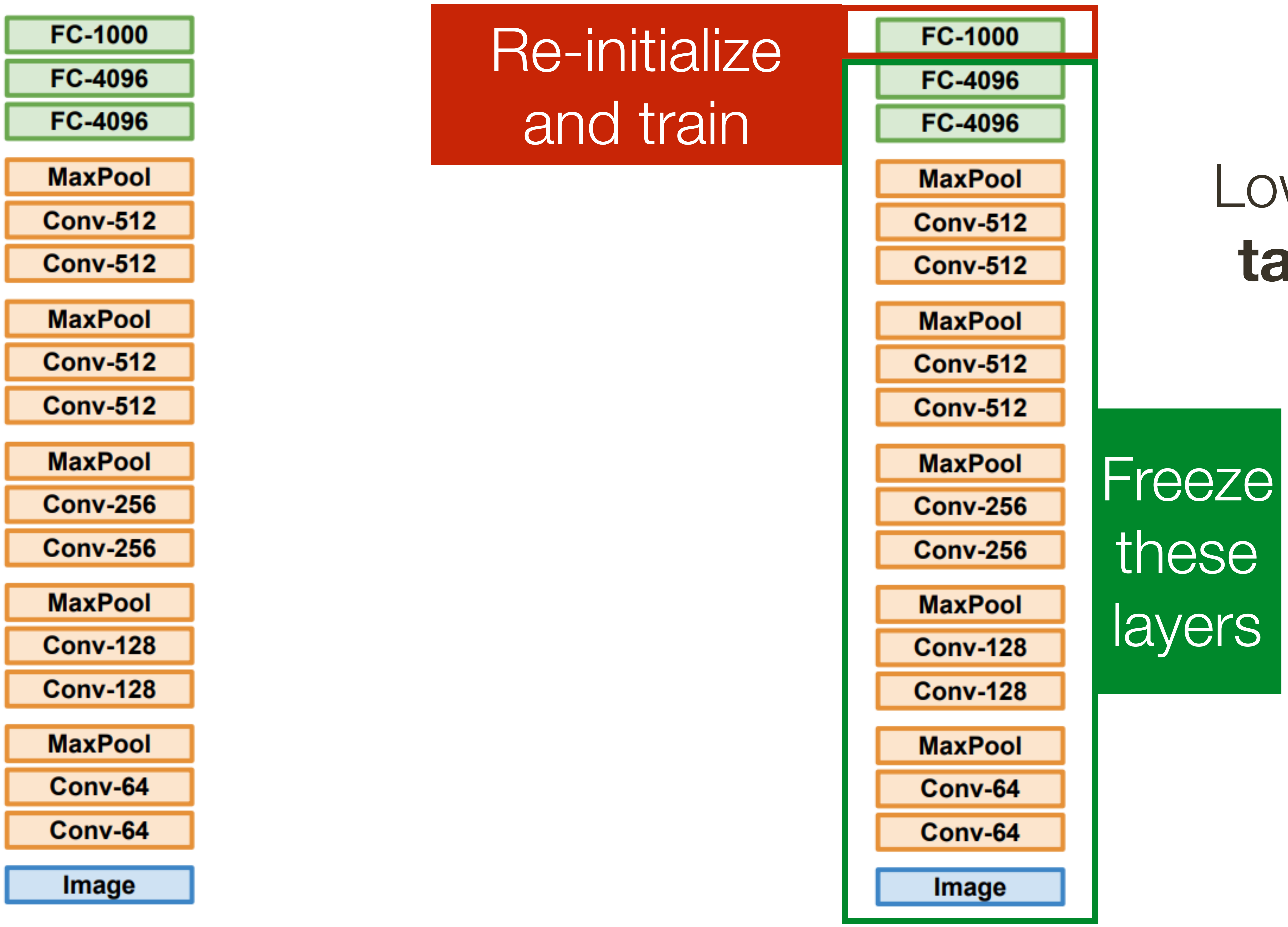

Lower levels of the CNN are at **task independent** anyways

Transfer Learning with CNNs

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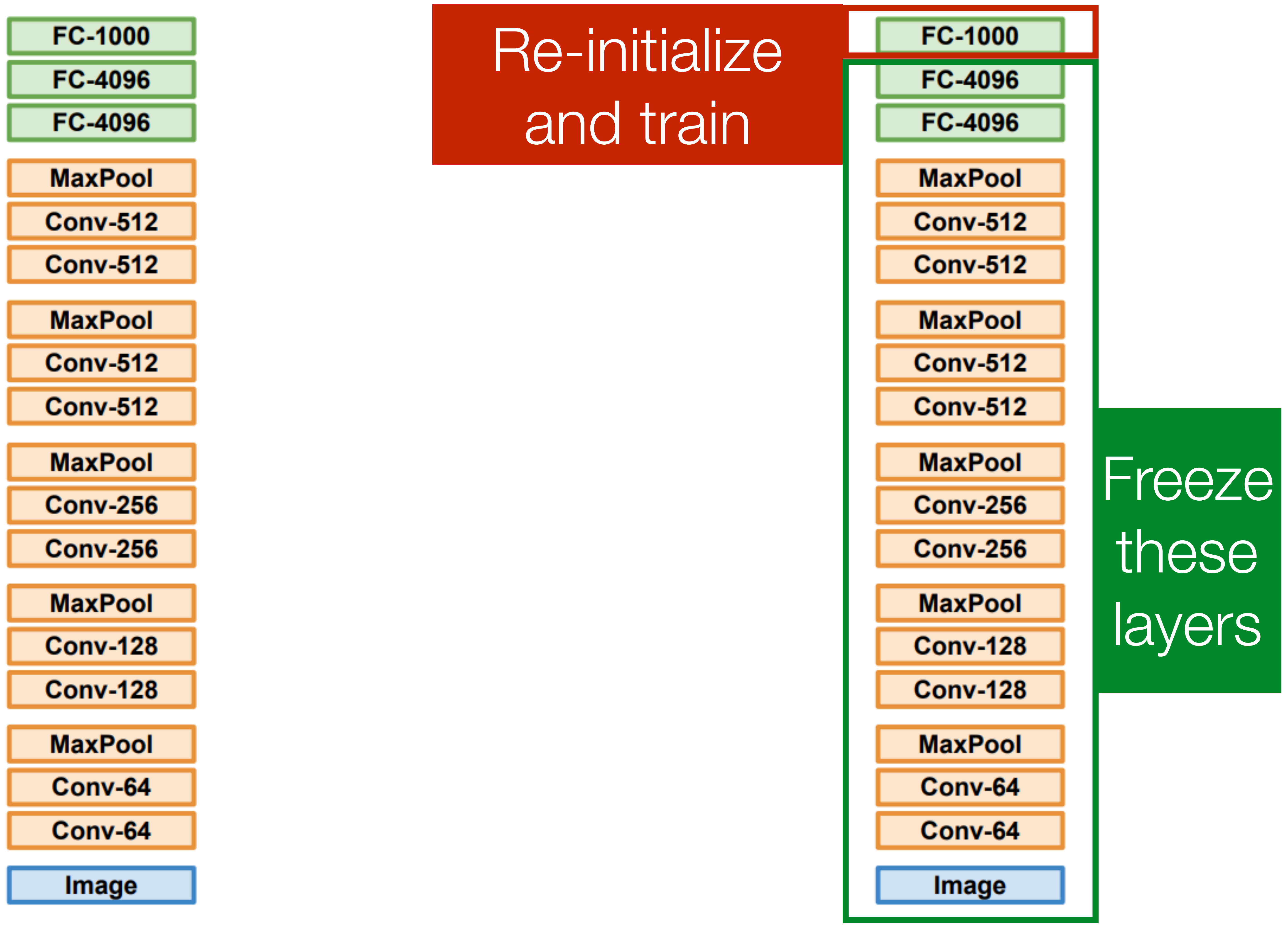
Train on **ImageNet** | **Small dataset** with C classes | **Larger dataset**



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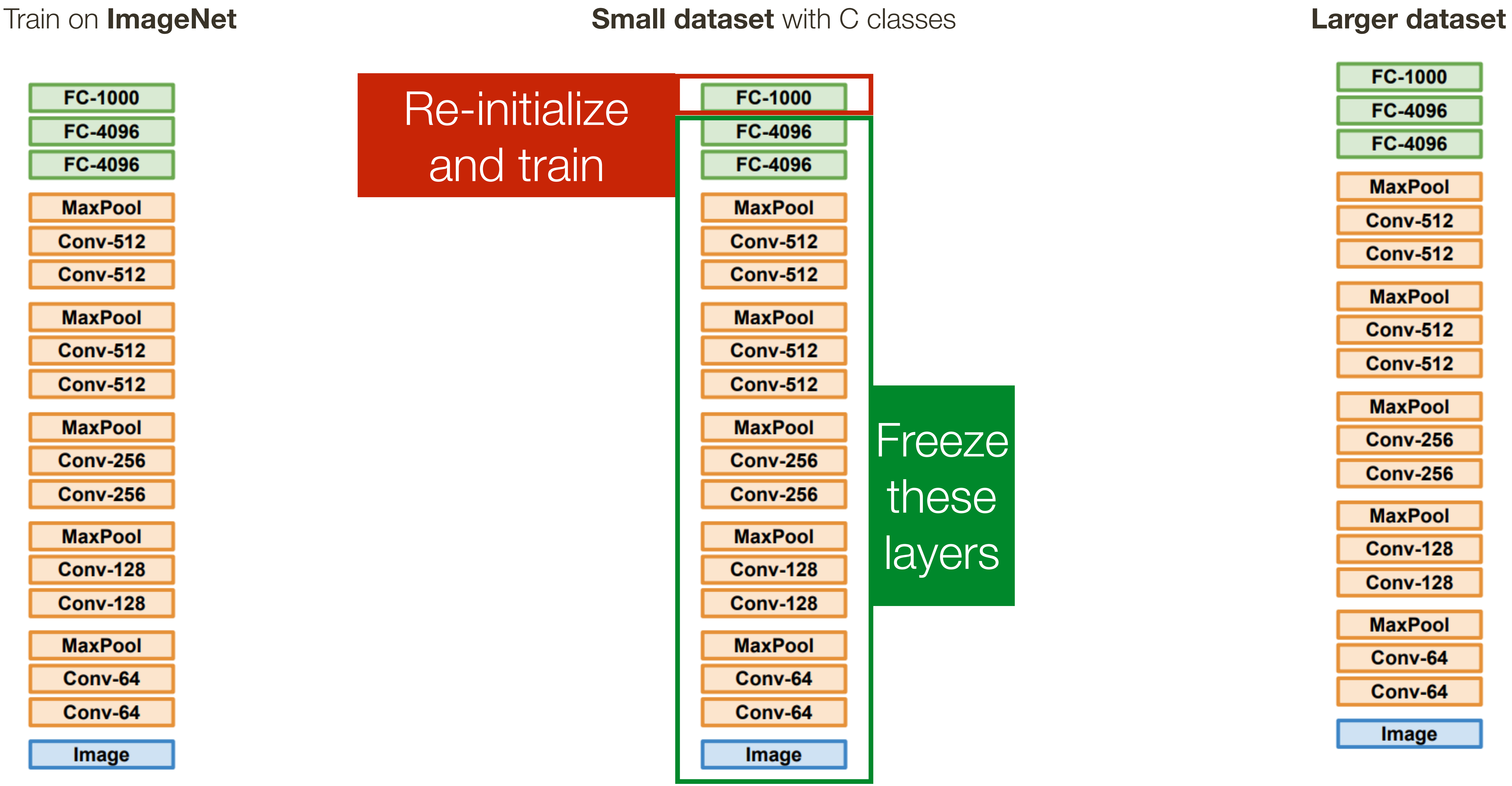

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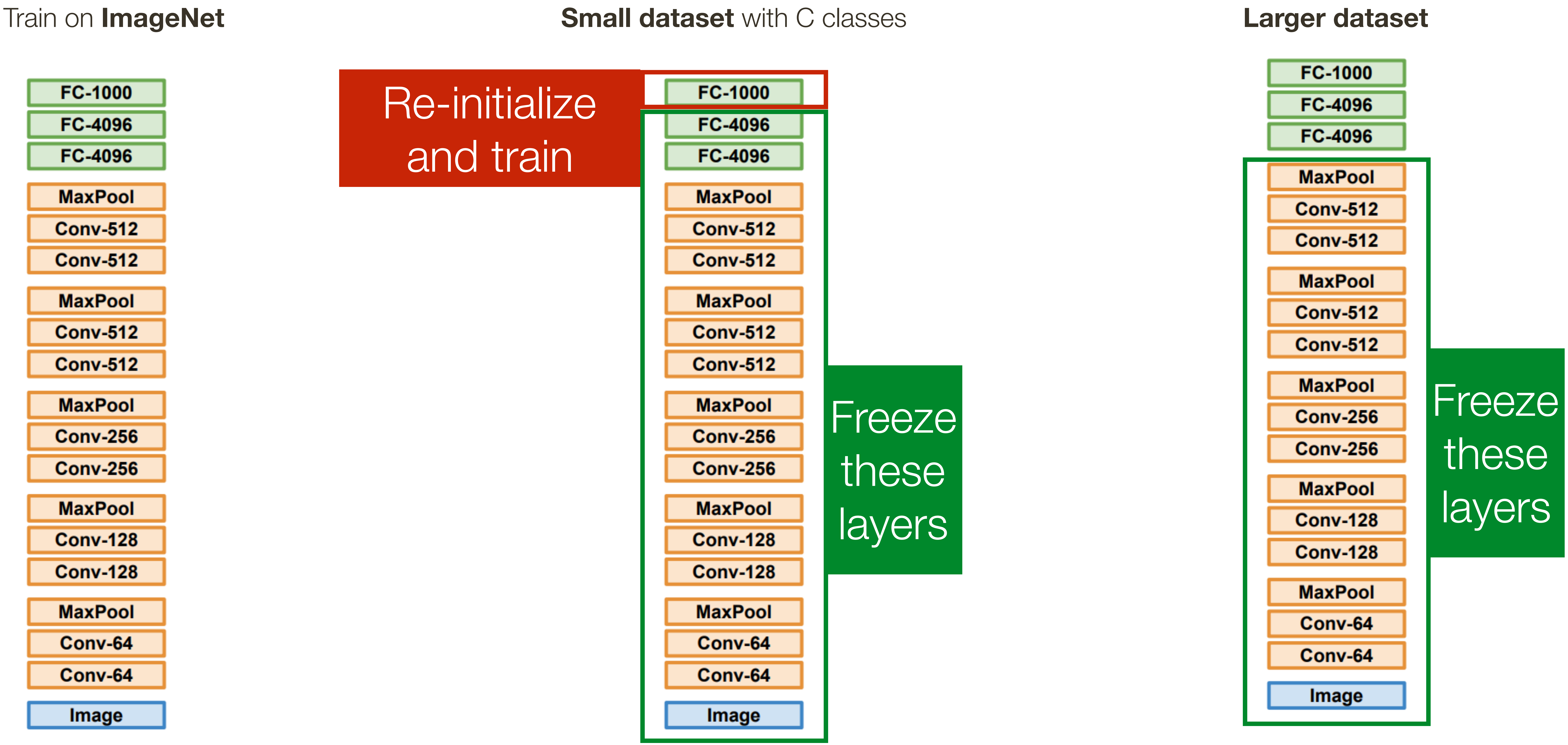

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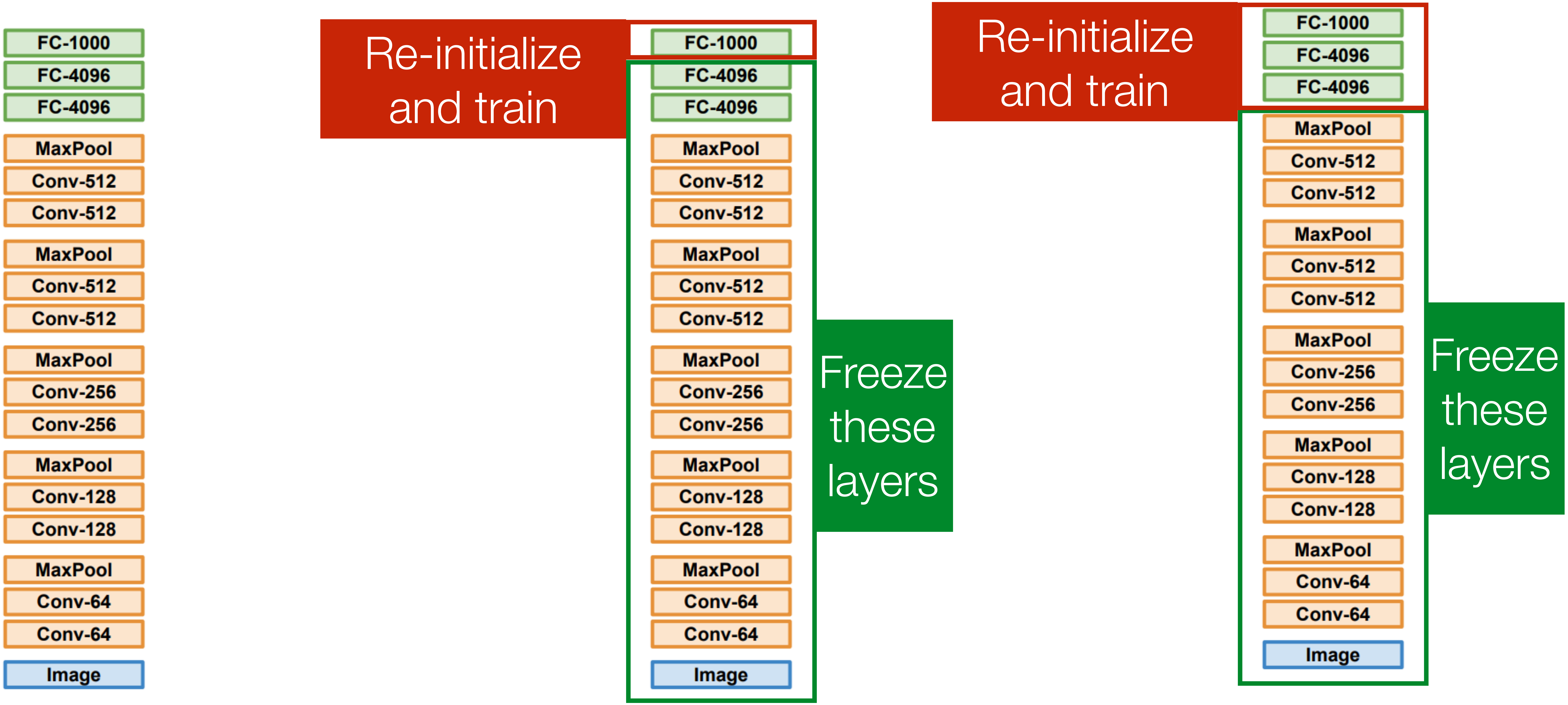

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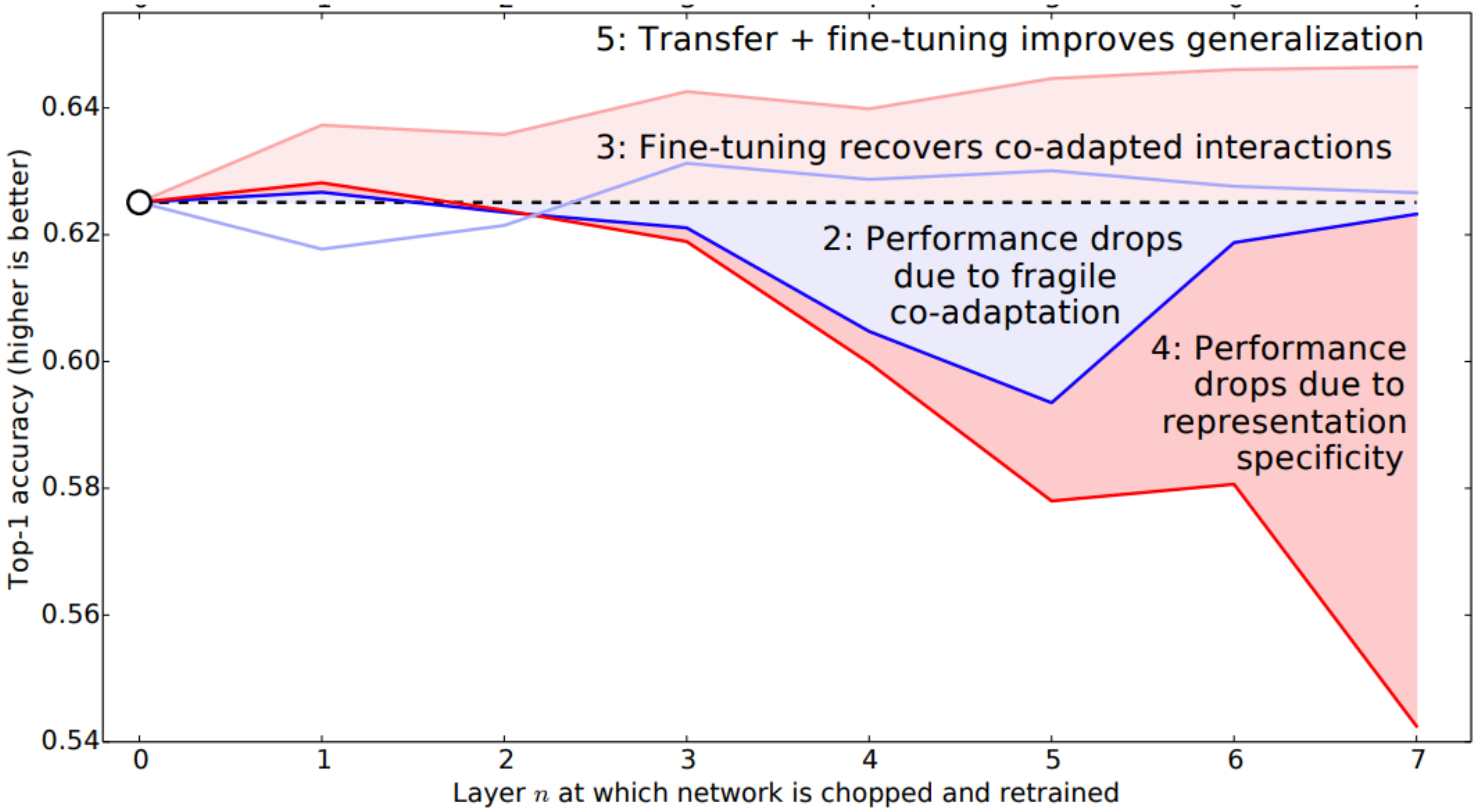

[Yosinski et al., NIPS 2014]

Model **Ensemble**

Training: Train multiple independent models

Test: Average their results

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~ 2% improved performance in practice

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Alternative: Multiple snapshots of the single model during training!

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Model **Ensemble**

Training: Train multiple independent models

Test: Average their results

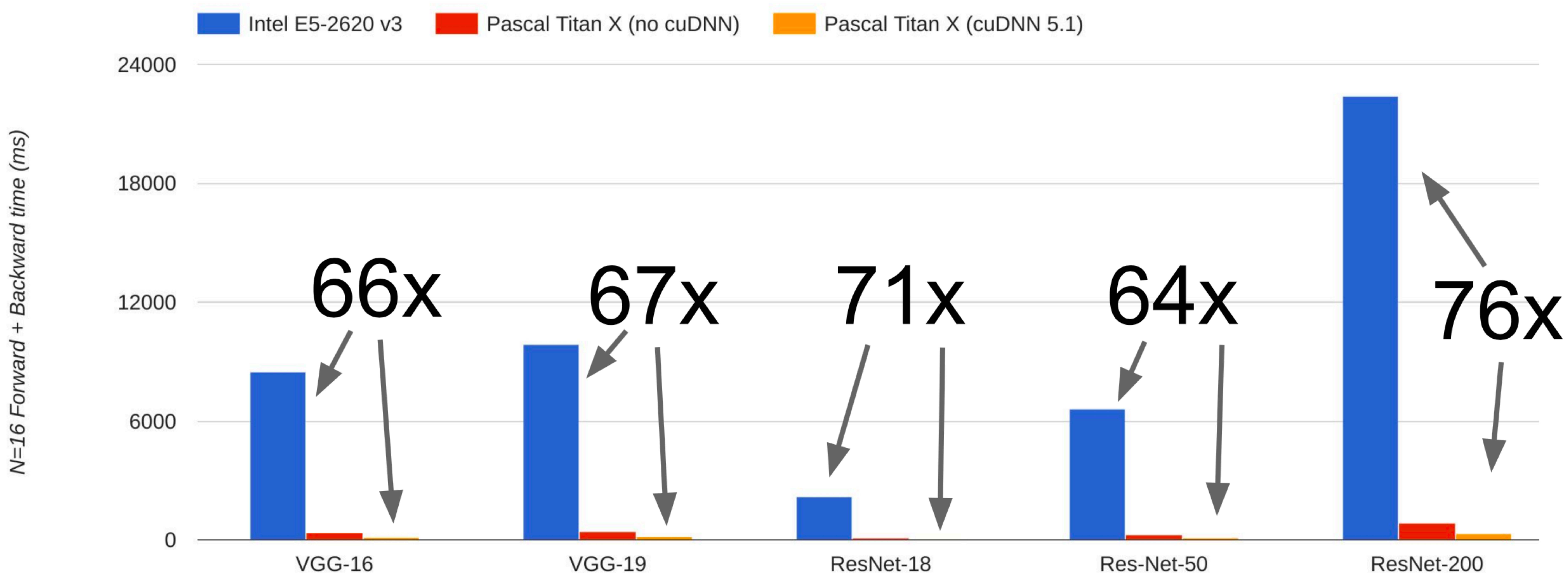
~ 2% improved performance in practice

Alternative: Multiple snapshots of the single model during training!

Improvement: Instead of using the actual parameter vector, keep a moving average of the parameter vector and use that at test time (Polyak averaging)

* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

CPU vs. **GPU** (Why do we need Azure?)



Data from https://github.com/jcjohnson/cnn-benchmarks

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Frameworks: Super quick overview

1. Easily **build computational graphs**

2. Easily **compute gradients** in computational graphs

3. **Run it all efficiently** on a GPU (weap cuDNN, cuBLAS, etc.)

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Frameworks: Super quick overview

Core DNN Frameworks		
Caffe (UC Berkeley)	Caffe 2 (Facebook)	Puddle (Baidu)
Torch (NYU/Facebook)	**PyTorch** (Facebook)	CNTK (Microsoft)
Theano (U Montreal)	**TensorFlow** (Google)	MXNet (Amazon)

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Wrapper Libraries
Keras
TFLearn
TensorLayer
tf.layers
TF-Slim
tf.contrib.learn
Pretty Tensor

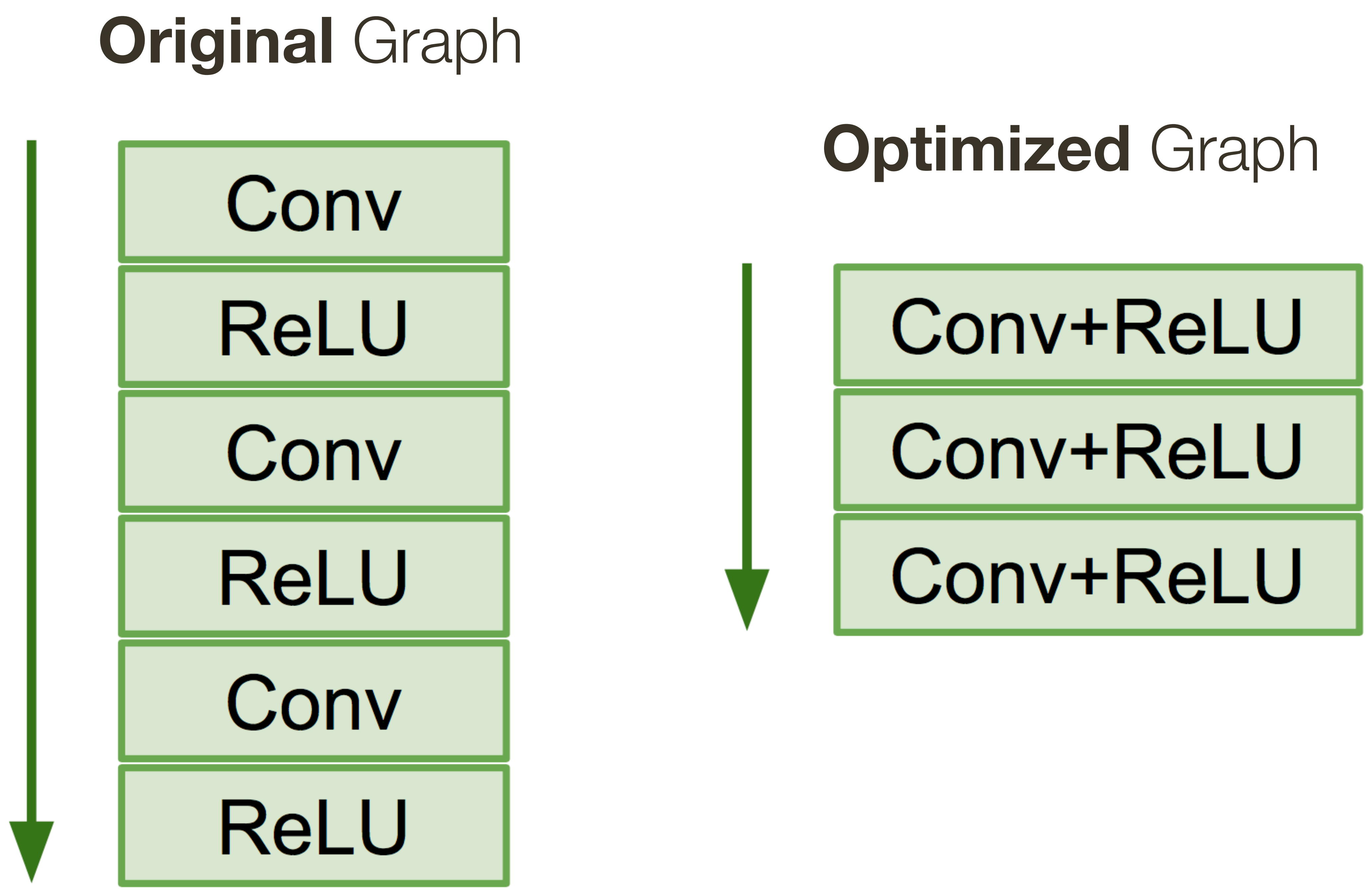
Frameworks: PyTorch vs. TensorFlow

Dynamic vs. Static computational graphs

Frameworks: PyTorch vs. TensorFlow

Dynamic vs. **Static** computational graphs

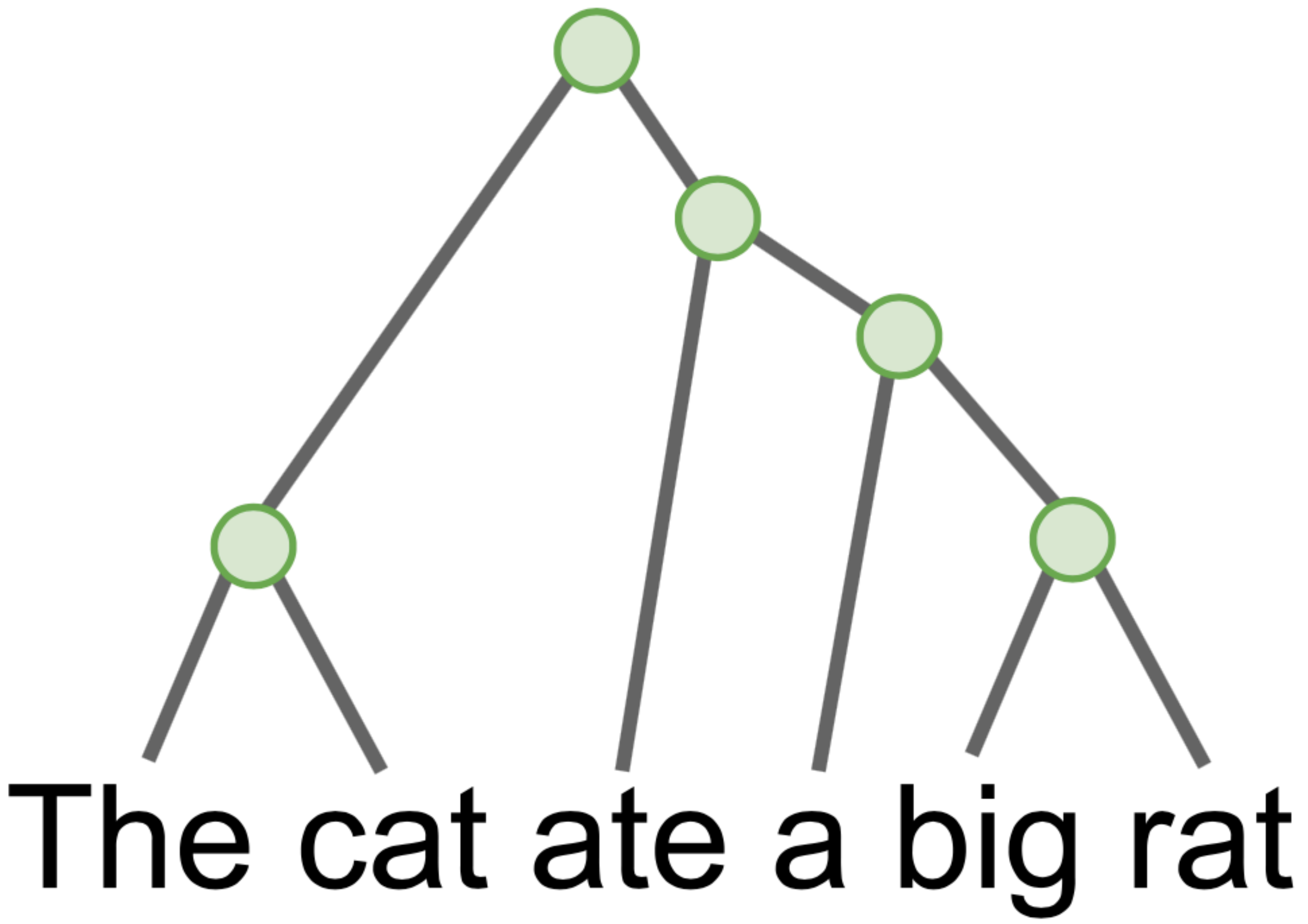
With static graphs, framework can **optimize** the graph for you before it runs!



Frameworks: PyTorch vs. TensorFlow

Dynamic vs. Static computational graphs

Graph building and execution is intertwined. Graph can be different for every sample.



PyTorch: Three levels of abstraction

Tensor: Imperative ndarray, but runs on GPU

Variable: Node in a computational graph; stores data and gradients

Module: A neural network layer; may store state or learnable weights

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