THE UNIVERSITY OF BRITISH COLUMBIA

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

Lecture 5: Convolutional Neural Networks (Part 2)

Logistics:

Assignment 2 will be out tonight

— Data is reusable

get it on your Google Drive, will be used for Assignment 3 & 4

you **can** reduce the dataset size (e.g., 1/2 or 1/4 of data)

— Piazza (make questions public)

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Projects

— Some guidelines

— November 1 & 3 **Project Proposals** (two lectures week before the break)

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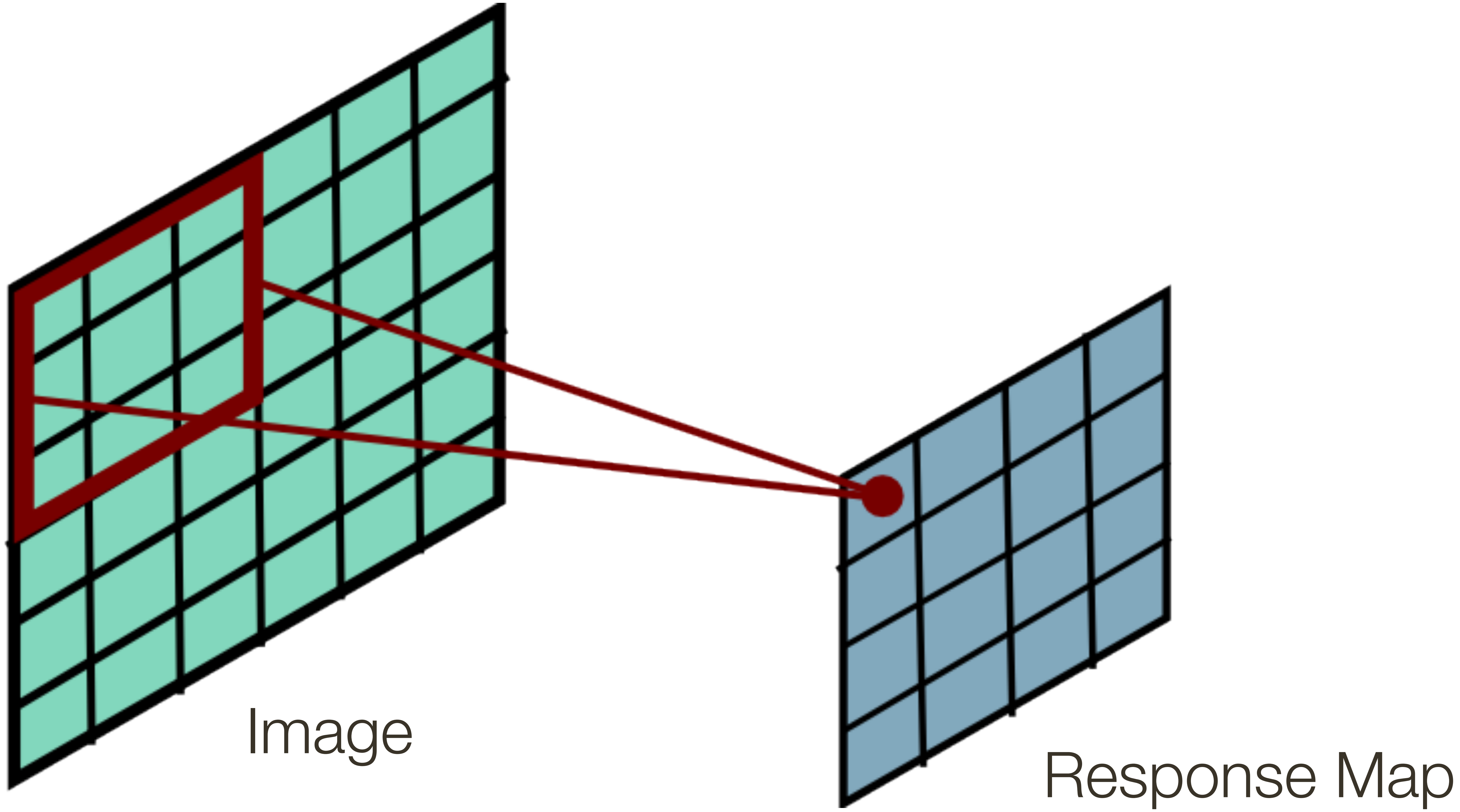
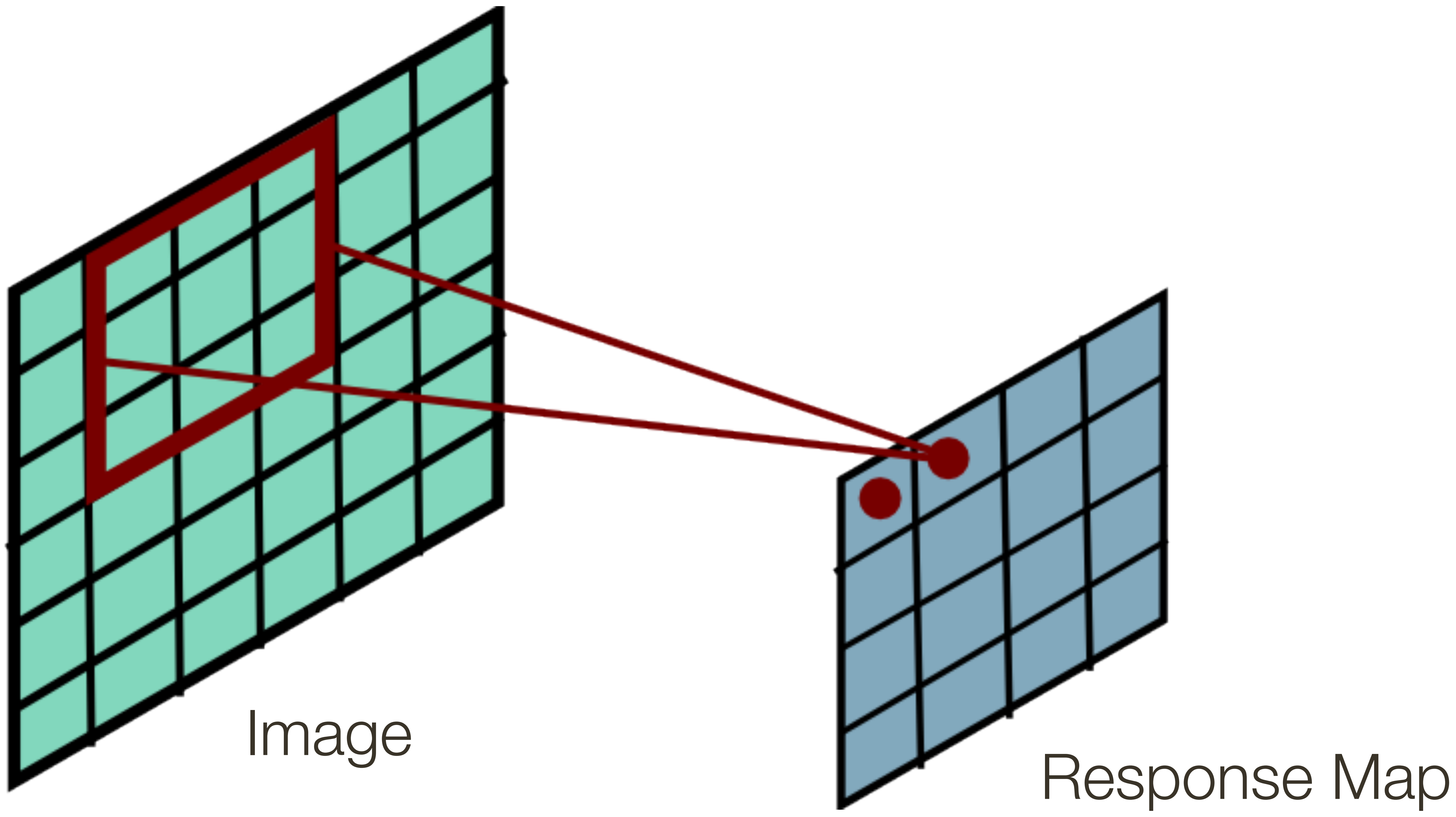
Paper presentations
— List of papers will be made available in the next 1 week

Last time: Convolutional Layer



* slide from Marc'Aurelio Renzato

Last time: **Convolutional** Layer



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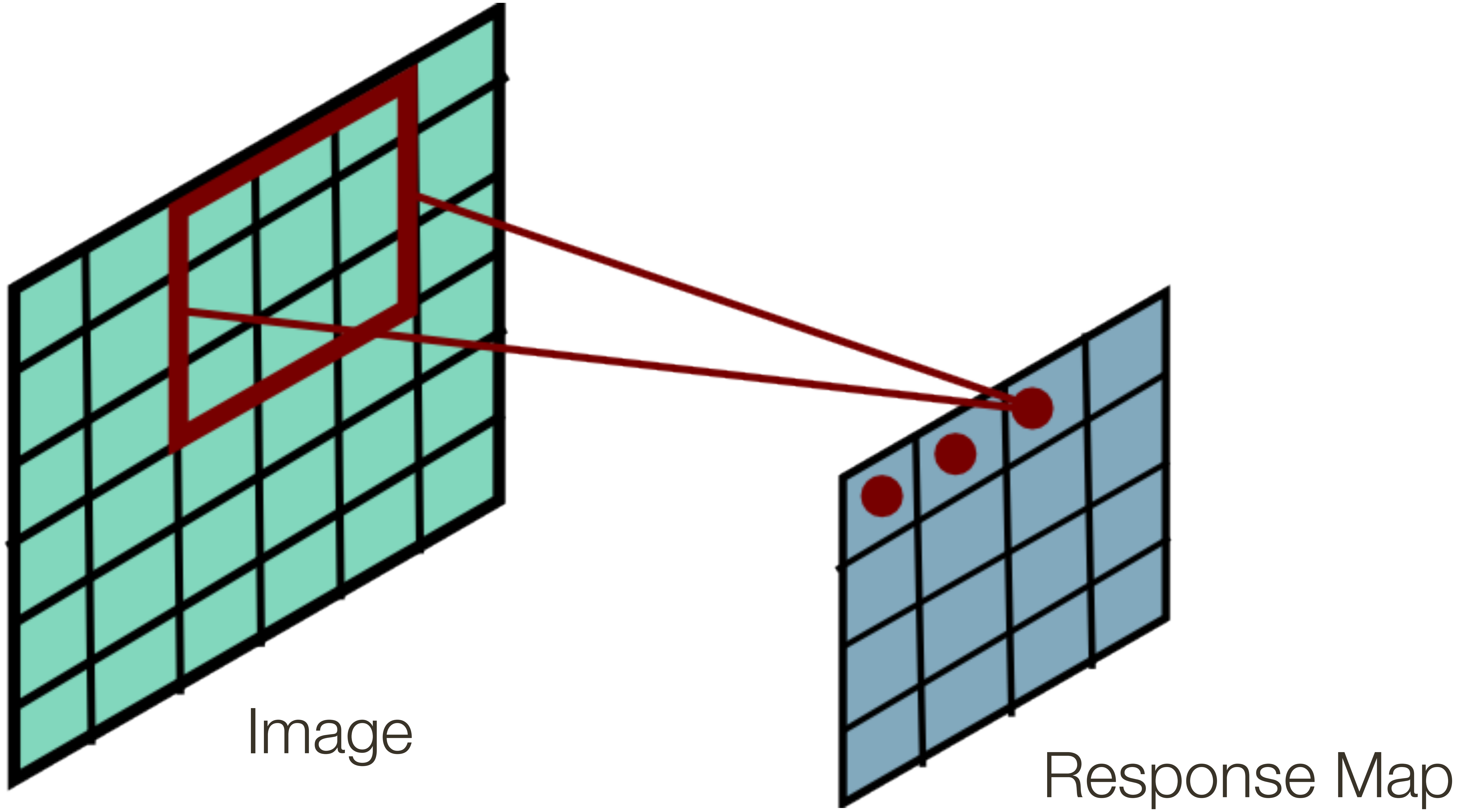

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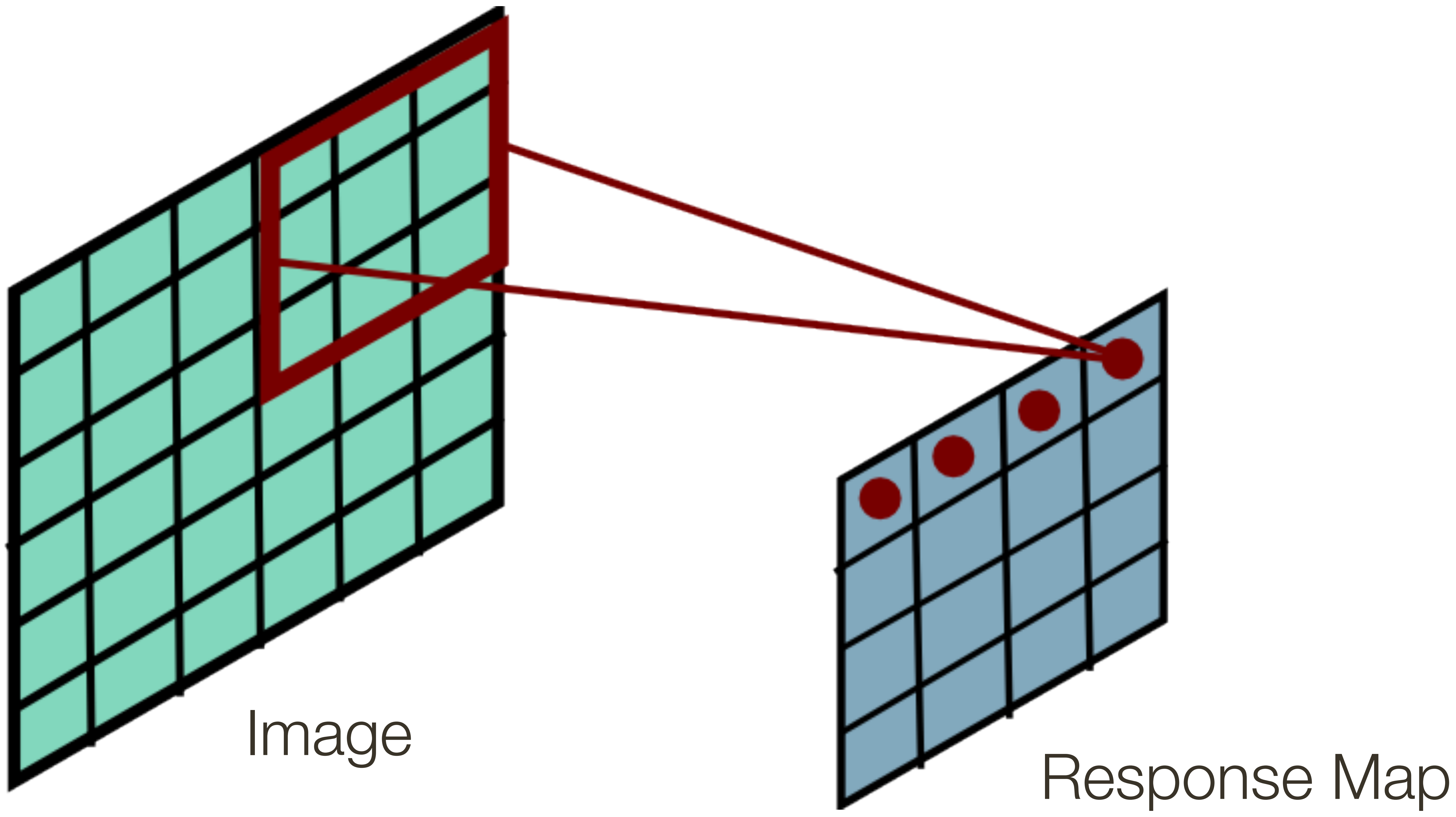

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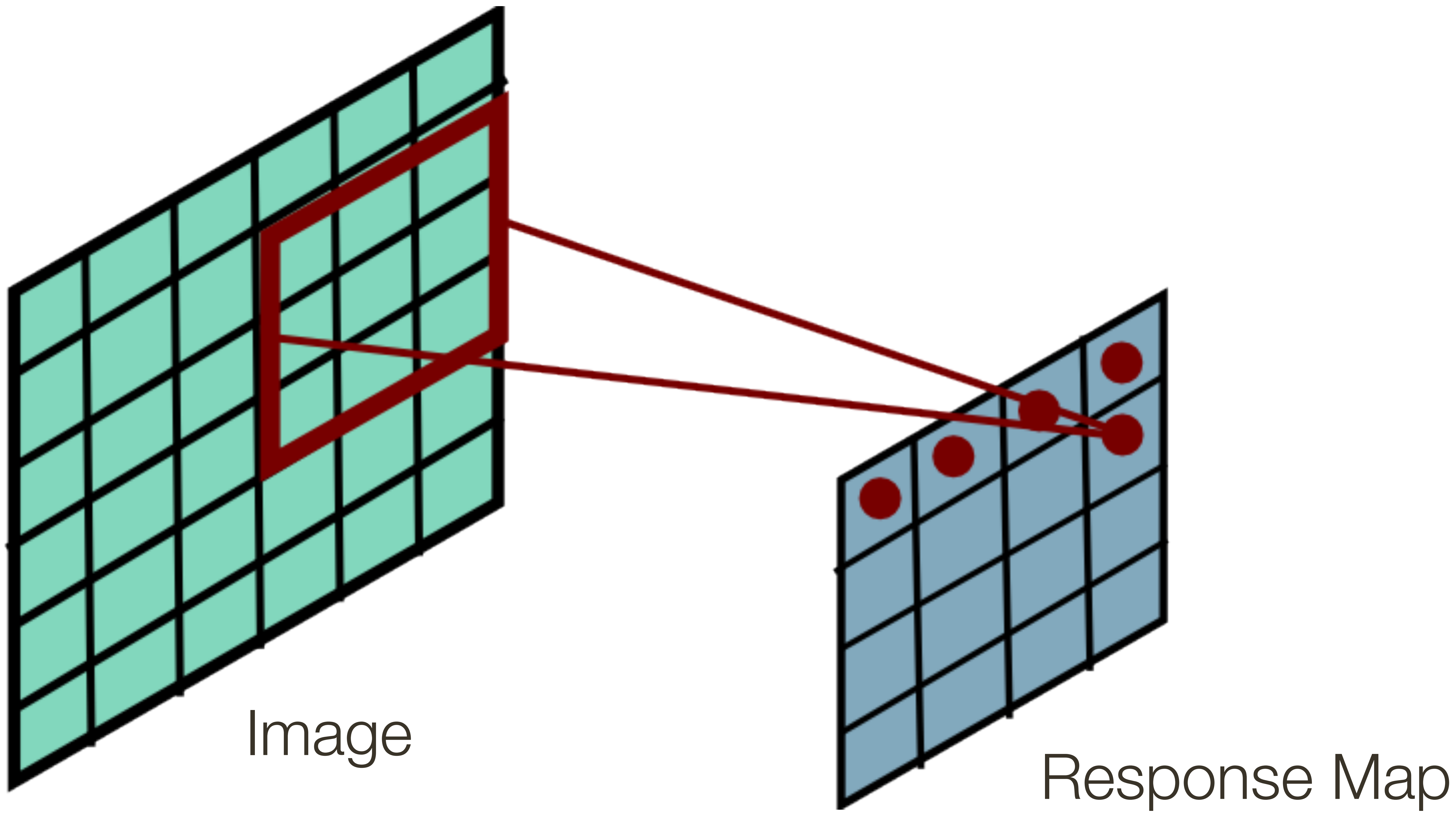

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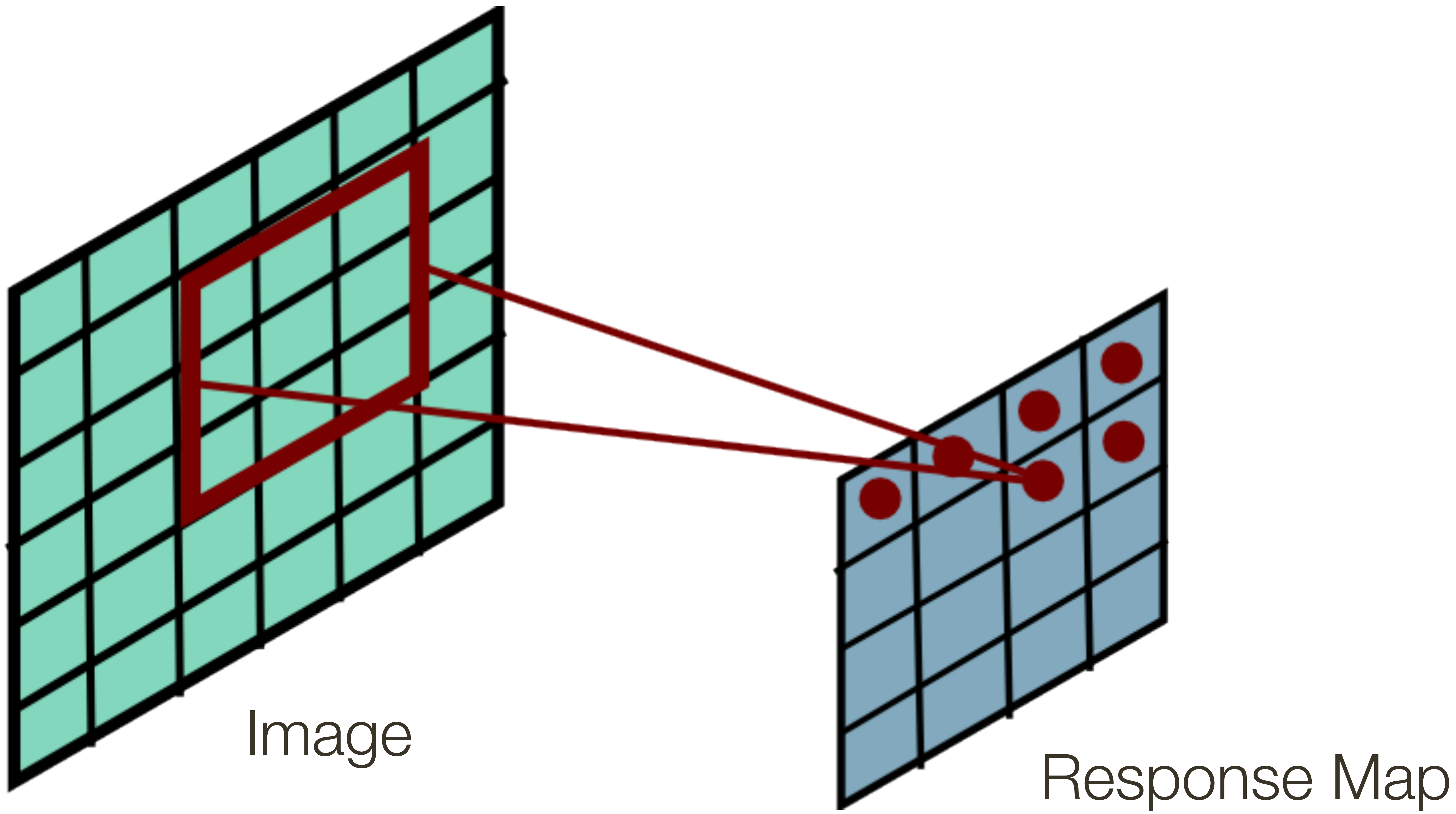

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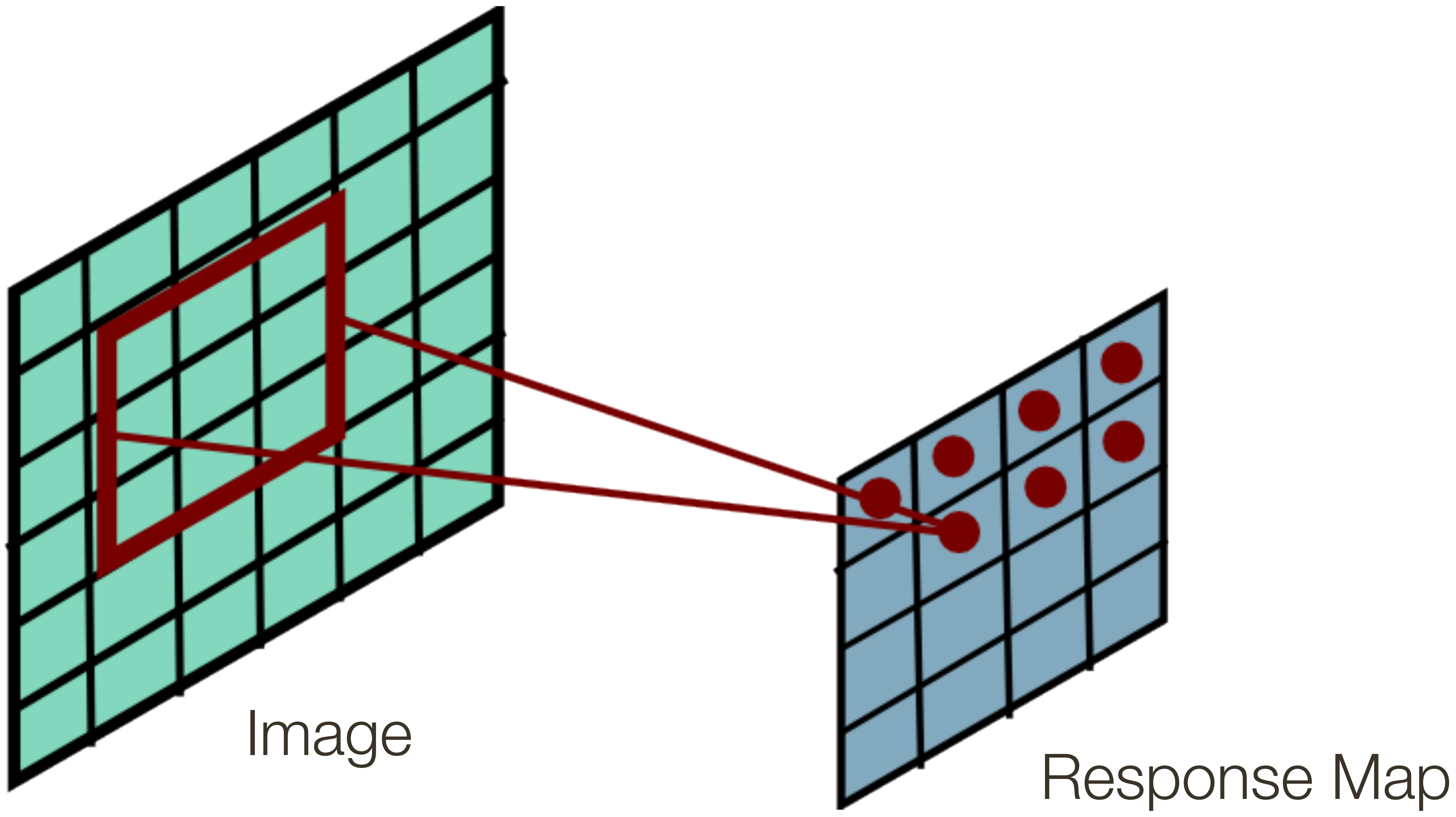

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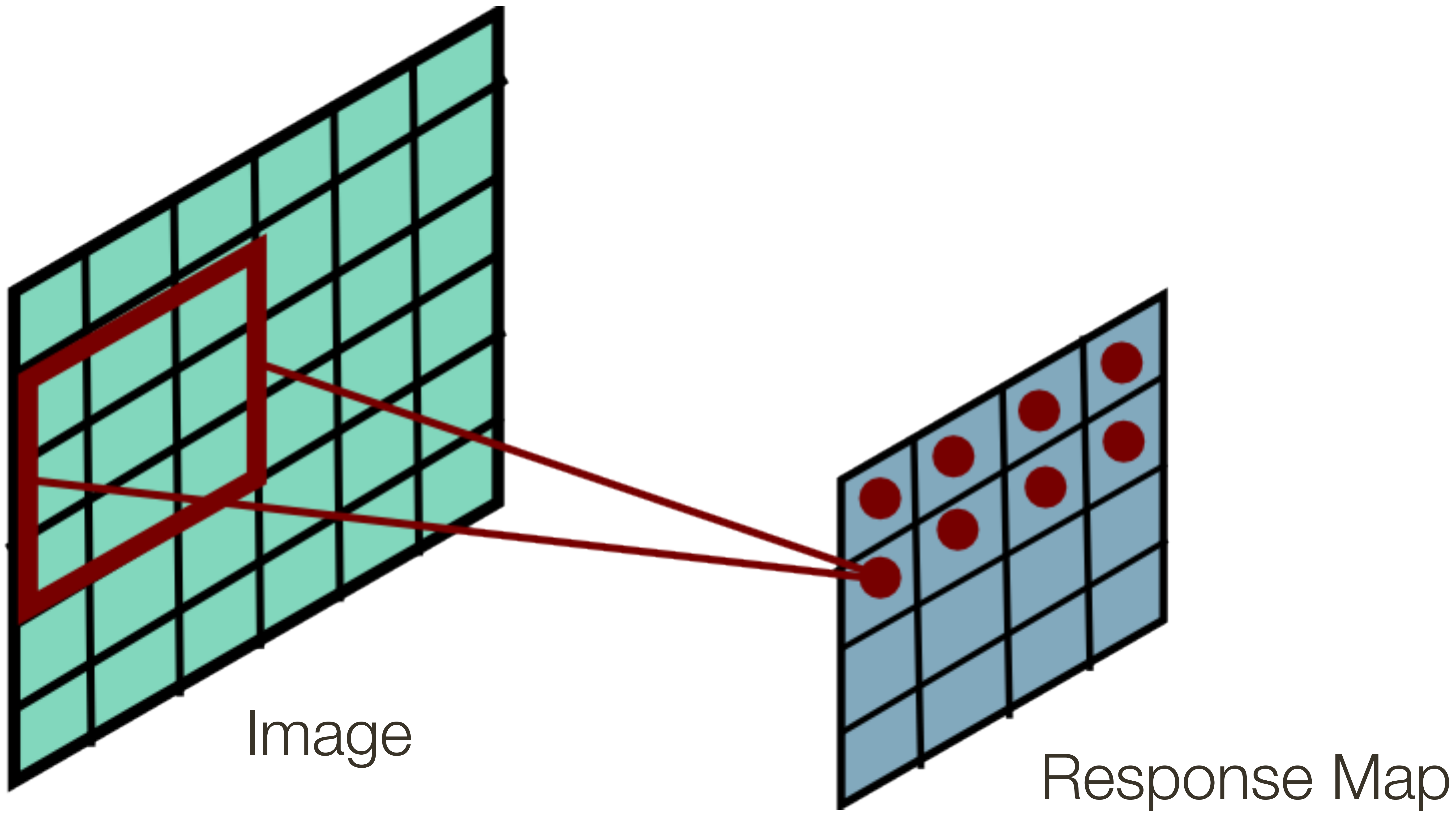

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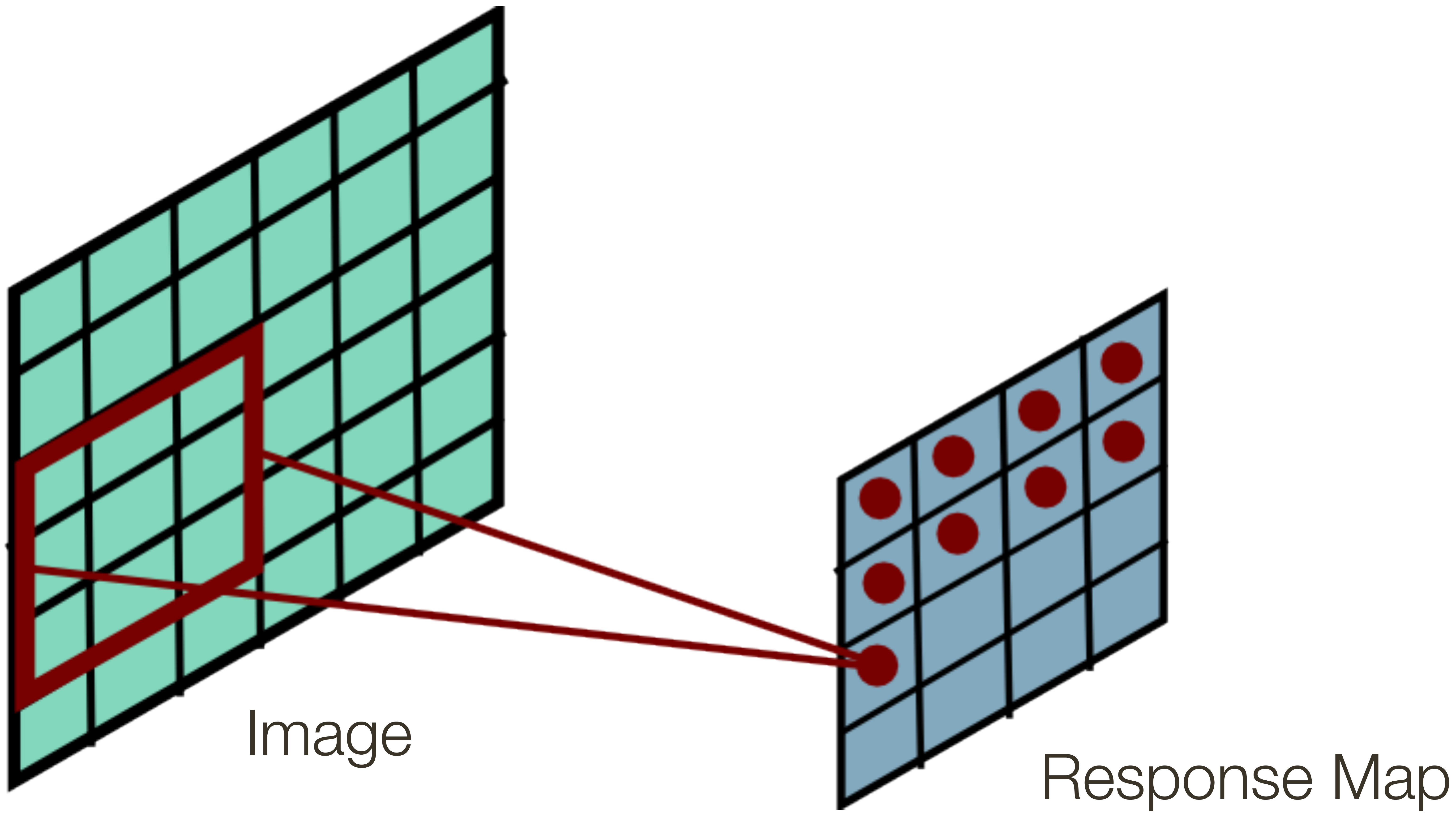

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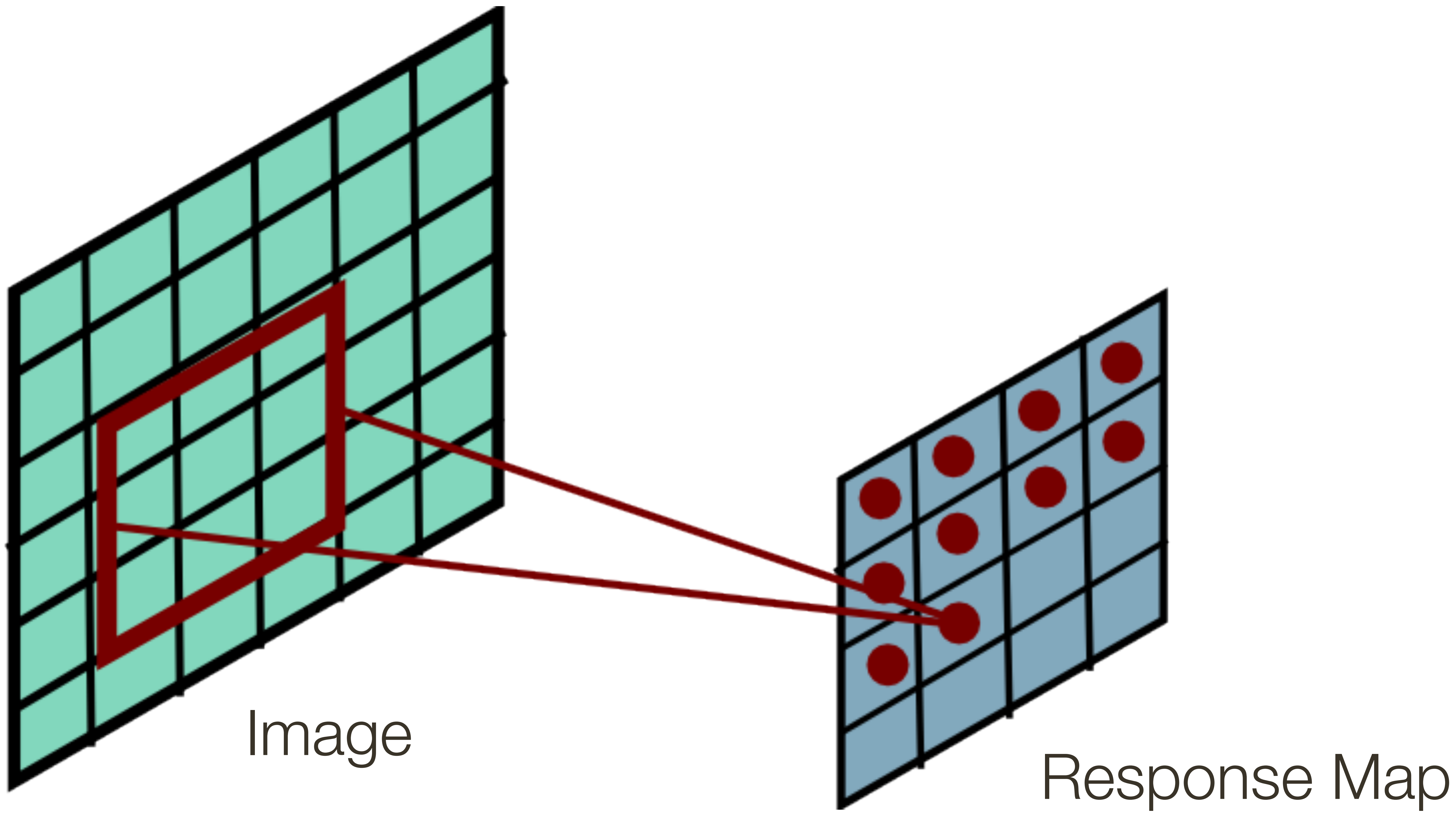

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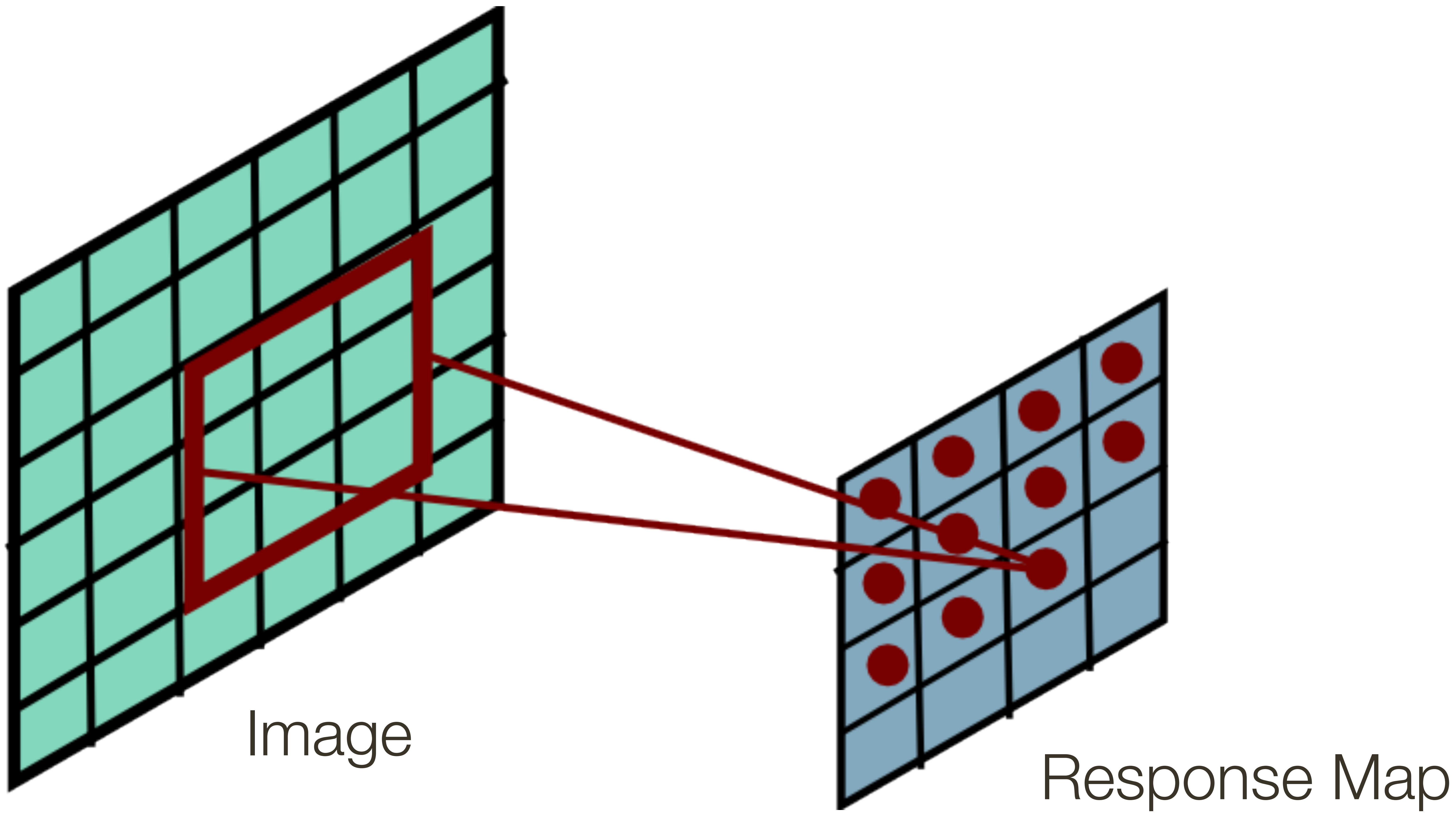

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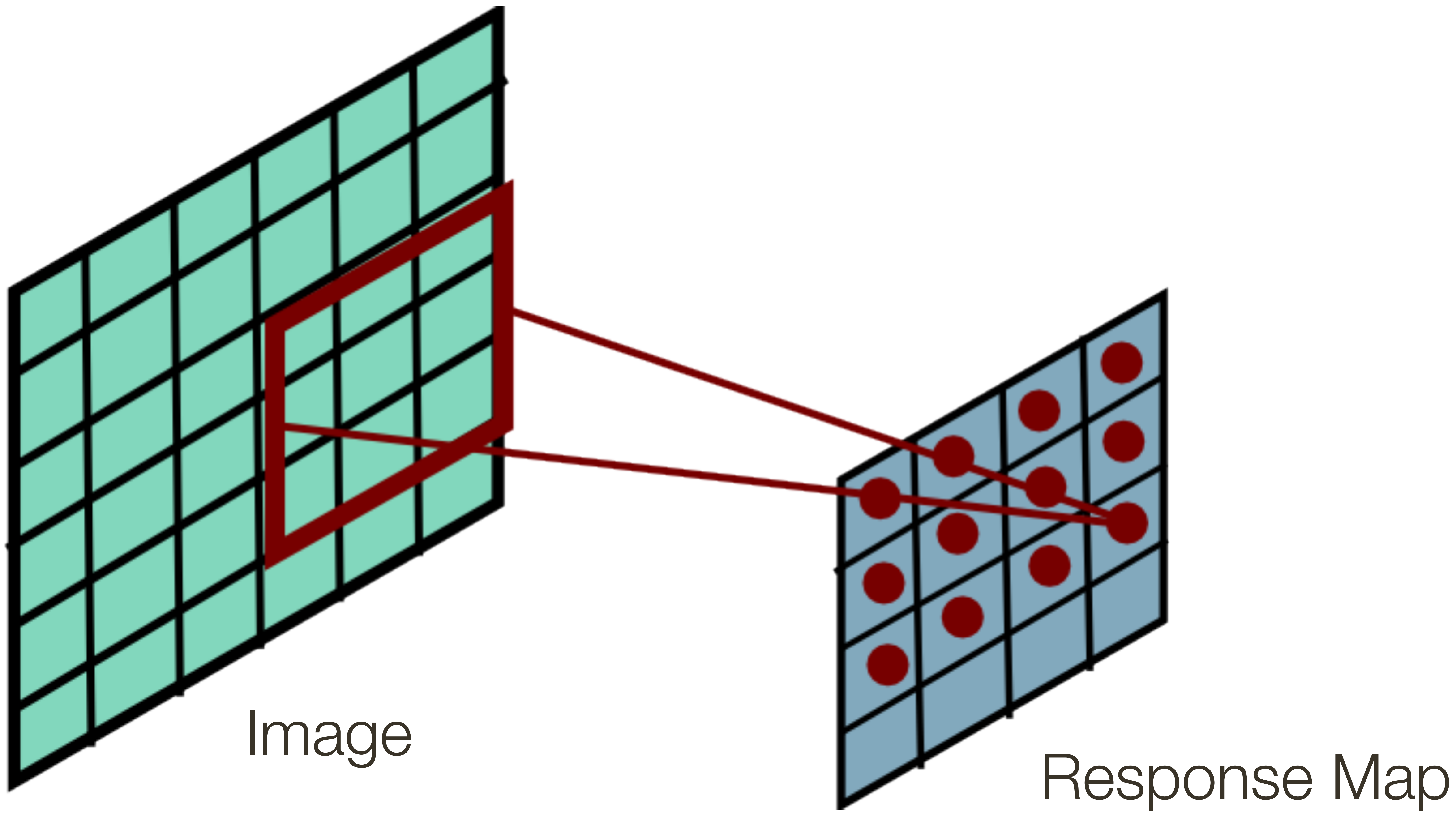

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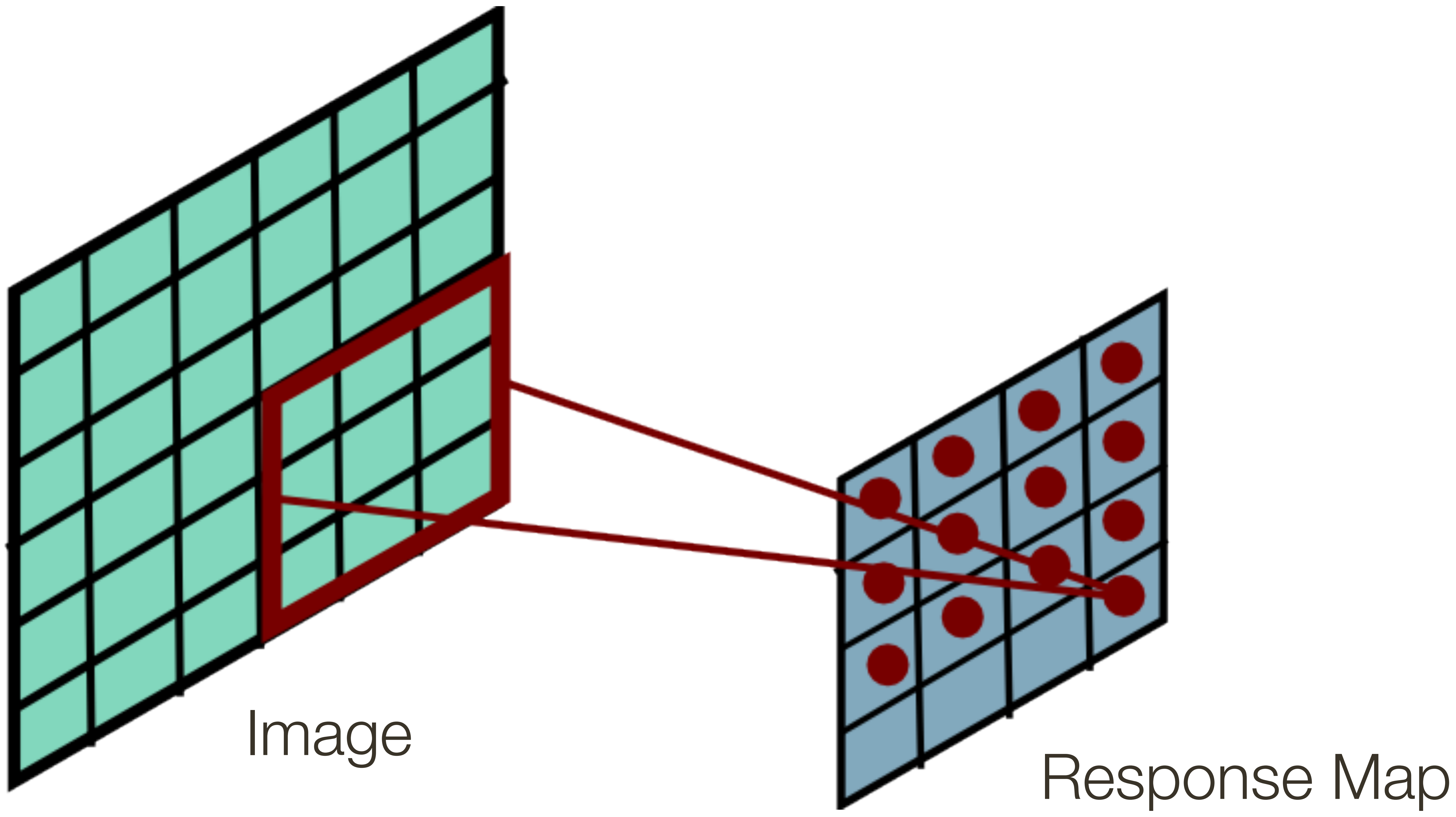

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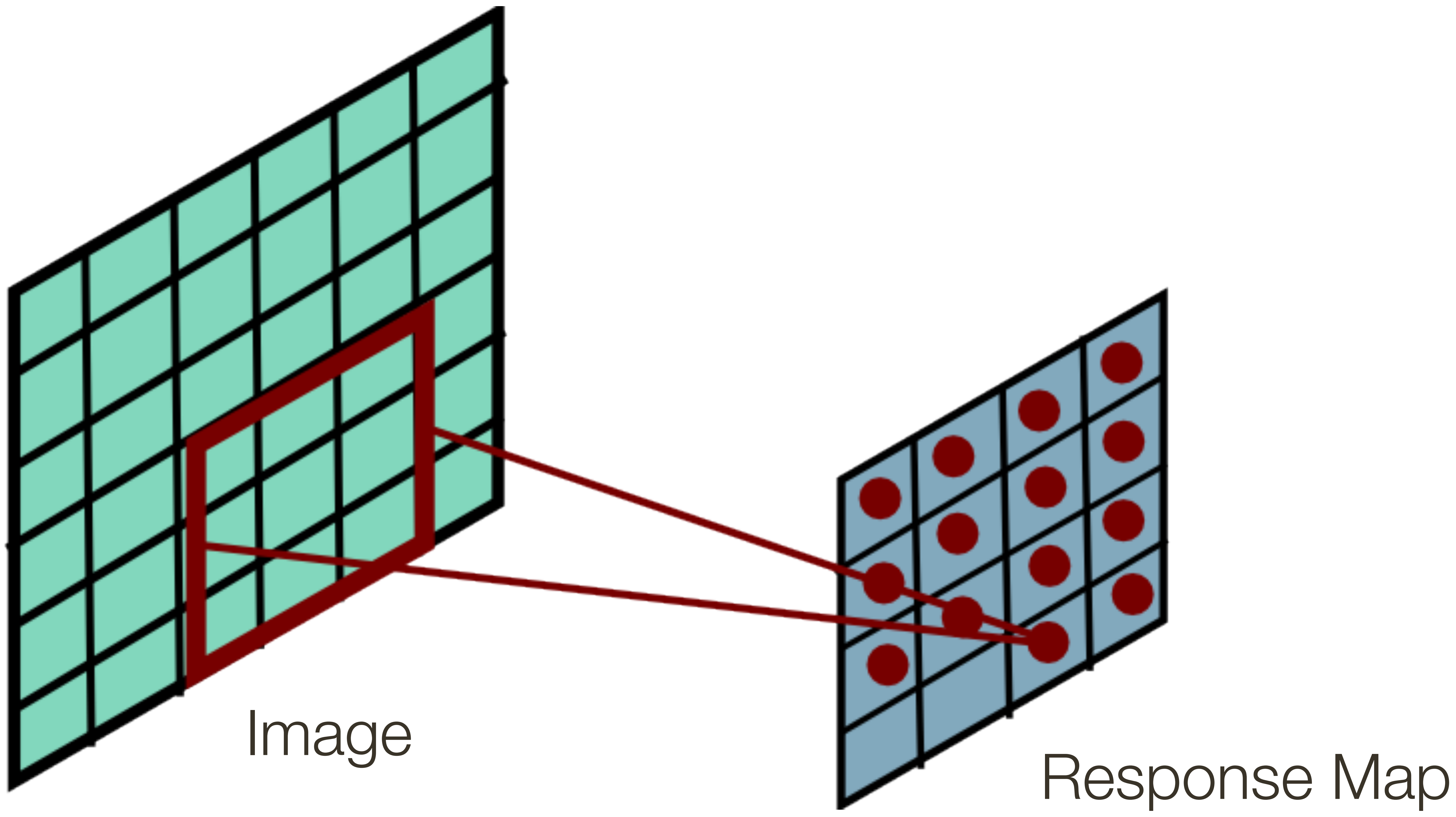

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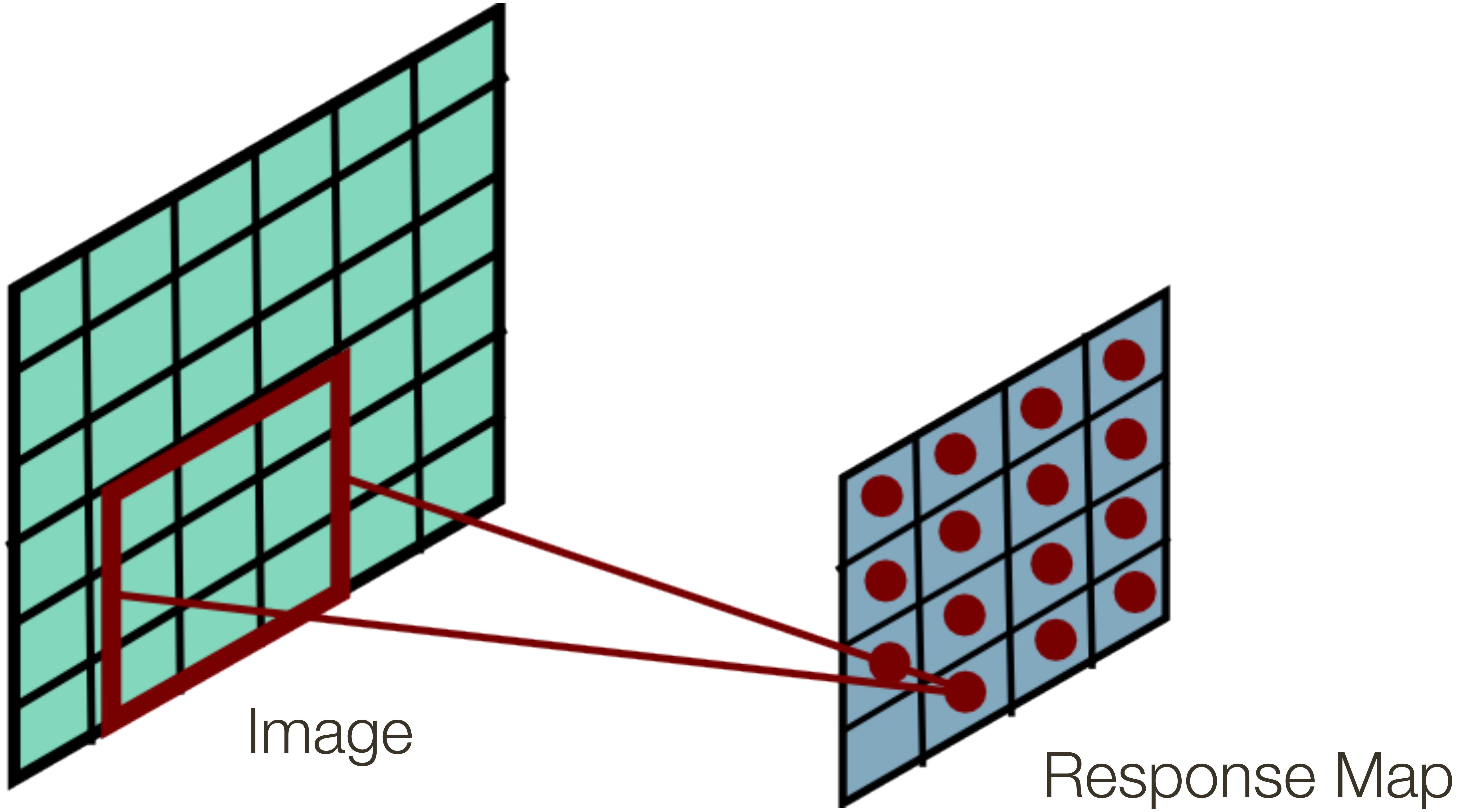

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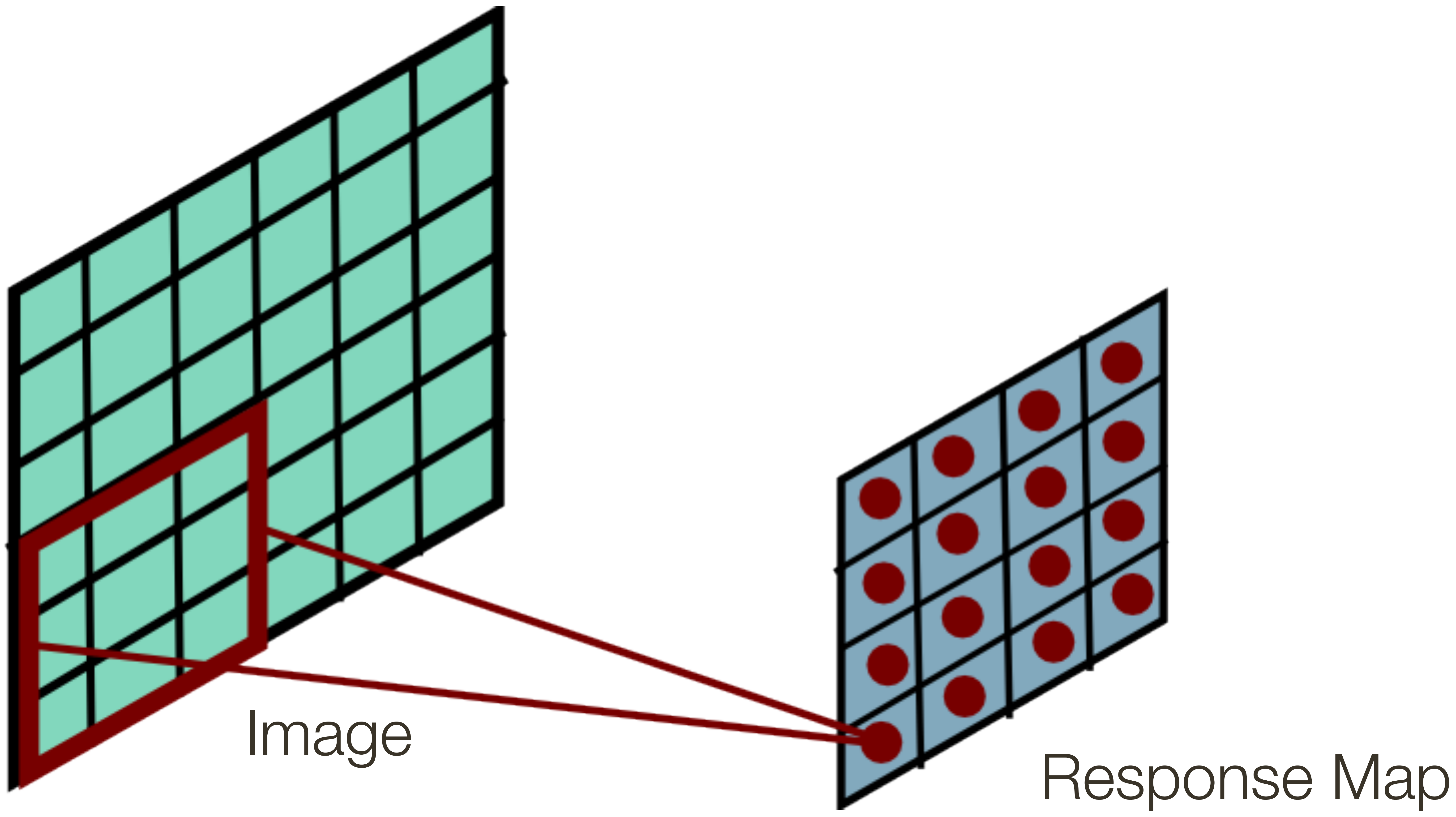

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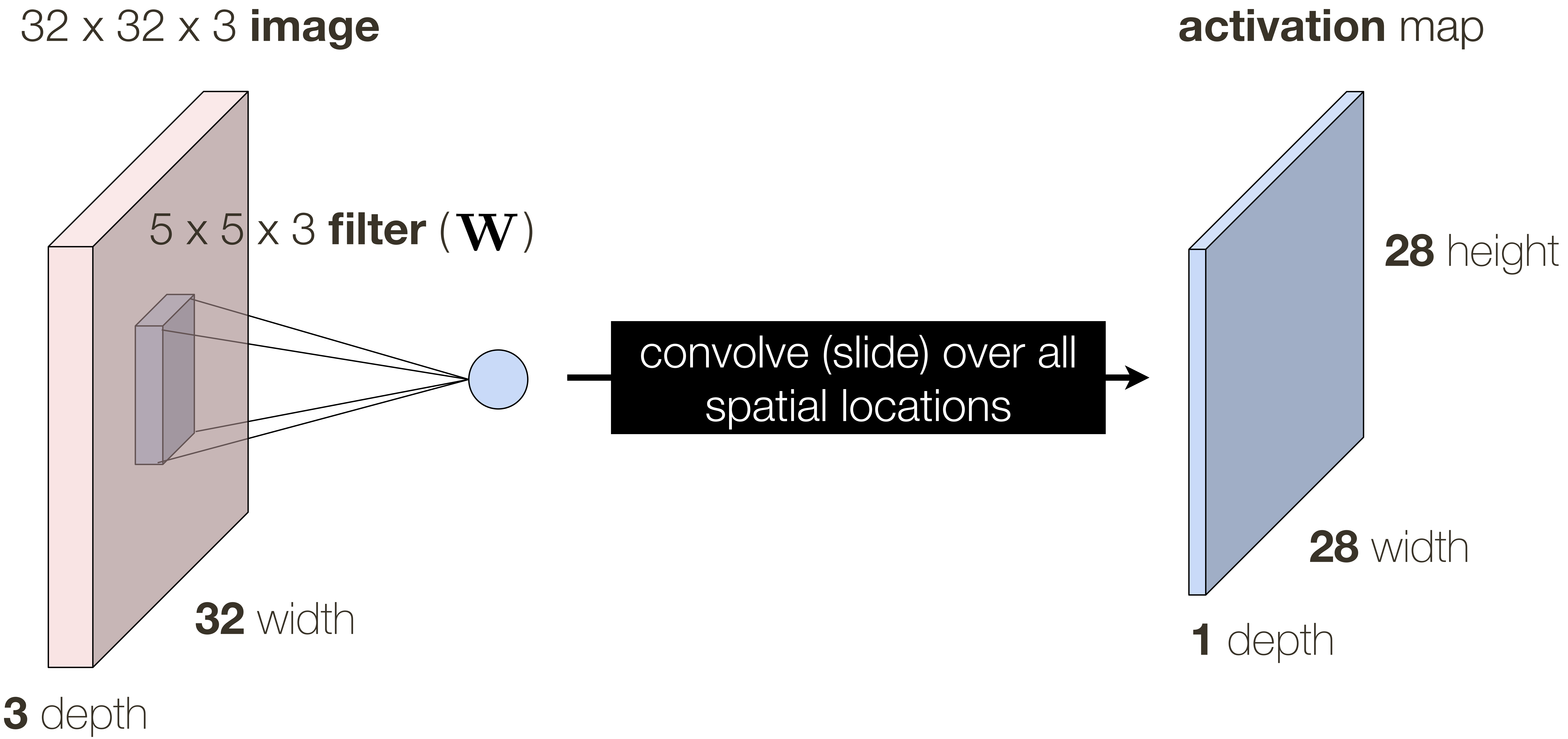
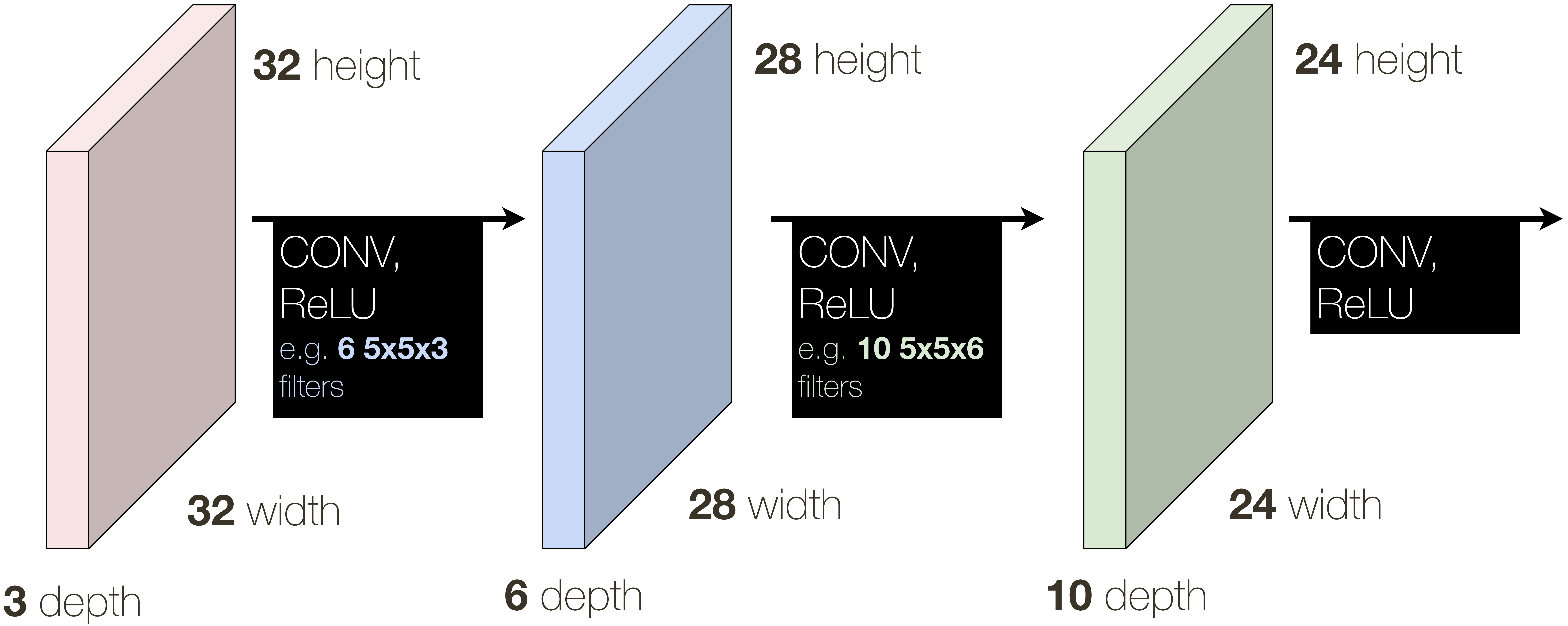


* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Last time: **Convolutional** Neural Network (ConvNet)



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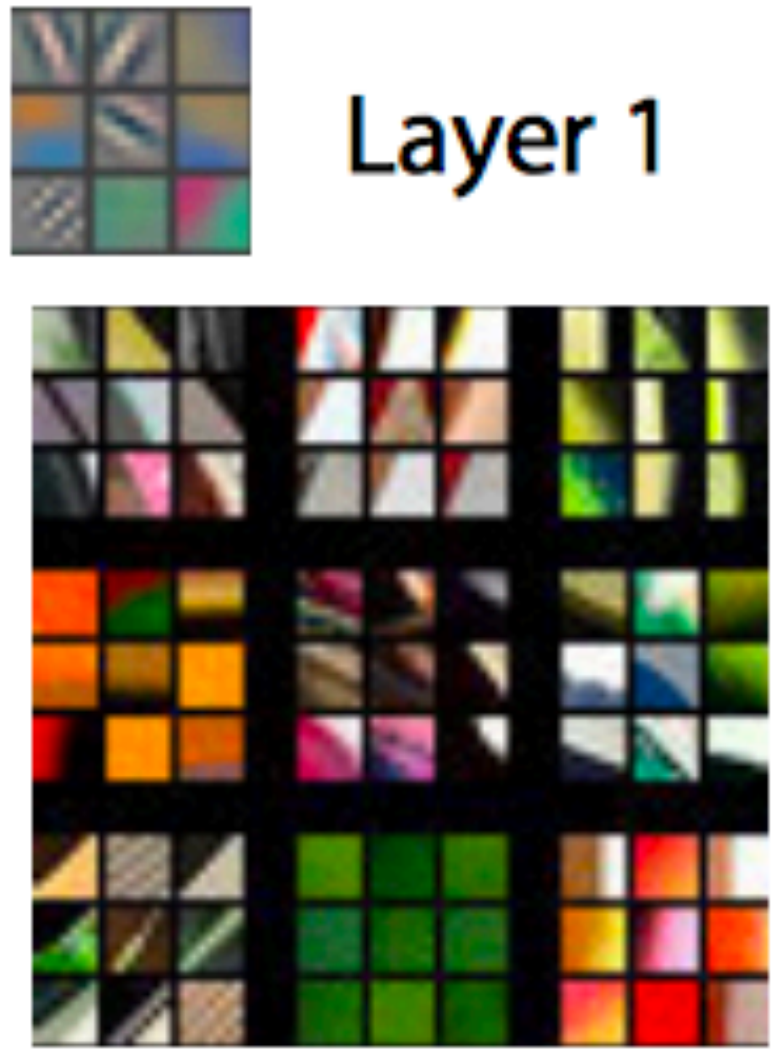
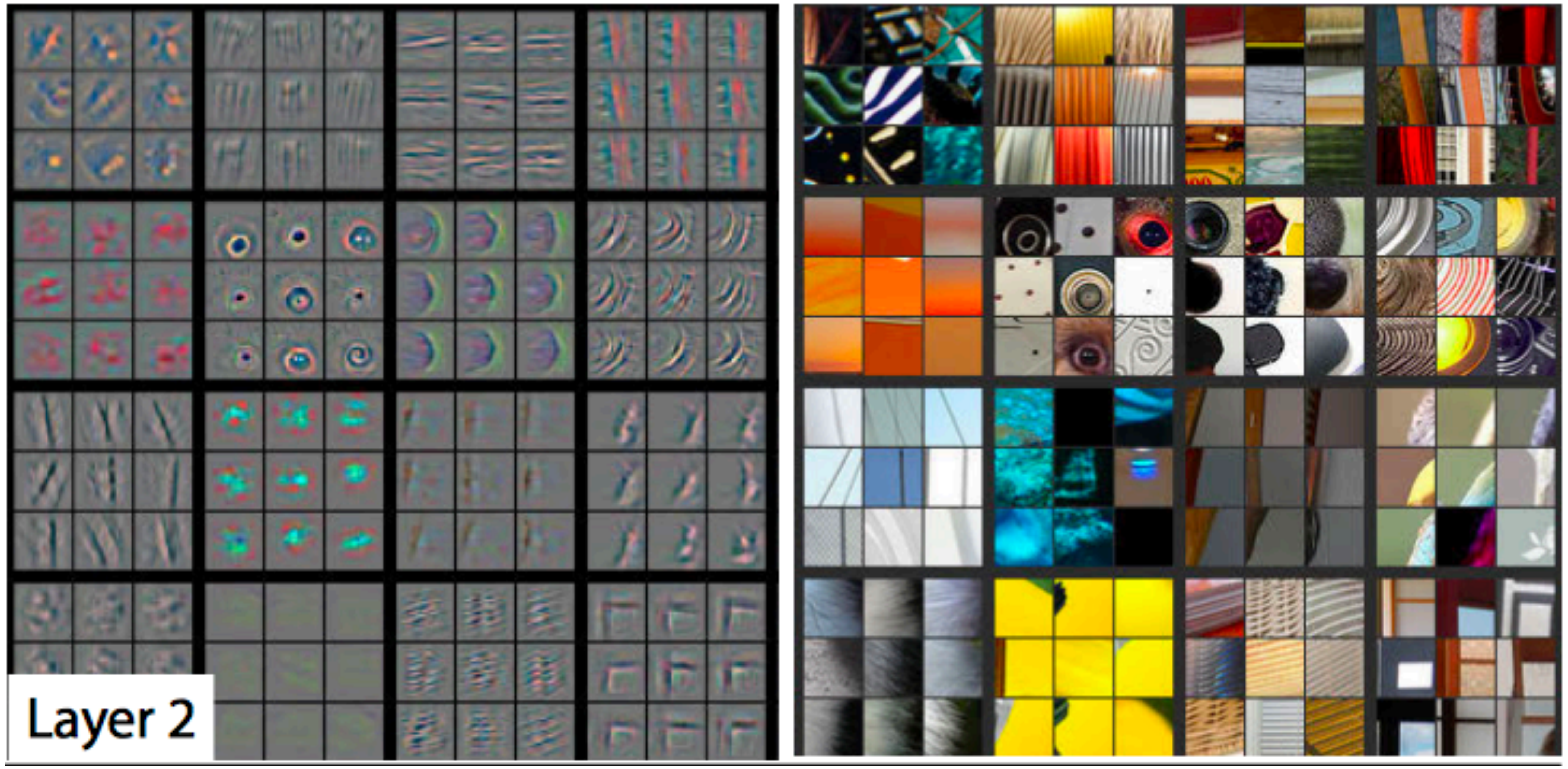
What **filters** do networks learn?





[Zeiler and Fergus, 2013]

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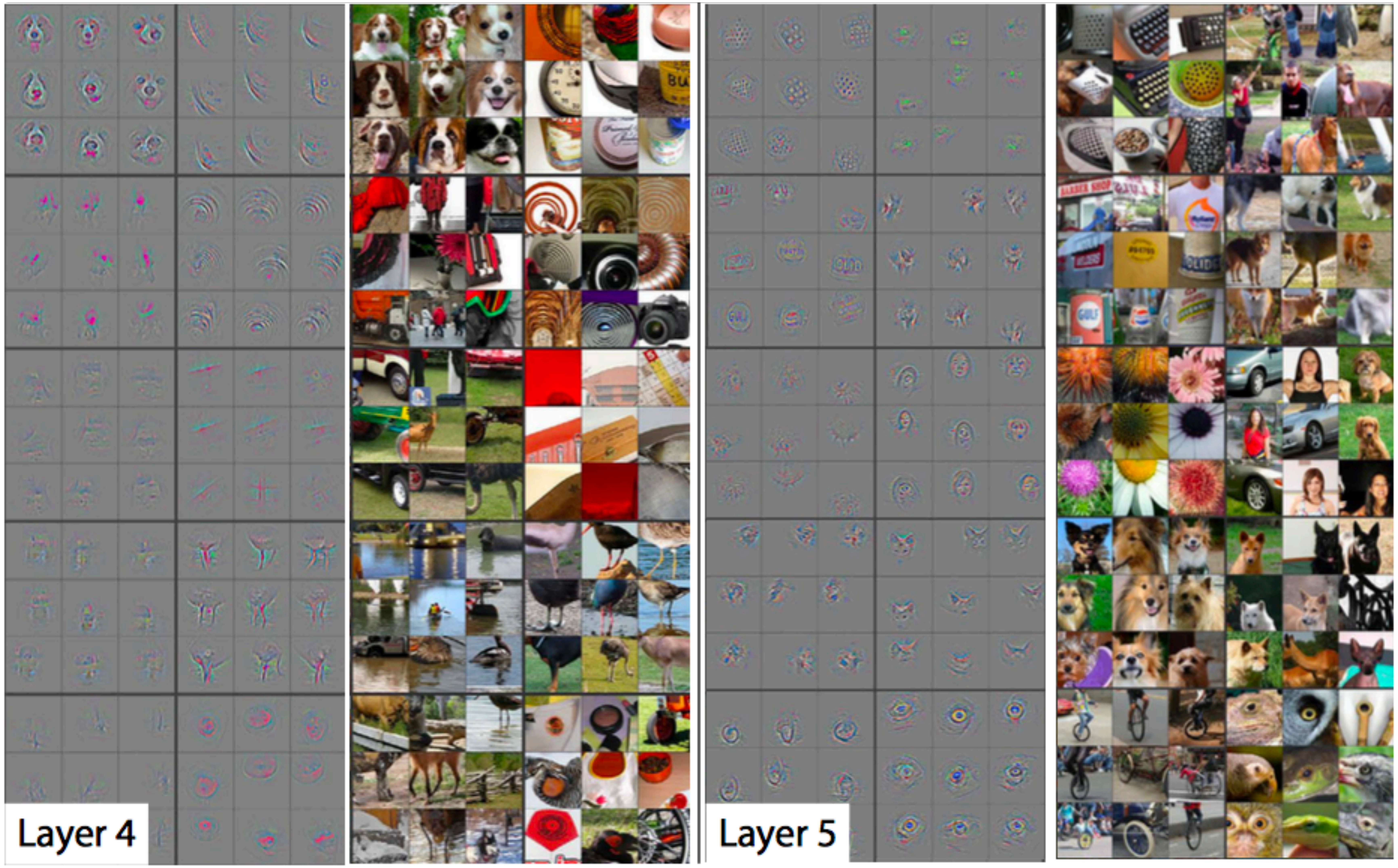
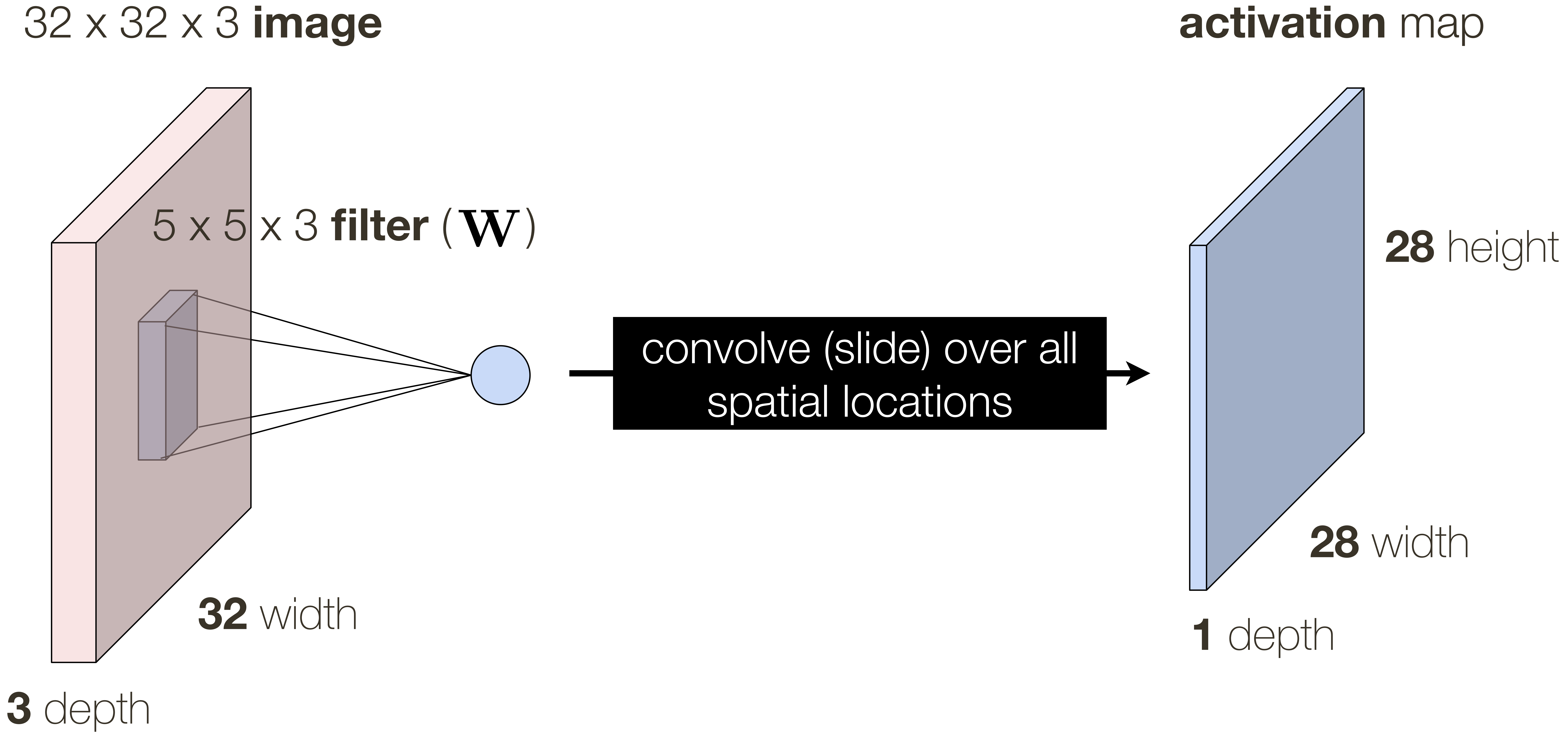


[Zeiler and Fergus, 2013]

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



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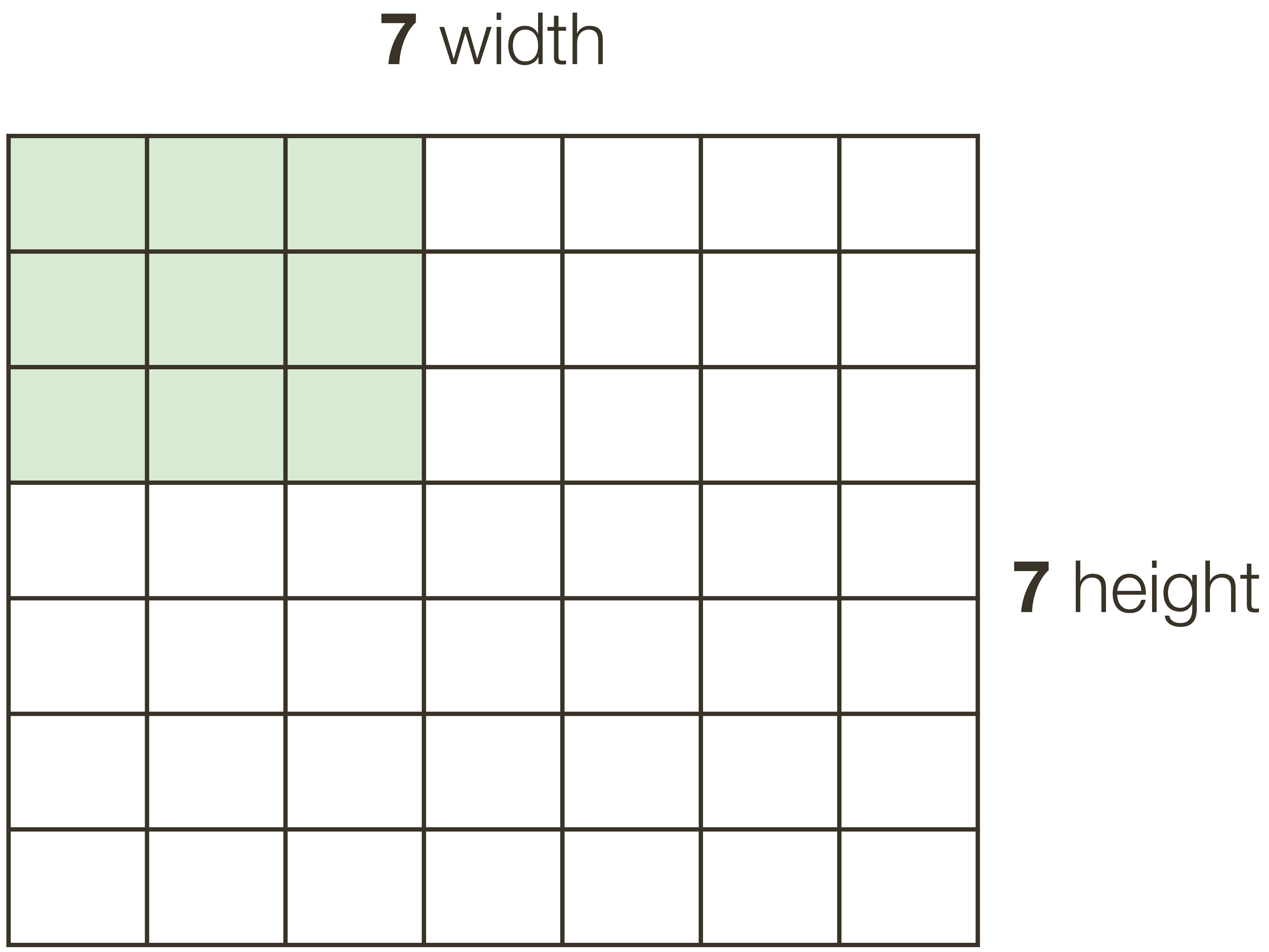

7 x 7 input image (spatially)
3 x 3 filter

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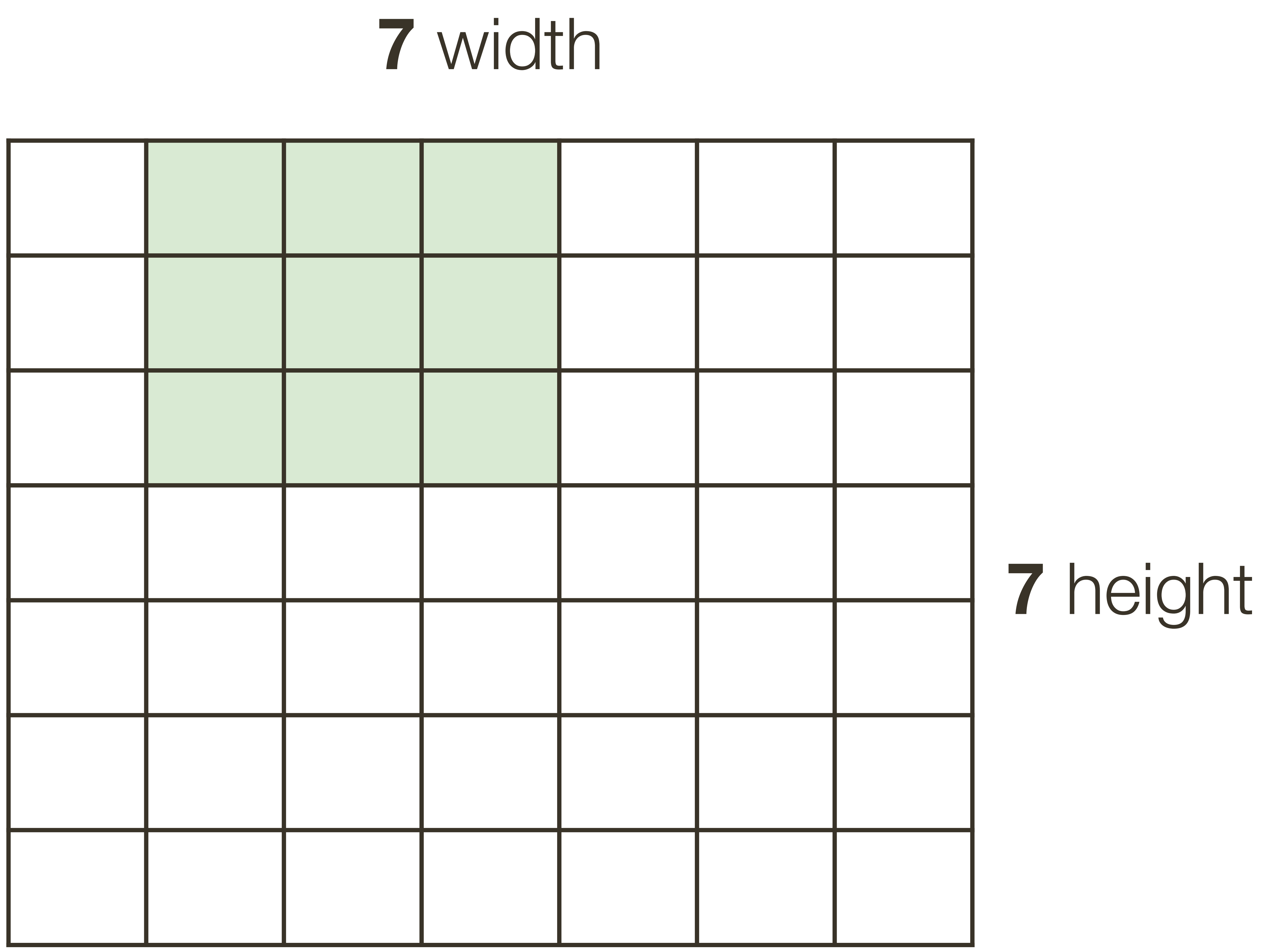

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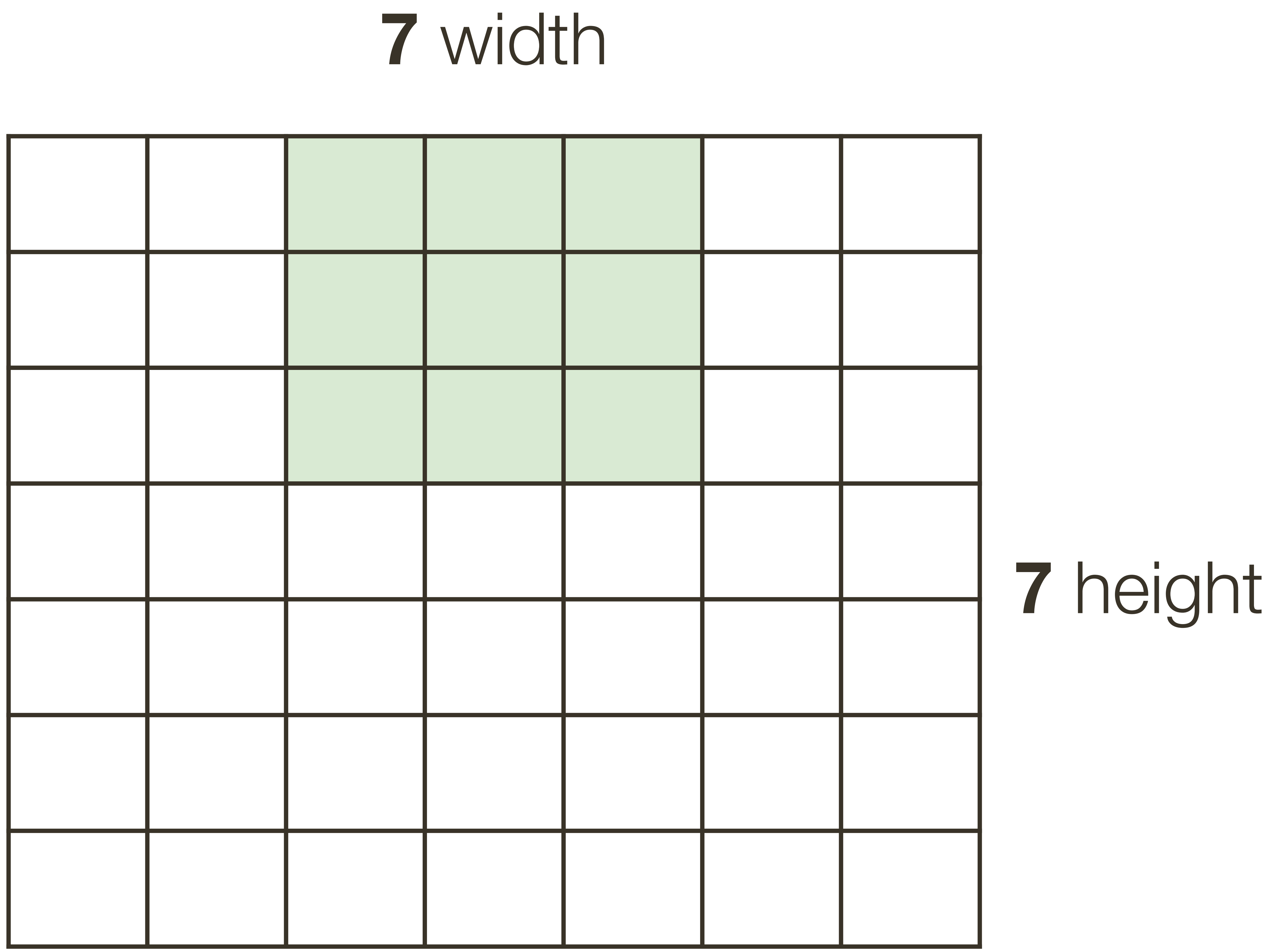

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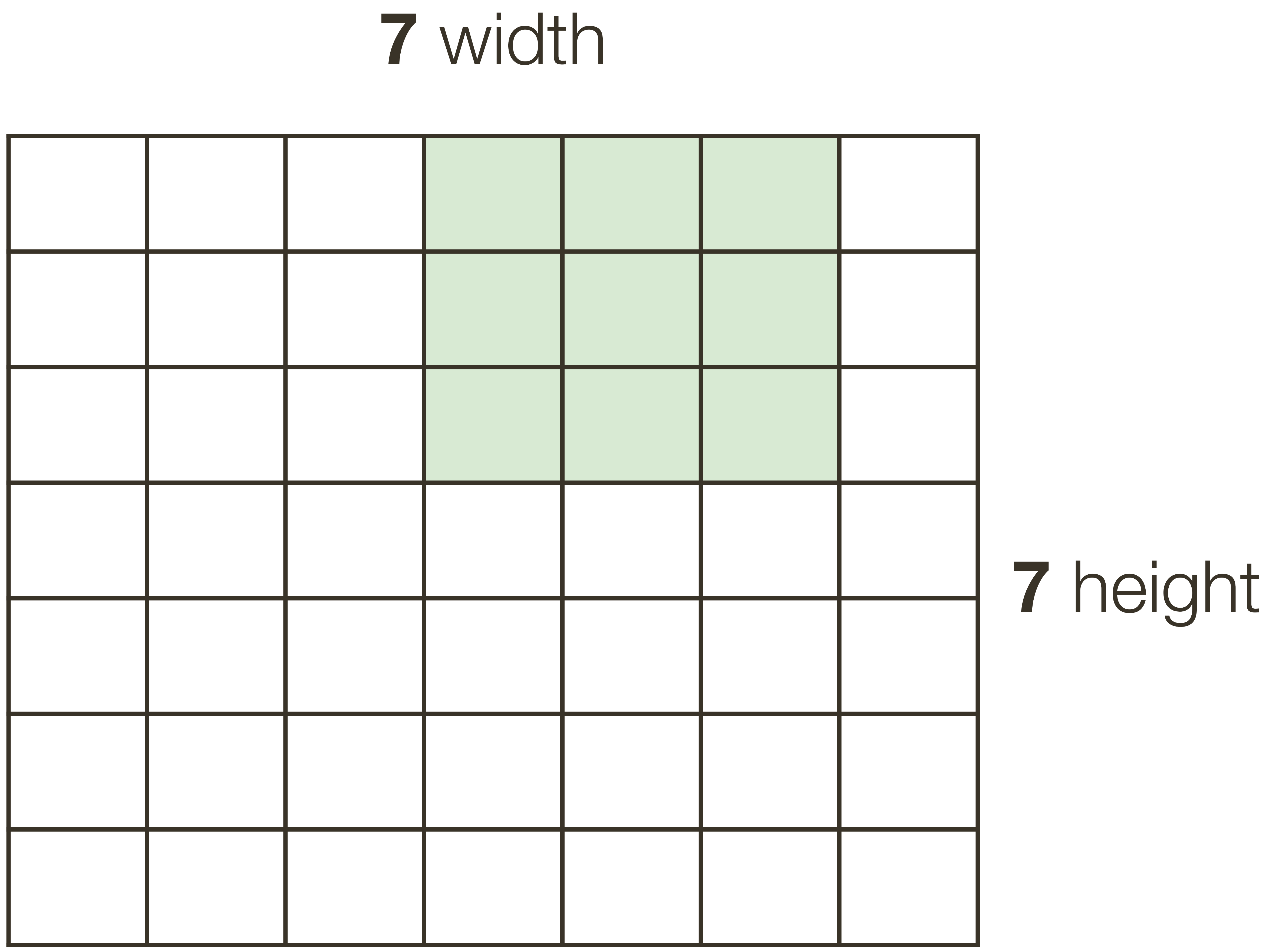

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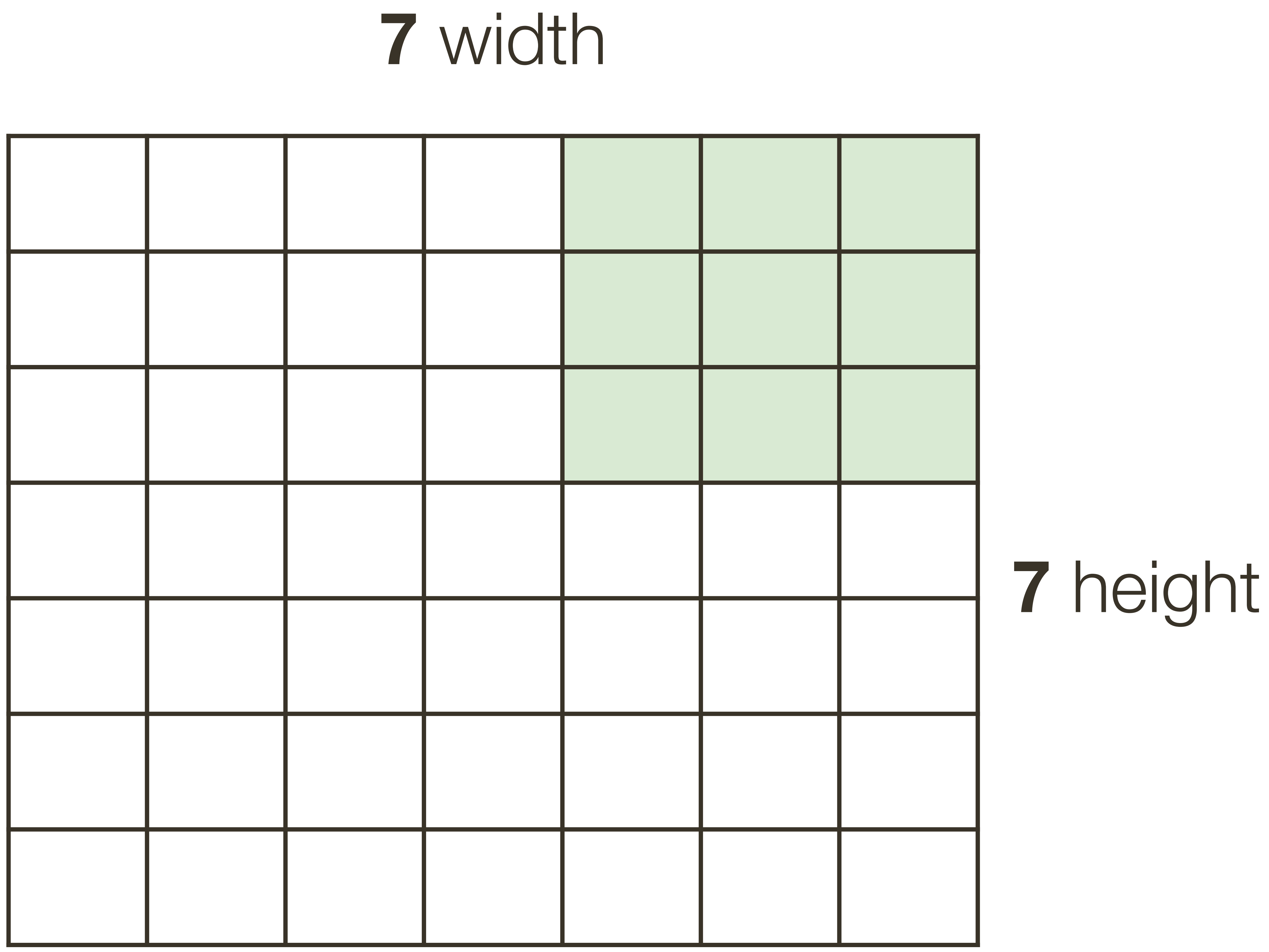

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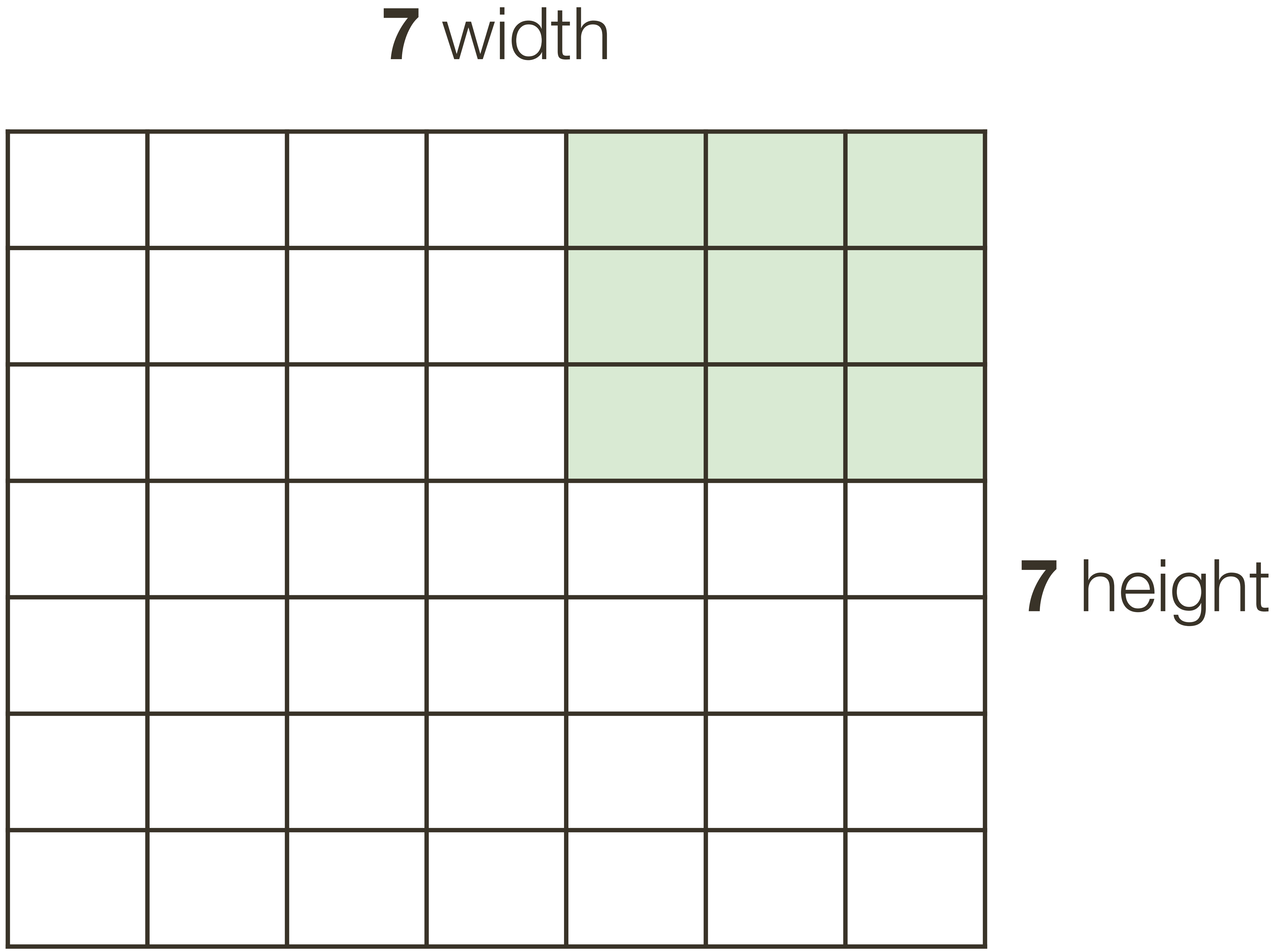
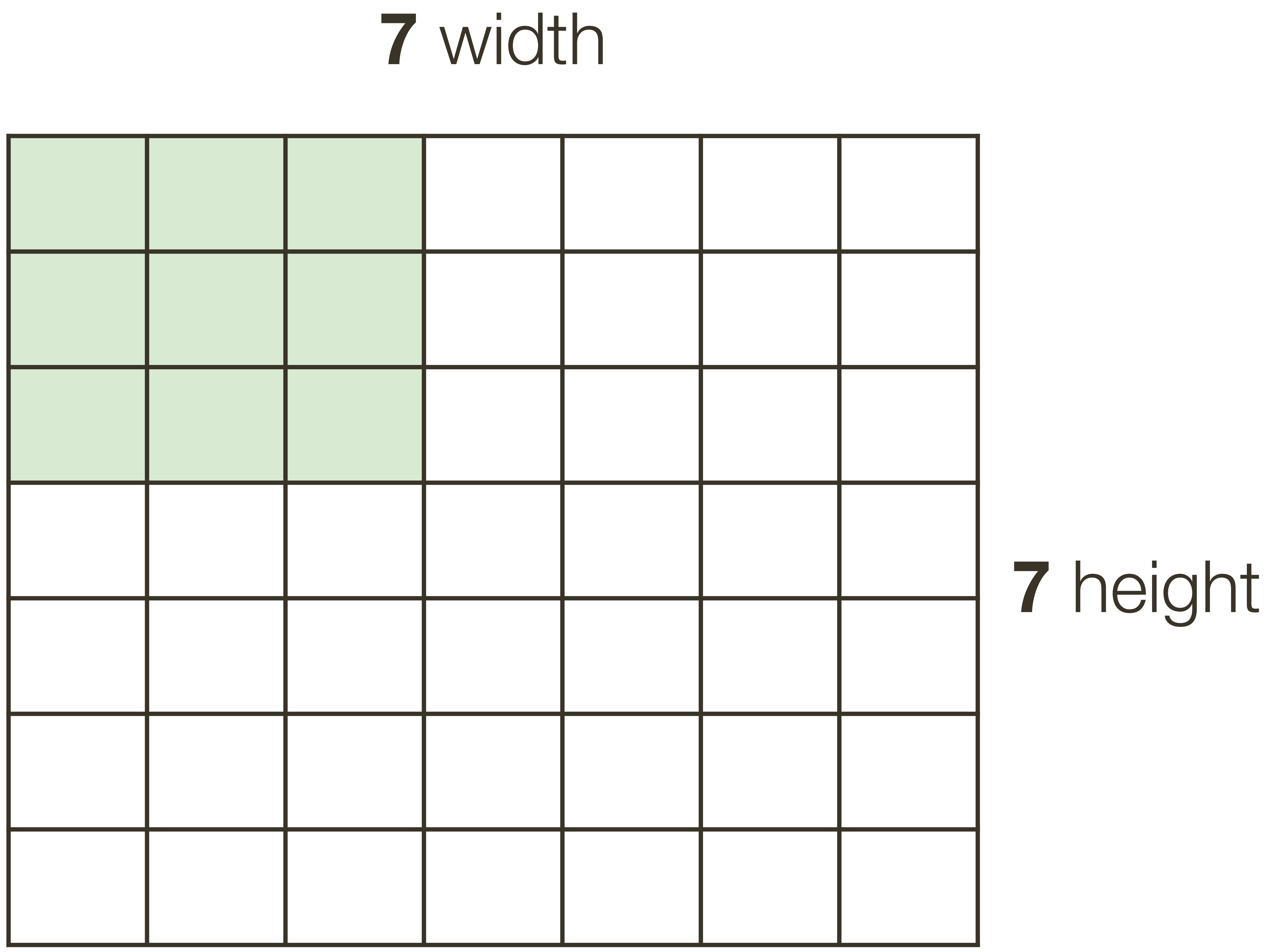


7 x 7 input image (spatially)
3 x 3 filter

=> **5 x 5 output**

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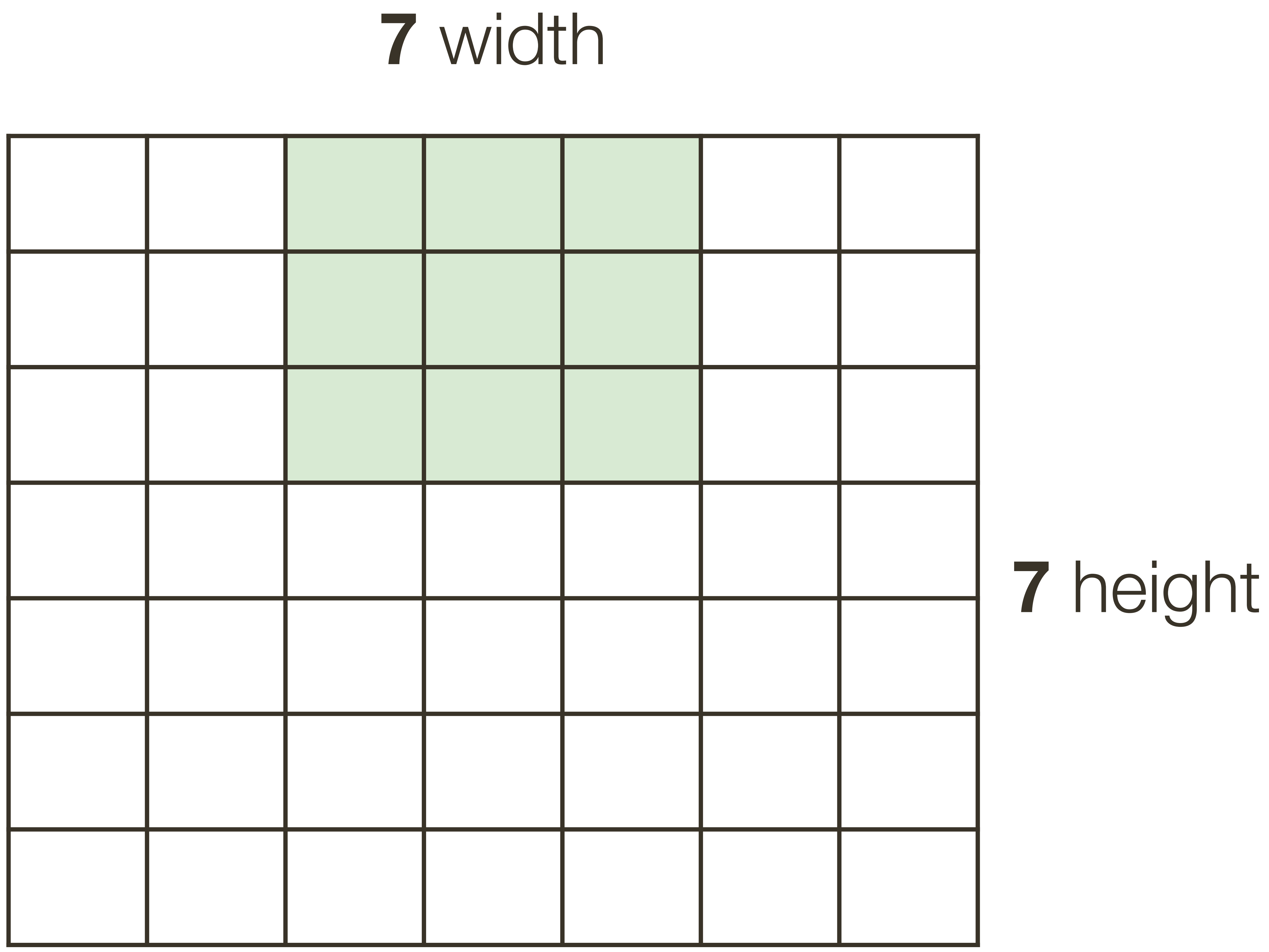
Convolutional Layer: Closer Look at **Spatial Dimensions**



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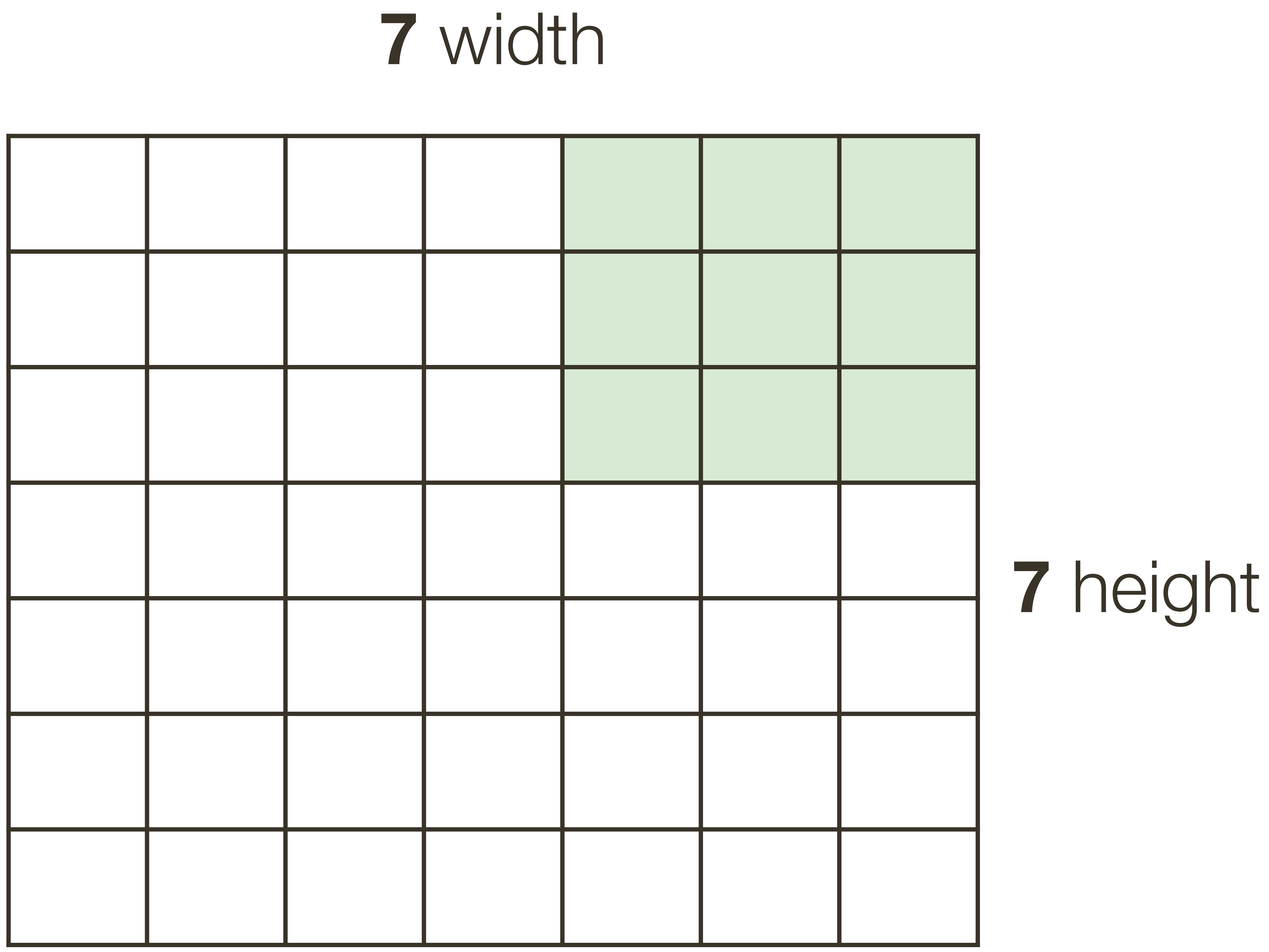

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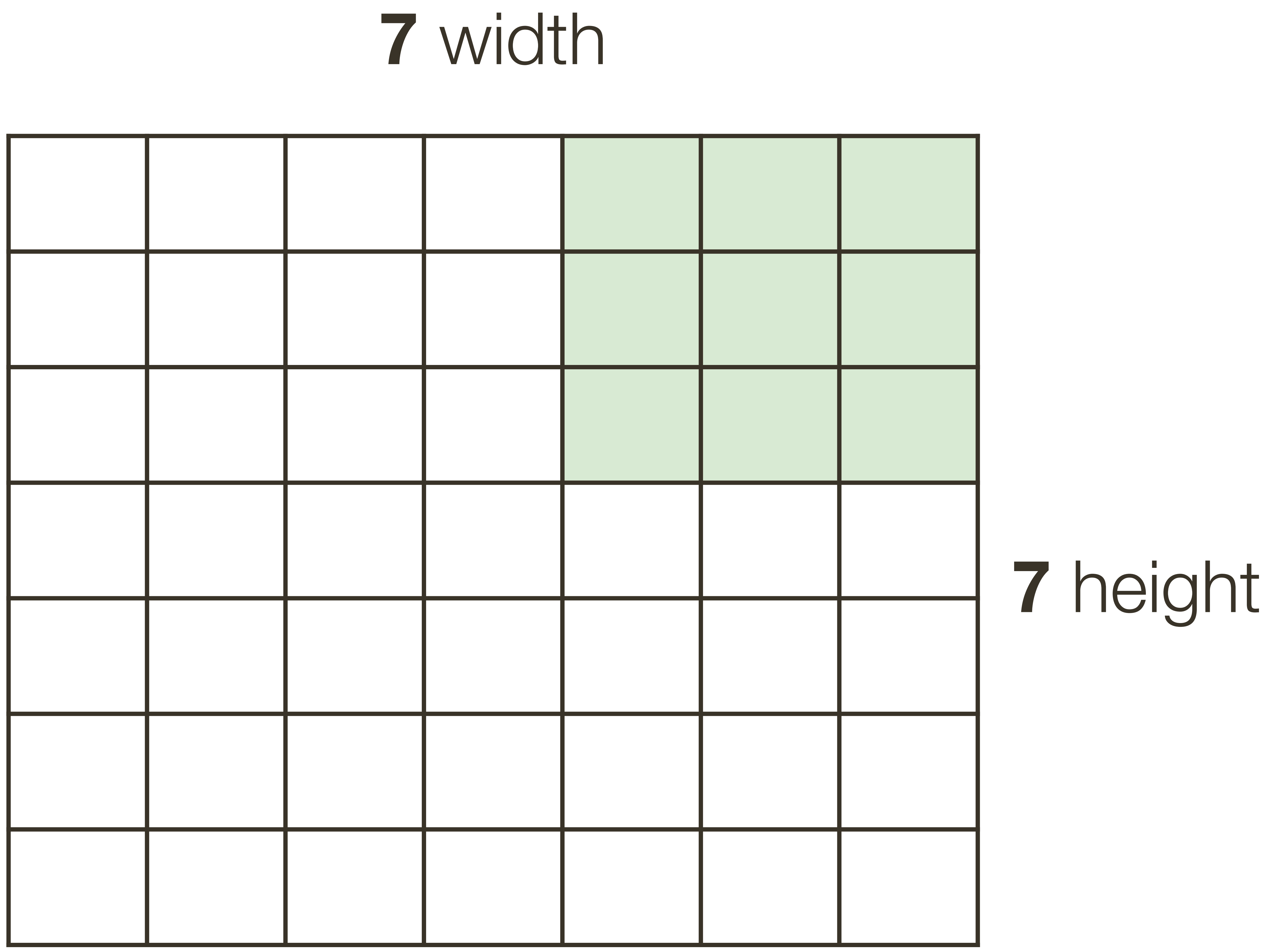

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3 x 3 filter
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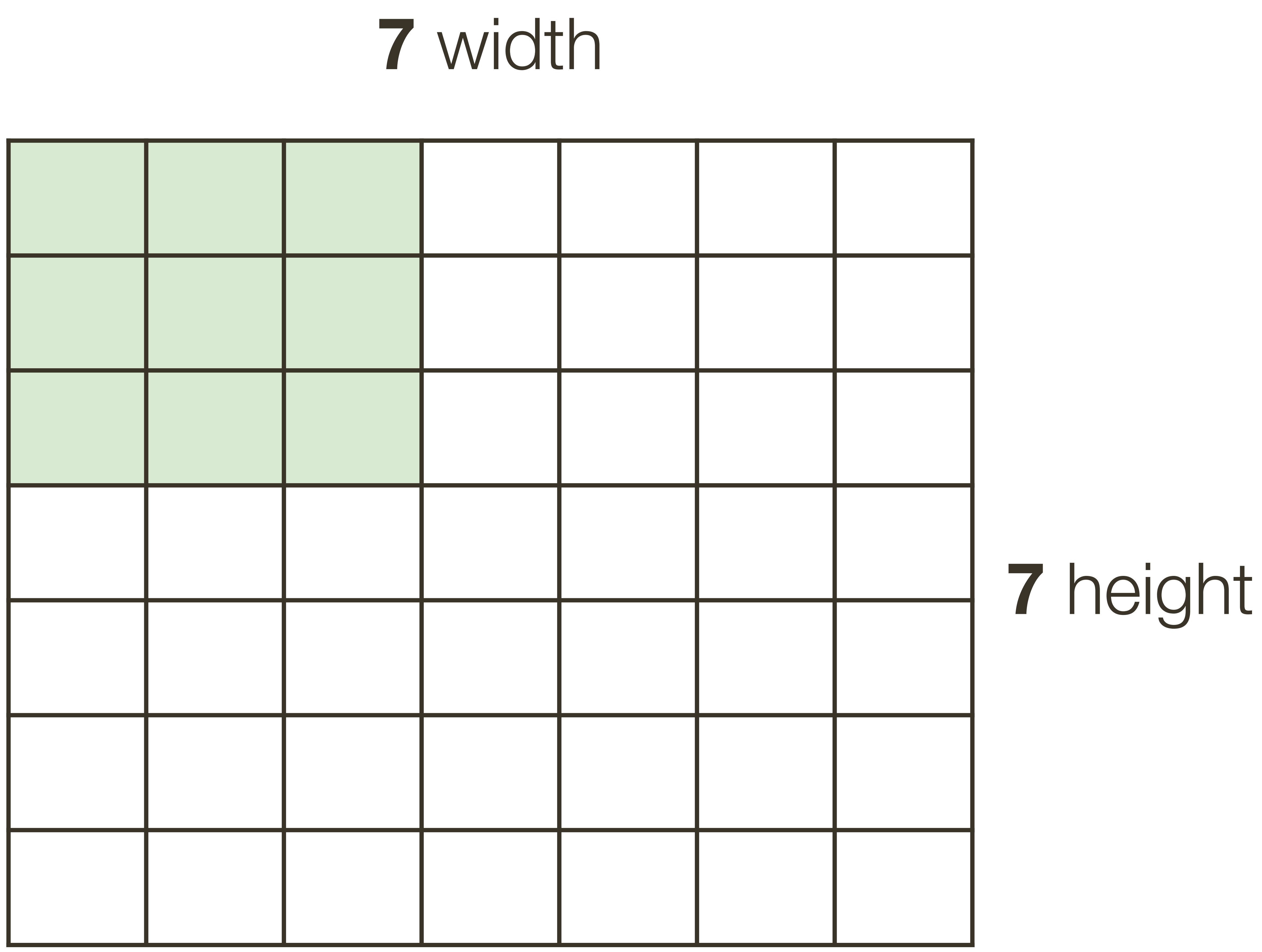
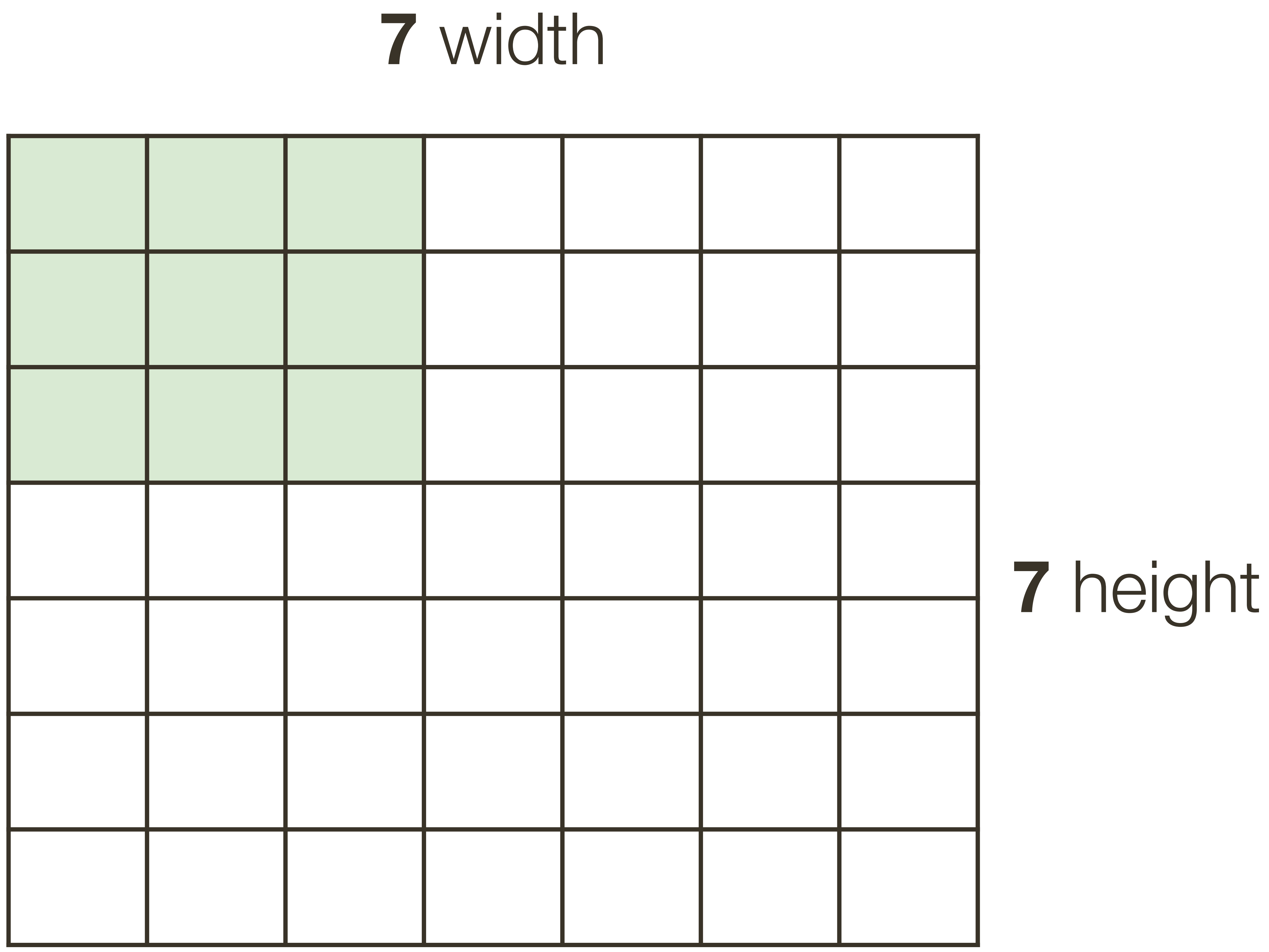
=> **3 x 3 output**

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



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

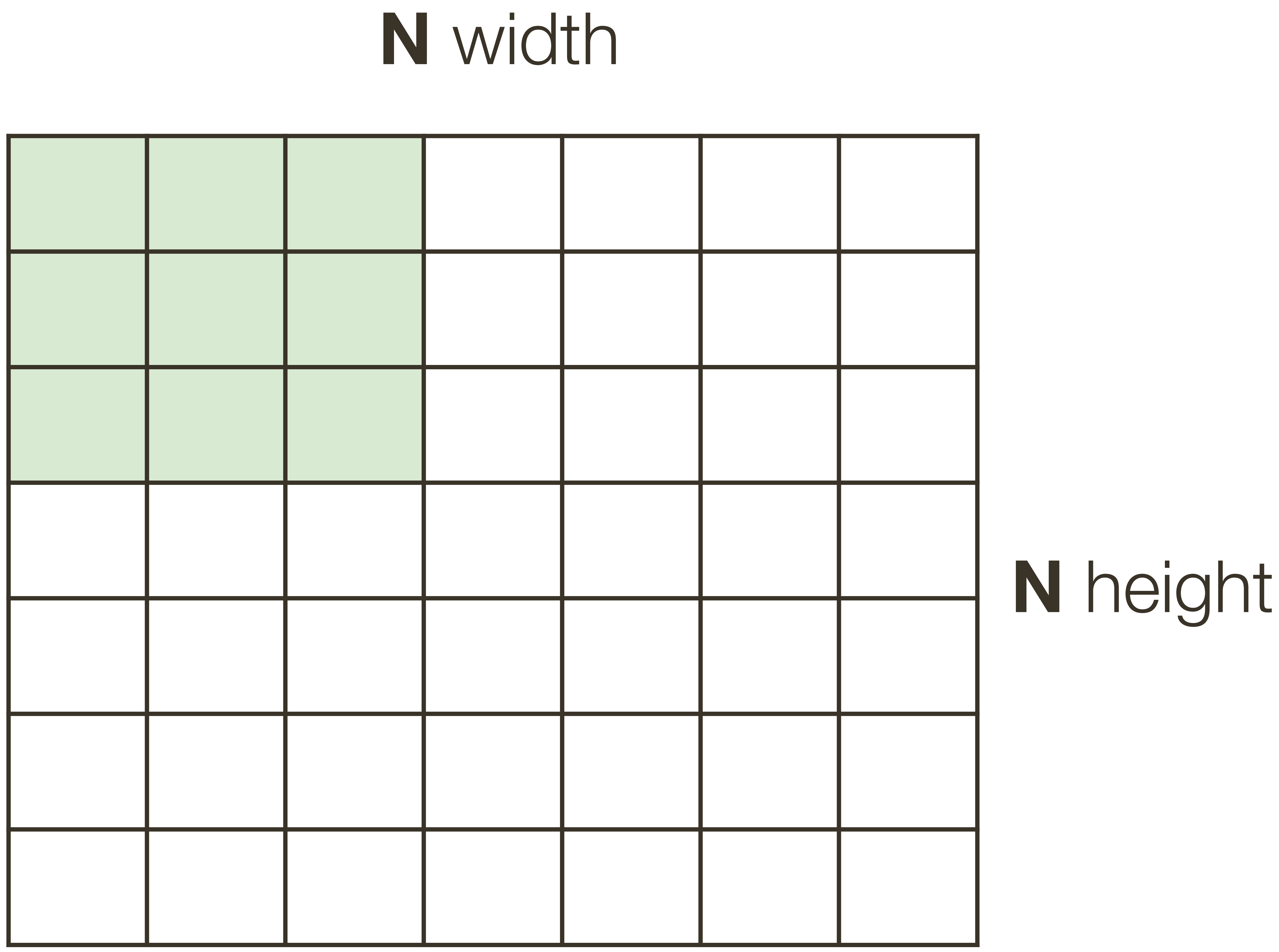
Convolutional Layer: Closer Look at **Spatial Dimensions**



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**

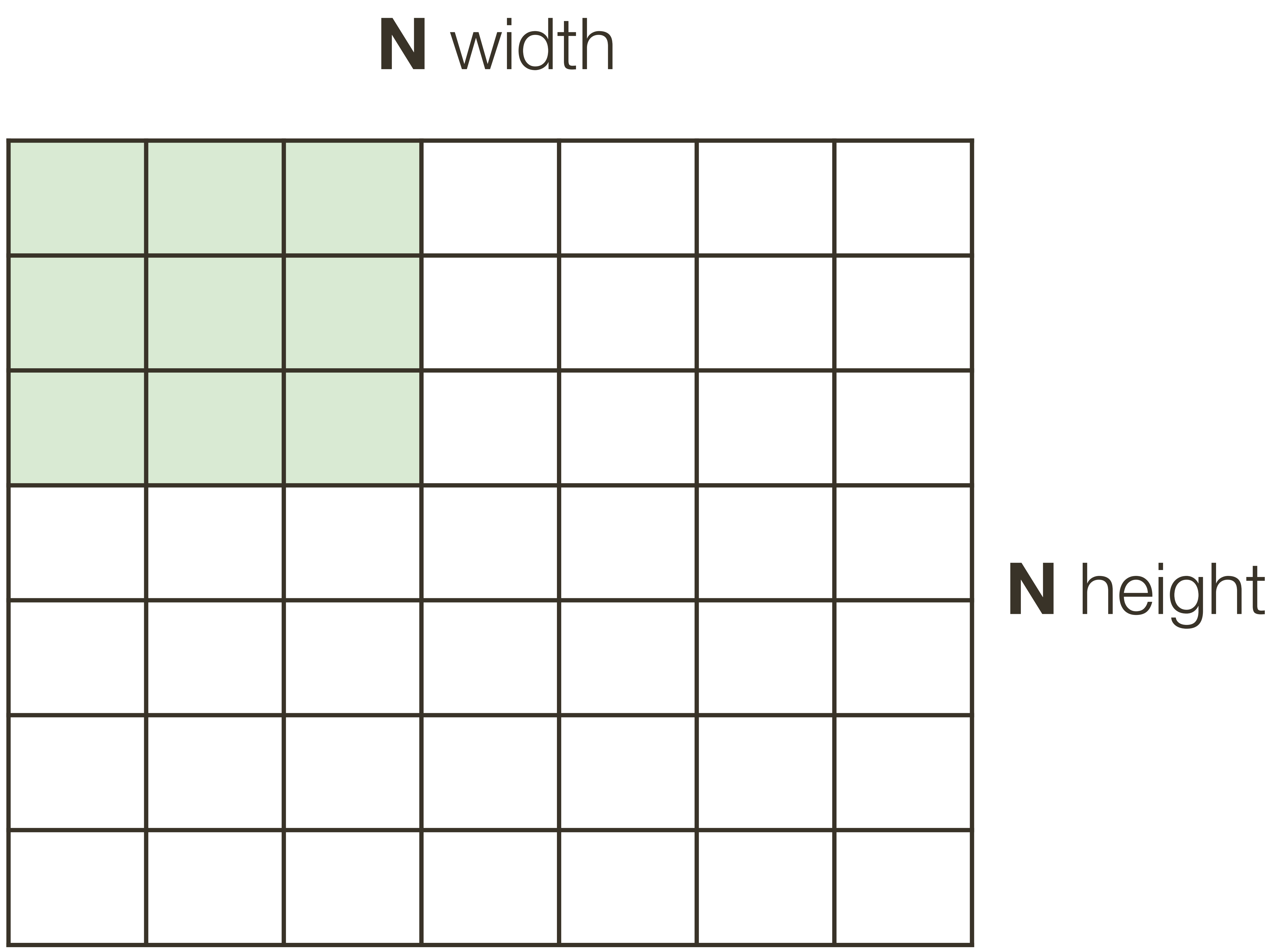


N x N input image (spatially)
F x F filter

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

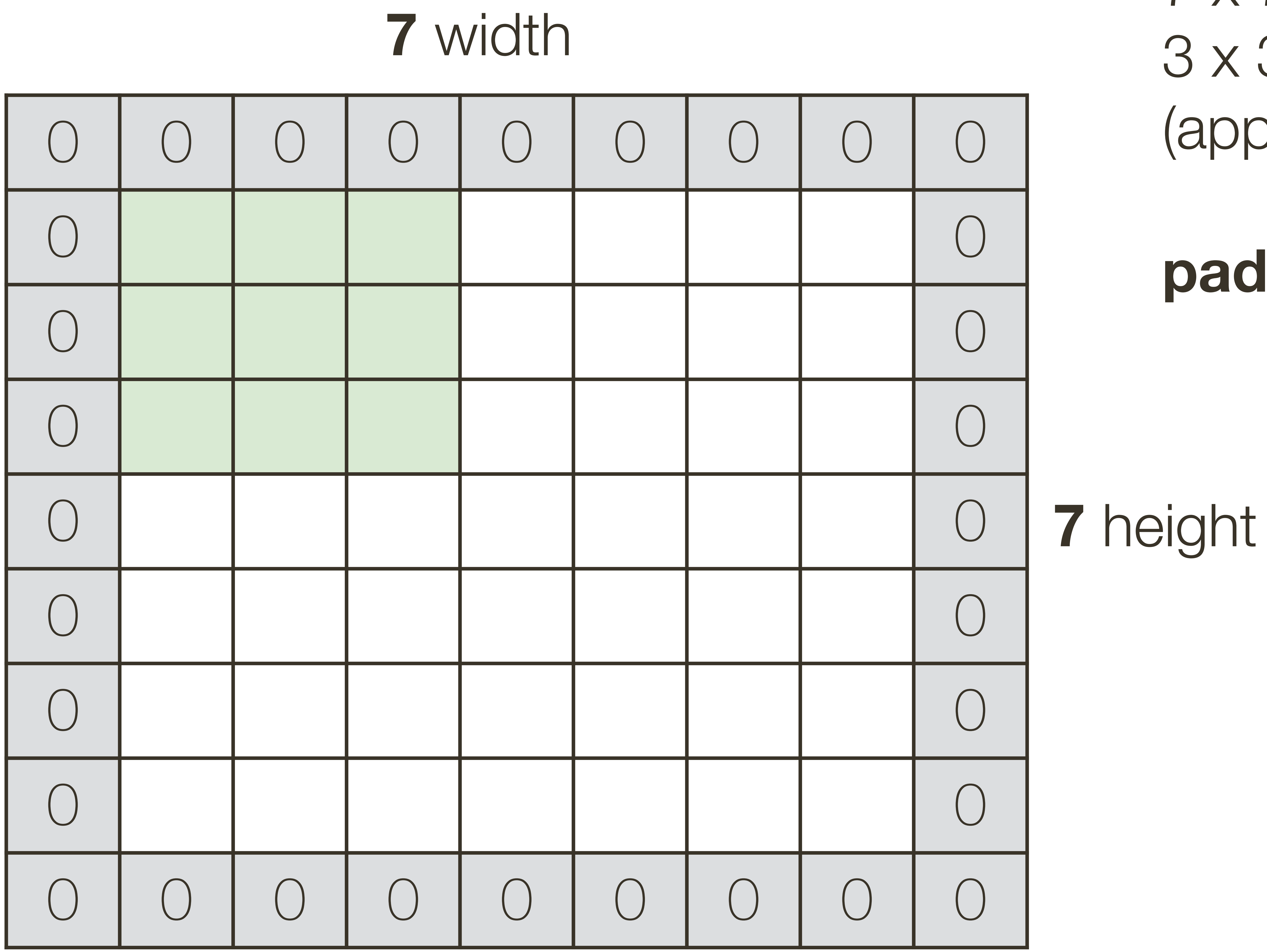
Output size: (N-F) / stride + 1

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**

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

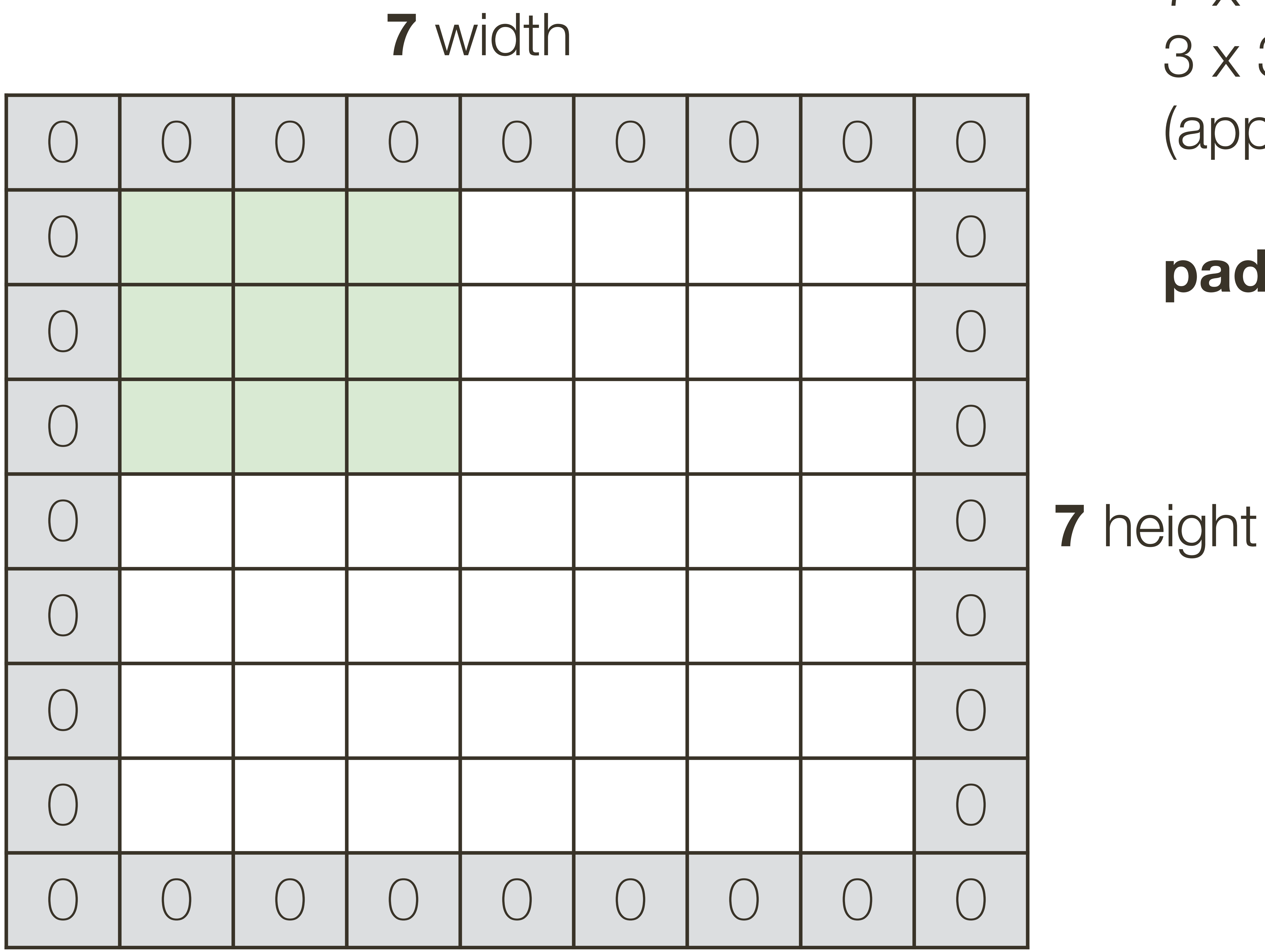
Convolutional Layer: **Border padding**



7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 1**)

pad with 1 pixel border

Convolutional Layer: **Border padding**



7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 1**)

pad with 1 pixel border

Output size: 7 x 7

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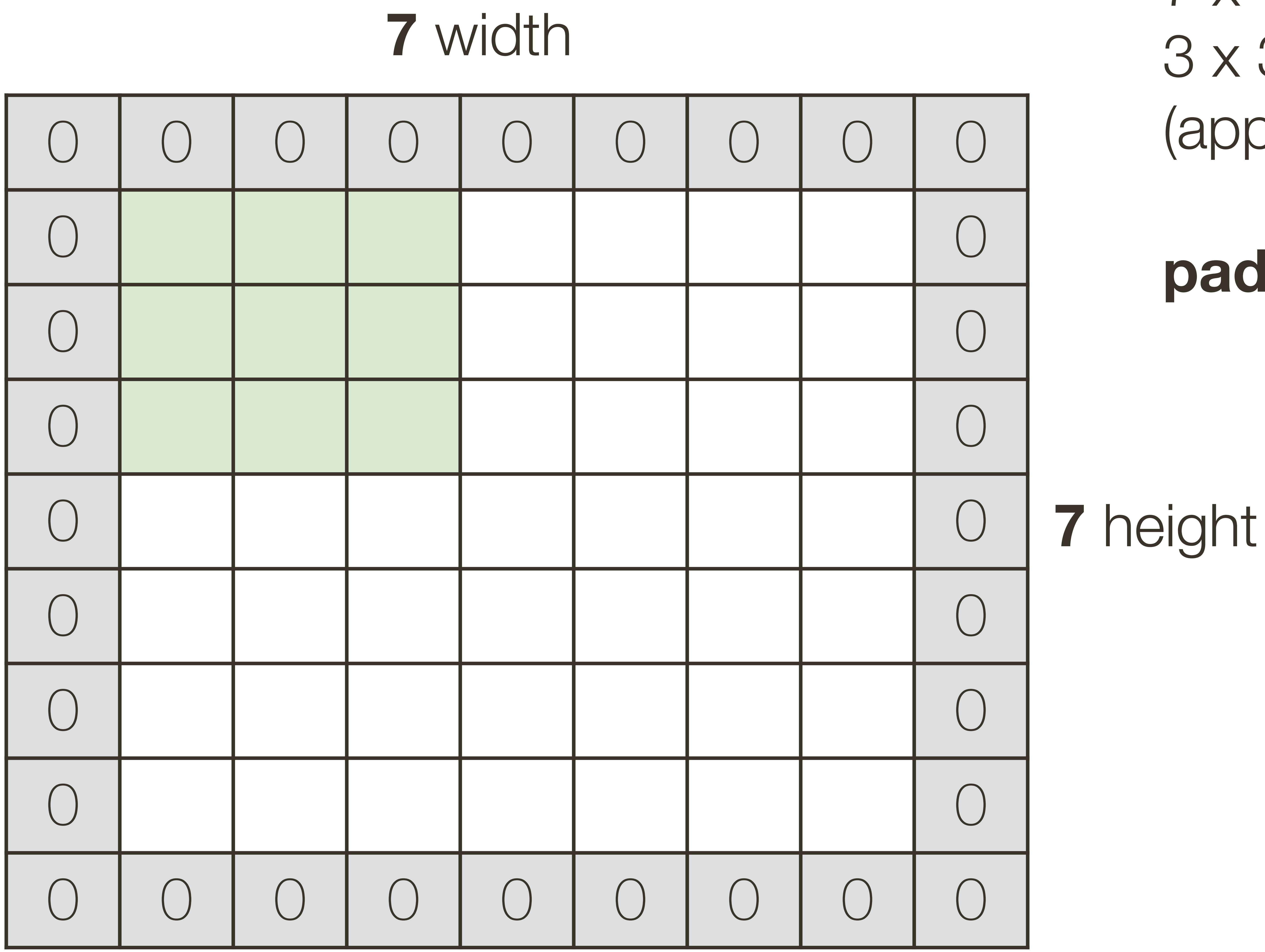
Convolutional Layer: **Border padding**



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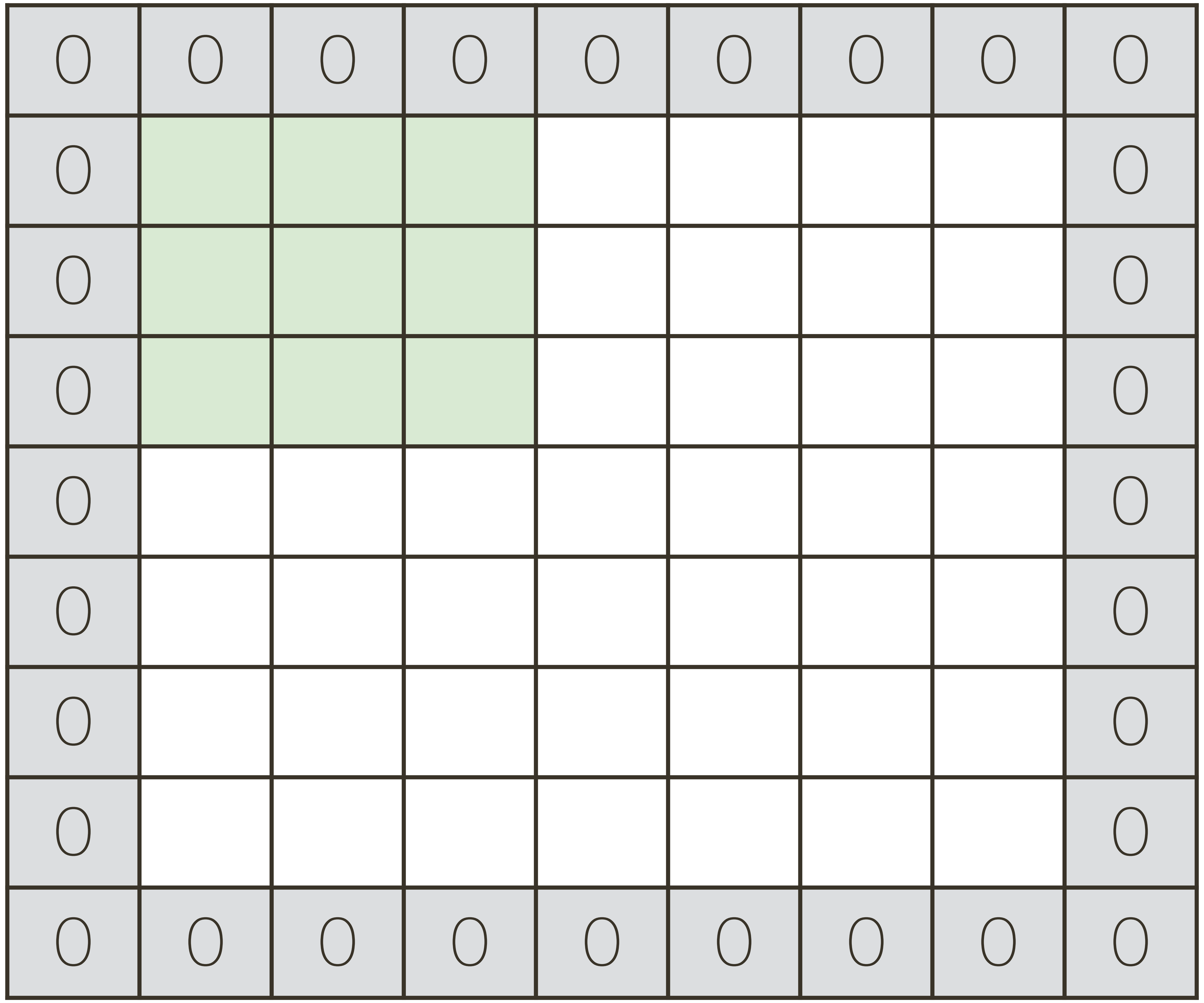
(applied with **stride 3**)

pad with 1 pixel border

Convolutional Layer: **Border padding**

7 width



7 height

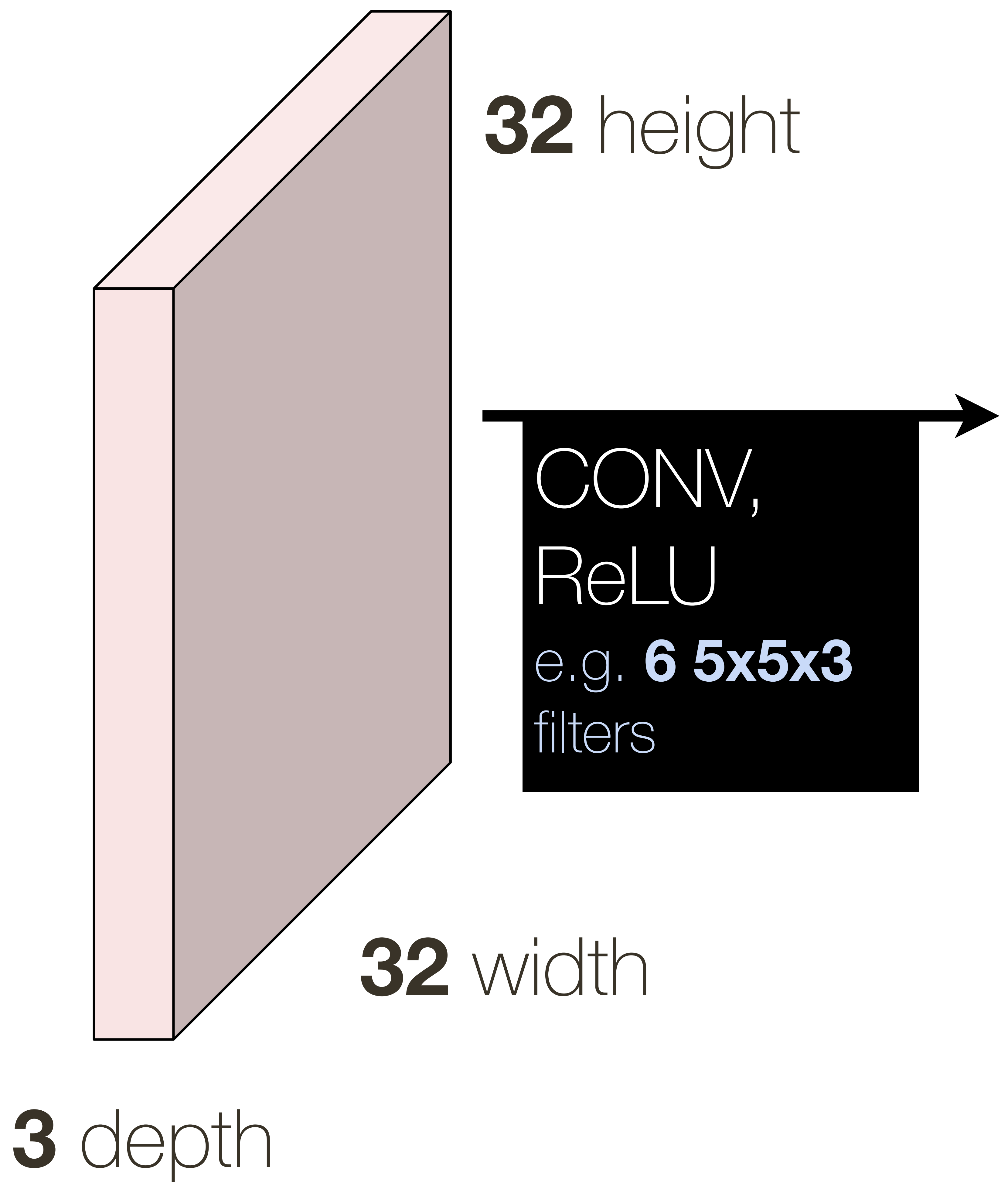
7 x 7 input image (spatially)
3 x 3 filter
(applied with **stride 3**)

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)



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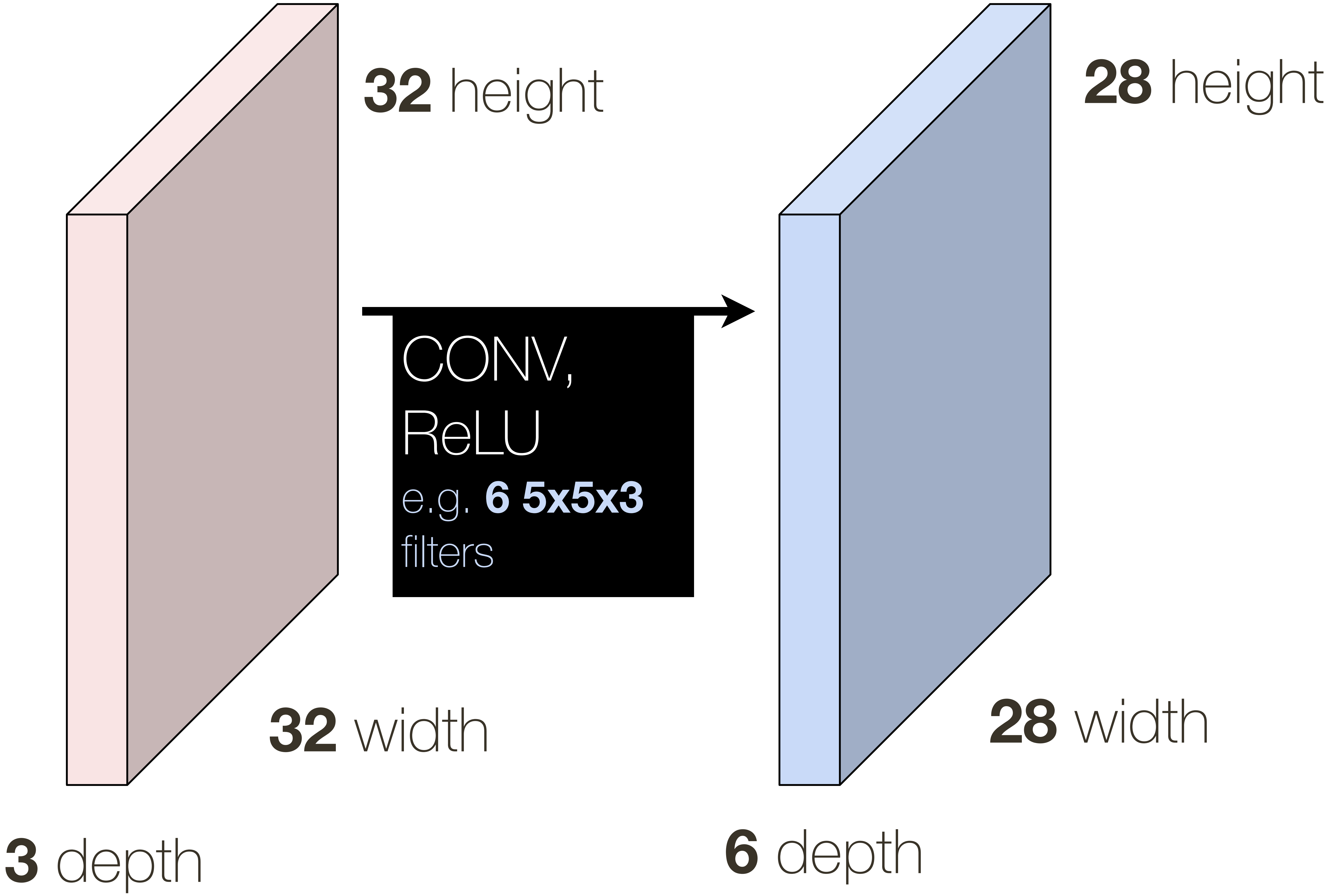

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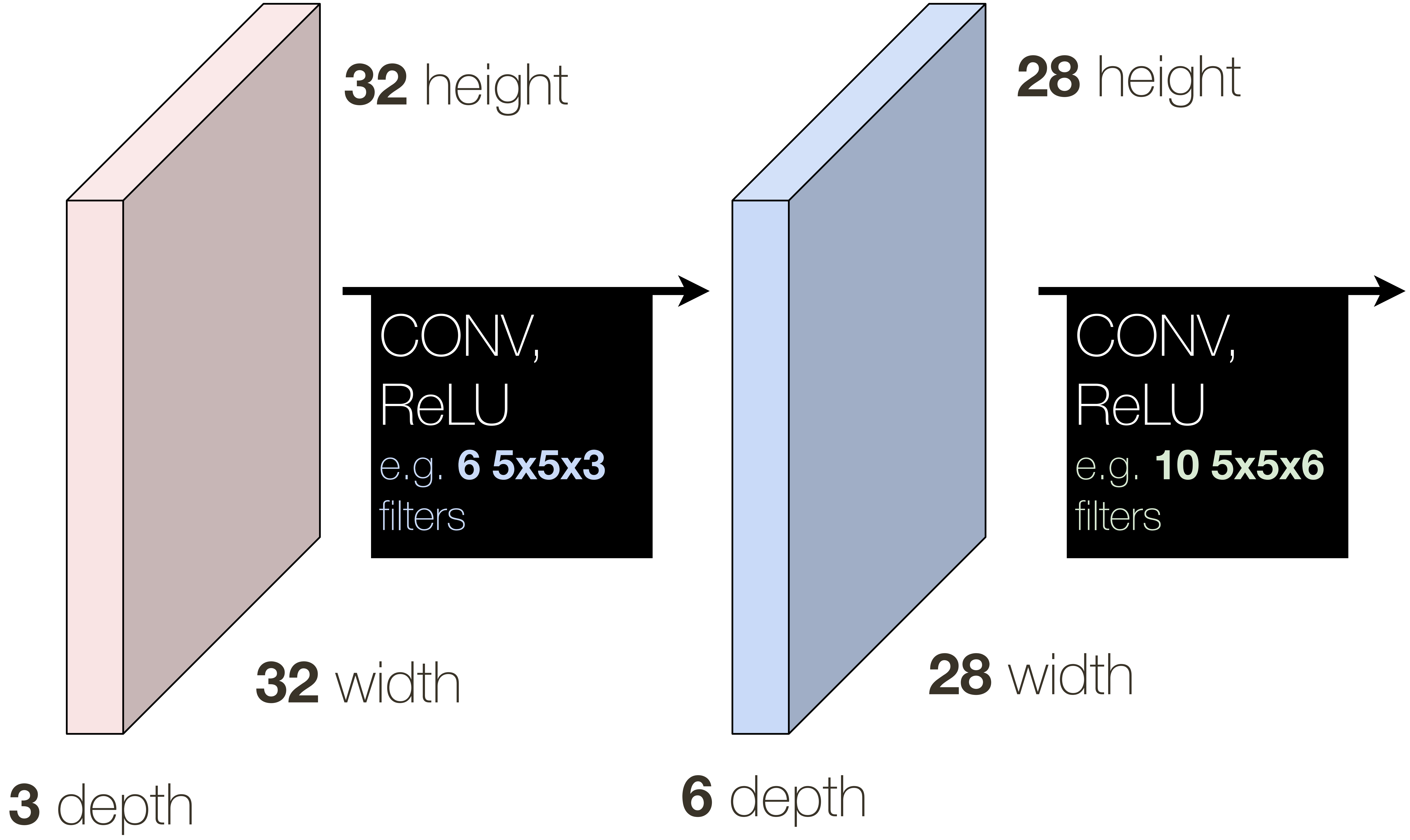

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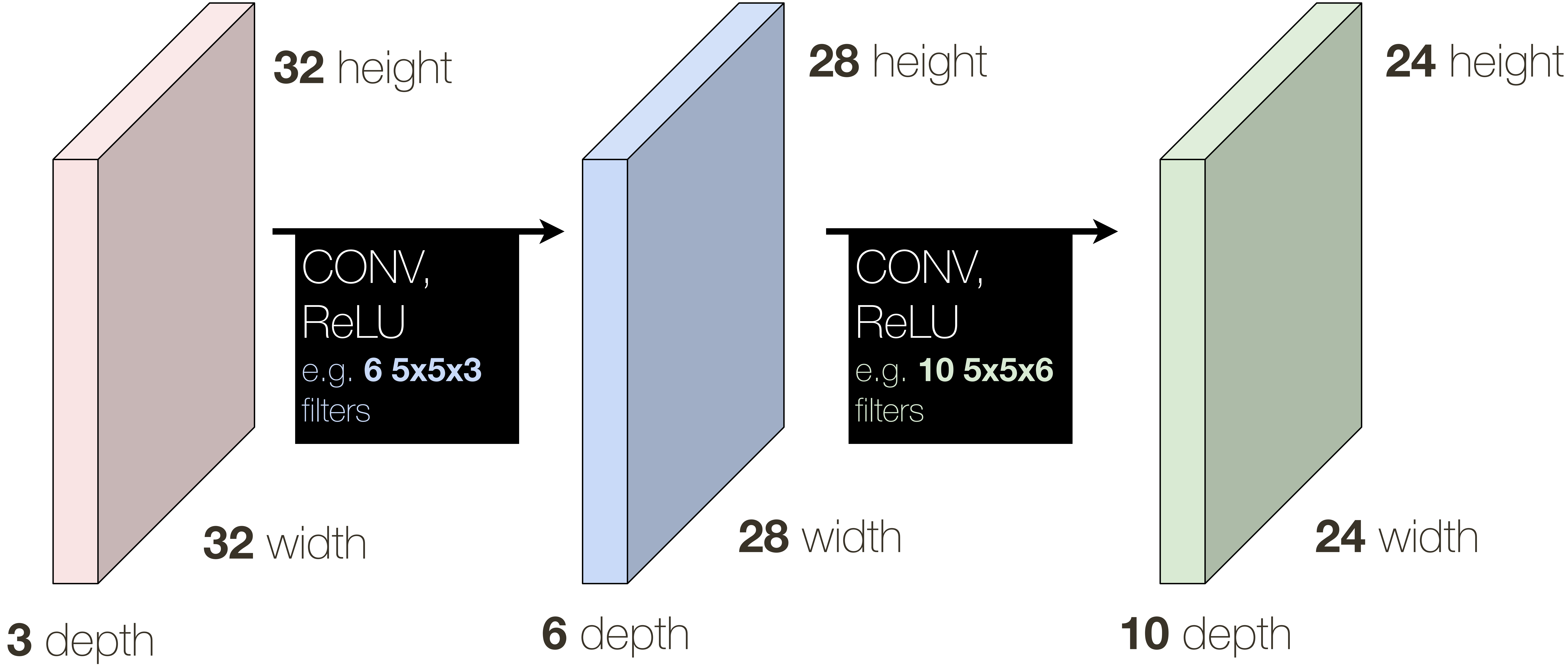

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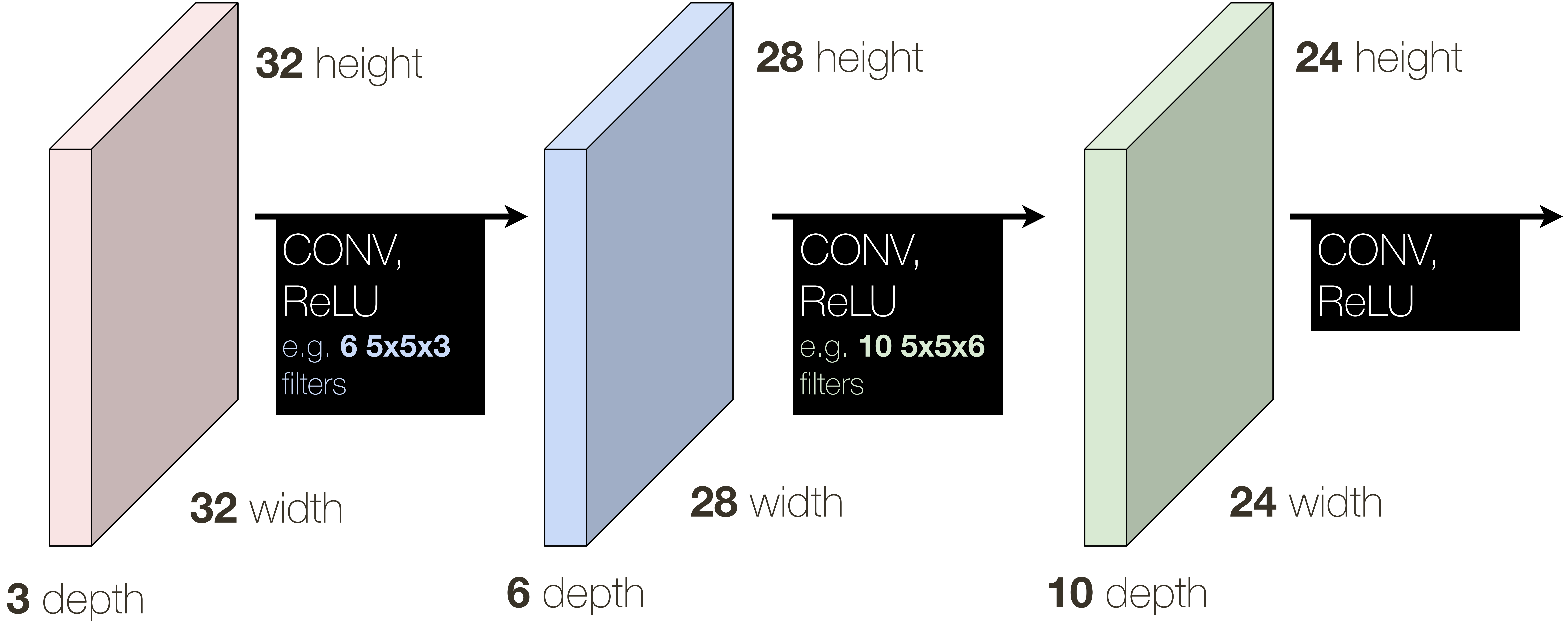
Convolutional Neural Network (ConvNet)



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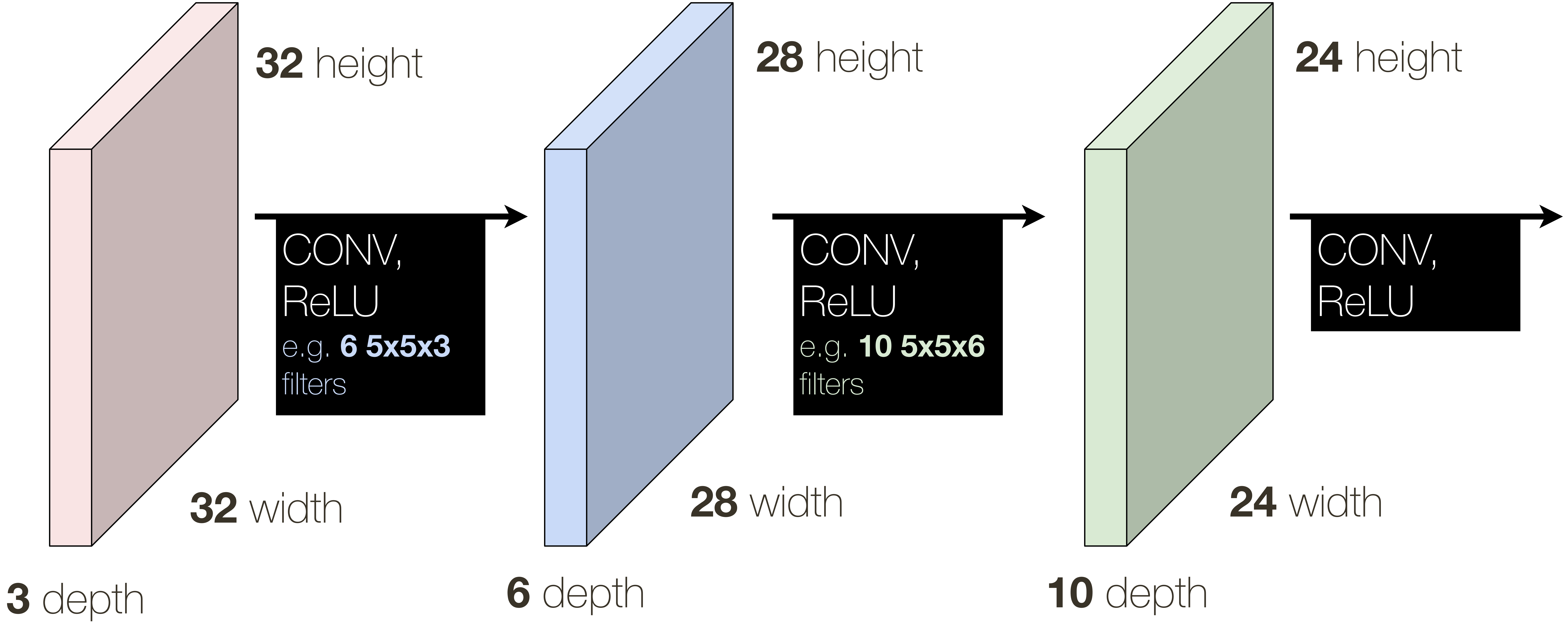
Convolutional Neural Network (ConvNet)

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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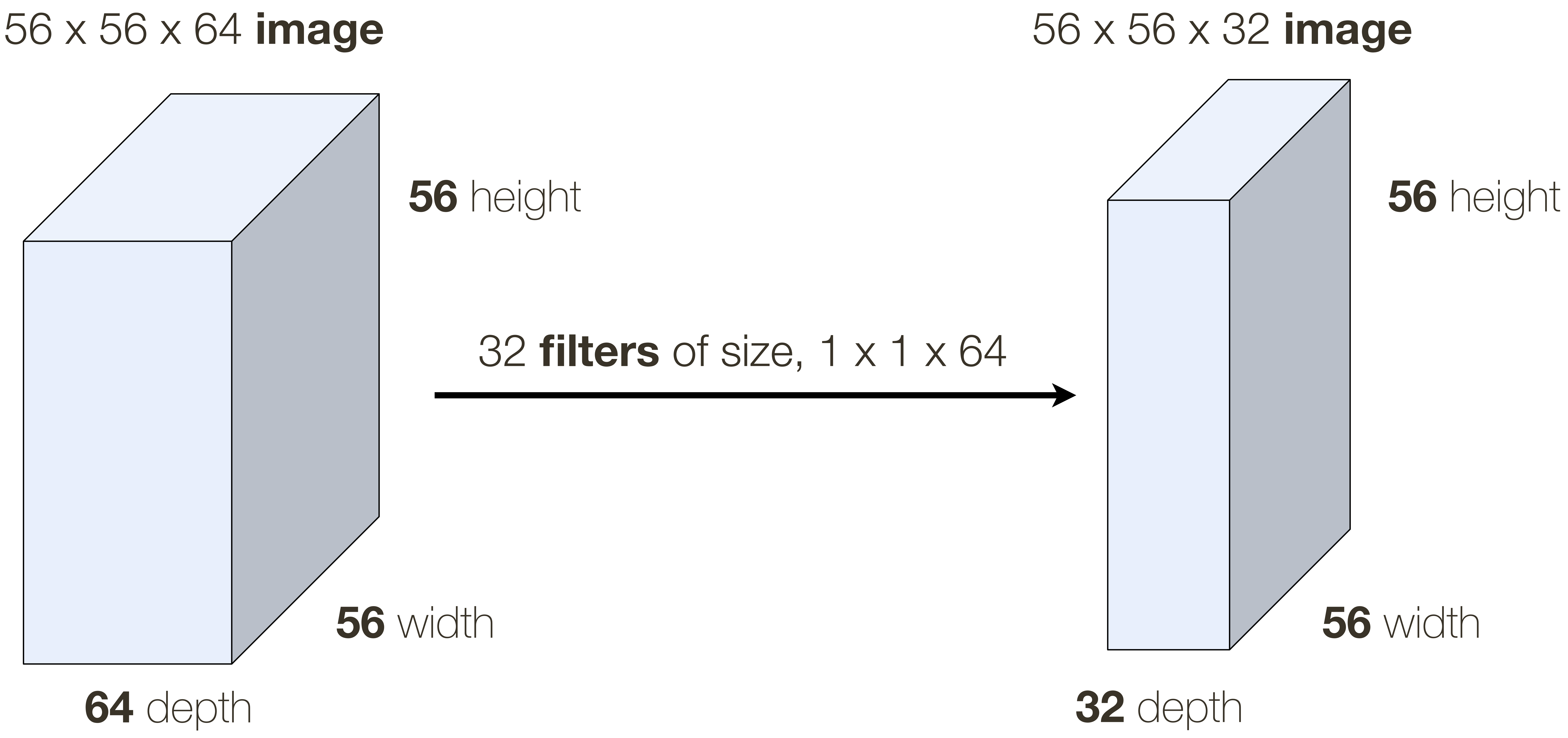
Convolutional Layer: **1x1 convolutions**



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Convolutional Layer **Summary**

Accepts a volume of size: $W_i \times H_i \times D_i$

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Requires hyperparameters:

— Number of filters: K (for typical networks $K \in \{32, 64, 128, 256, 512\}$)

— Spatial extent of filters: F (for a typical networks $F \in \{1, 3, 5, ...\}$)

— Stride of application: S (for a typical network $S \in \{1, 2\}$)

— Zero padding: P (for a typical network $P \in \{0, 1, 2\}$)

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Produces a volume of size: $W_o \times H_o \times D_o$

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Produces a volume of size: $W_o \times H_o \times D_o$

$$W_o = (W_i - F + 2P)/S + 1 \qquad H_o = (H_i - F + 2P)/S + 1 \qquad D_o = K$$

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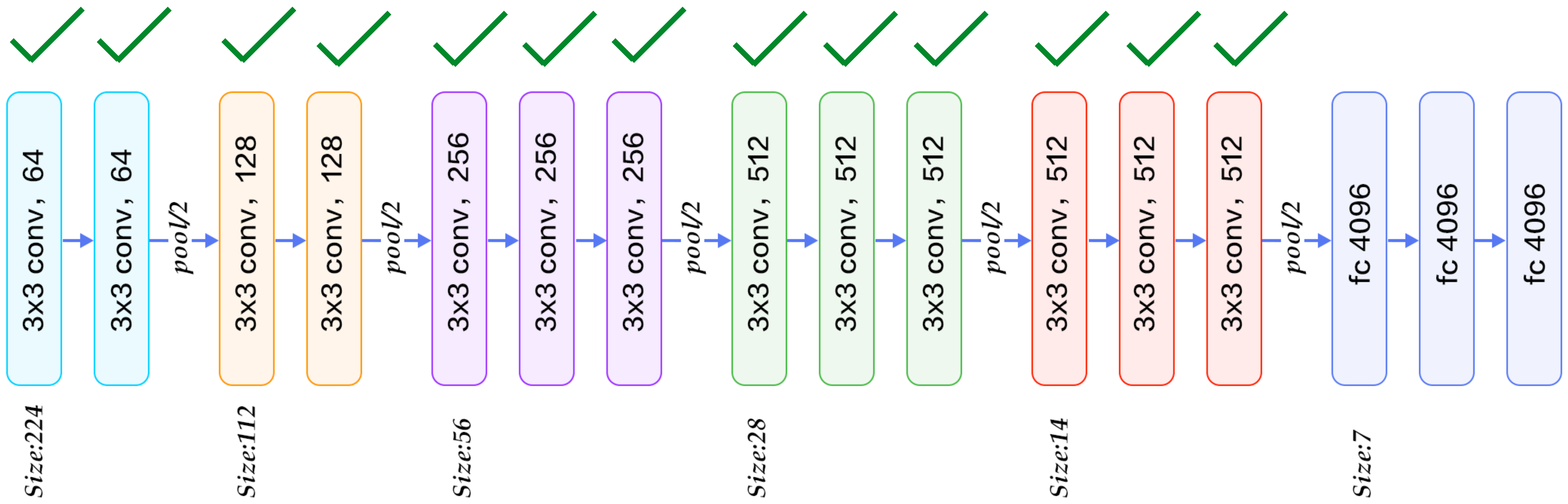
Produces a volume of size: $W_o \times H_o \times D_o$

$$W_o = (W_i - F + 2P)/S + 1 \qquad H_o = (H_i - F + 2P)/S + 1 \qquad D_o = K$$

Number of total learnable parameters: $(F \times F \times D_i) \times K + K$

Convolutional Neural Networks



VGG-16 Network

CNNs: Reminder Fully Connected Layers

Input

$$\mathbf{W}^T\mathbf{x} + \mathbf{b}, \text{ where } \mathbf{W} \in \mathbb{R}^{10\times 3072}$$

Activation

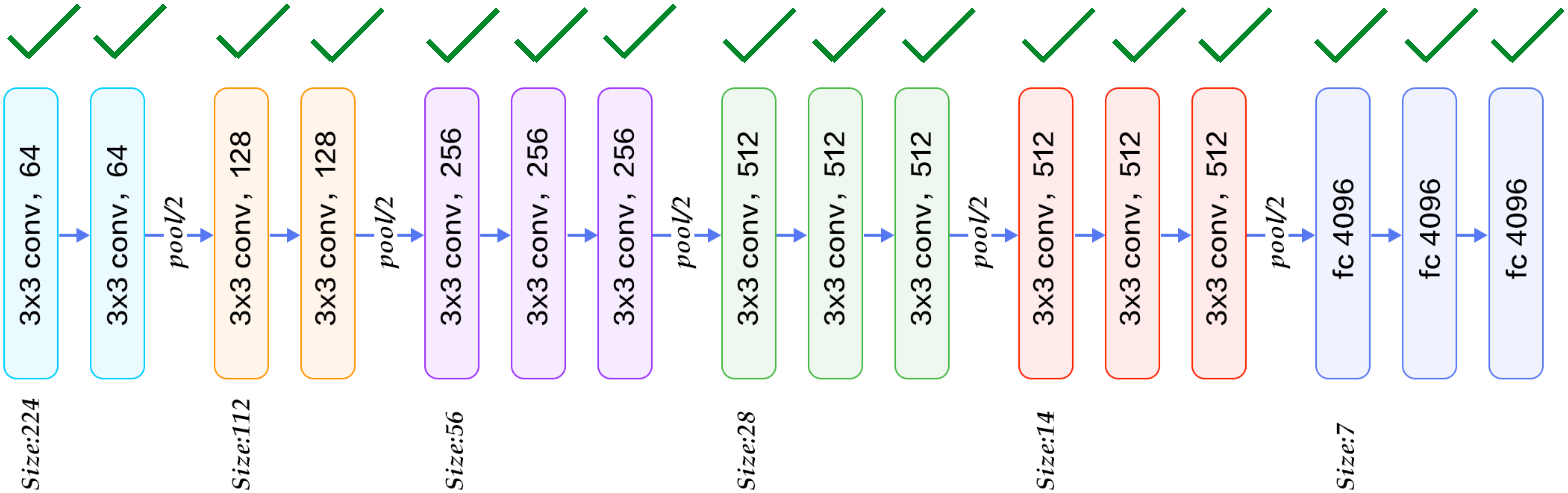
3072

(32 x 32 x 3 image -> stretches to 3072 x 1)

each neuron looks at the full input volume

10

Convolutional Neural Networks



VGG-16 Network

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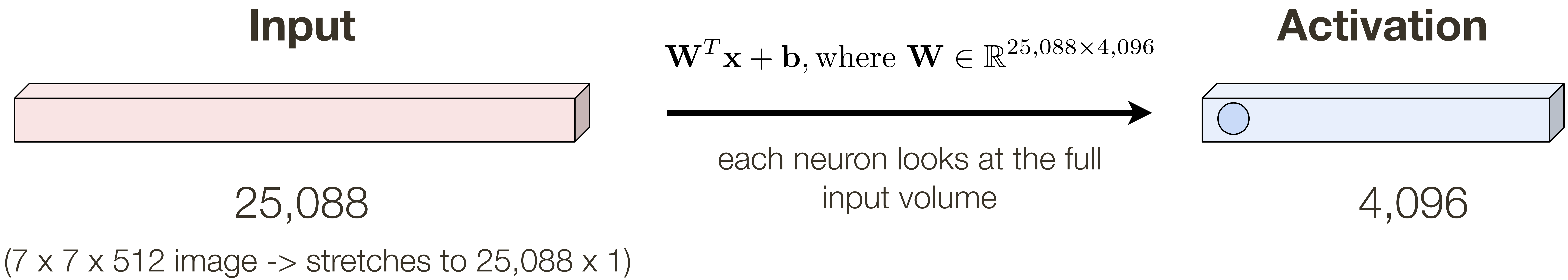


* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

CNNs: Reminder Fully Connected Layers

Input

Activation

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

each neuron looks at the full input volume

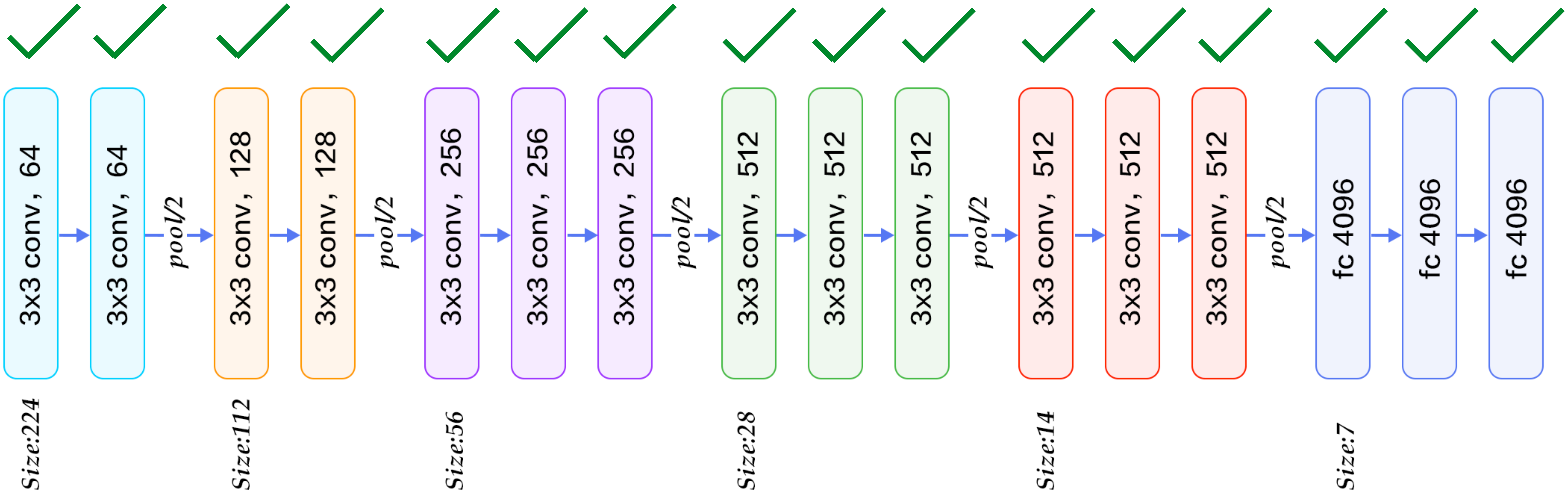
25,088

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

4,096

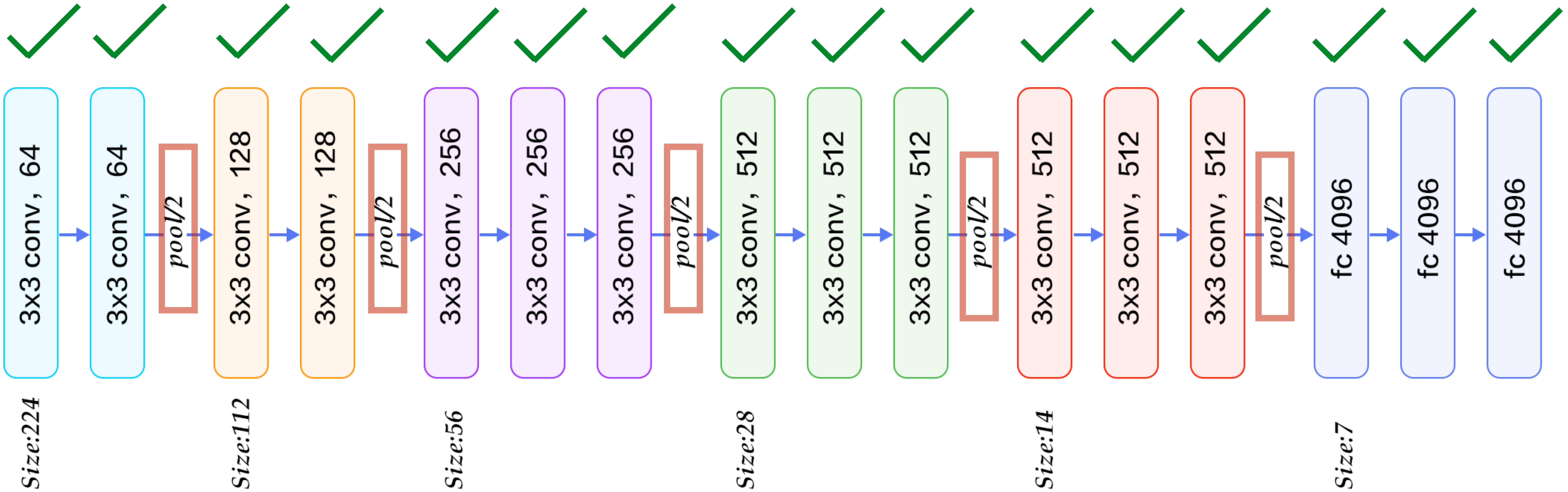
102,760,448 parameters!

Convolutional Neural Networks



VGG-16 Network

Convolutional Neural Networks



VGG-16 Network

Invariance vs. **Equivariance**

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Invariance: A mathematical object (or class of mathematical objects) remains unchanged after transformations of certain types applied to the objects

$$f(x) = f(g(x))$$

Invariance vs. **Equivariance**

Invariance: A mathematical object (or class of mathematical objects) remains unchanged after transformations of certain types applied to the objects

$$f(x) = f(g(x))$$

Equivariance: Applying a transformation and then computing the function produces the same result as computing the function and then applying a transformation

$$g(f(x)) = f(g(x))$$

Revisit **Layers** we Learned About

Fully Connected:

Revisit **Layers** we Learned About

Fully Connected:

— **<u>Not</u>** invariant to any transformations

— **<u>Not</u>** equivariant to any transformations

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Convolutional:

Revisit **Layers** we Learned About

Fully Connected:

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— **Not** equivariant to any transformations

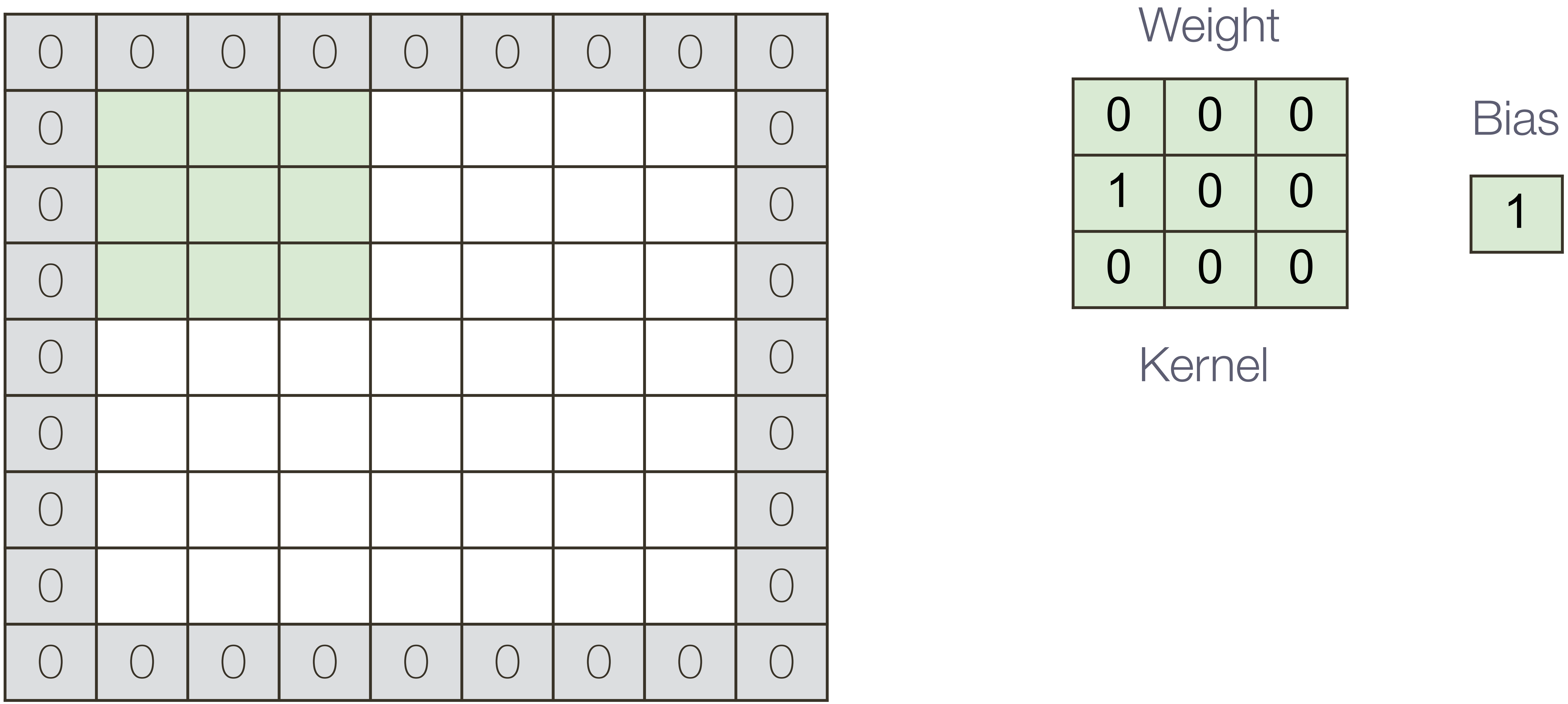
Convolutional:

— **Not** invariant to any transformations

— Convolution is **translation equivariant**

Note: convolution can “learn” not to be equivariant when padding is used.

Revisit **Layers** we Learned About



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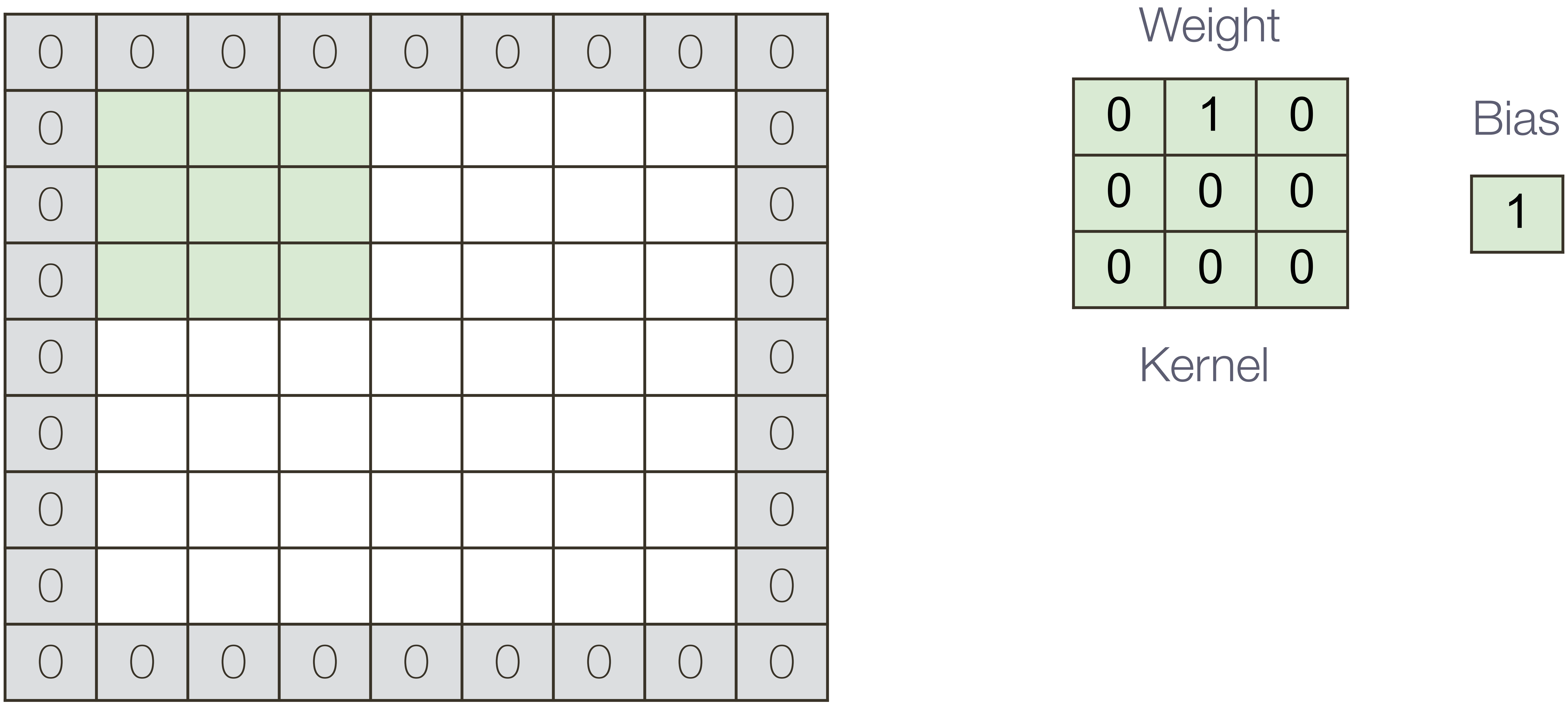
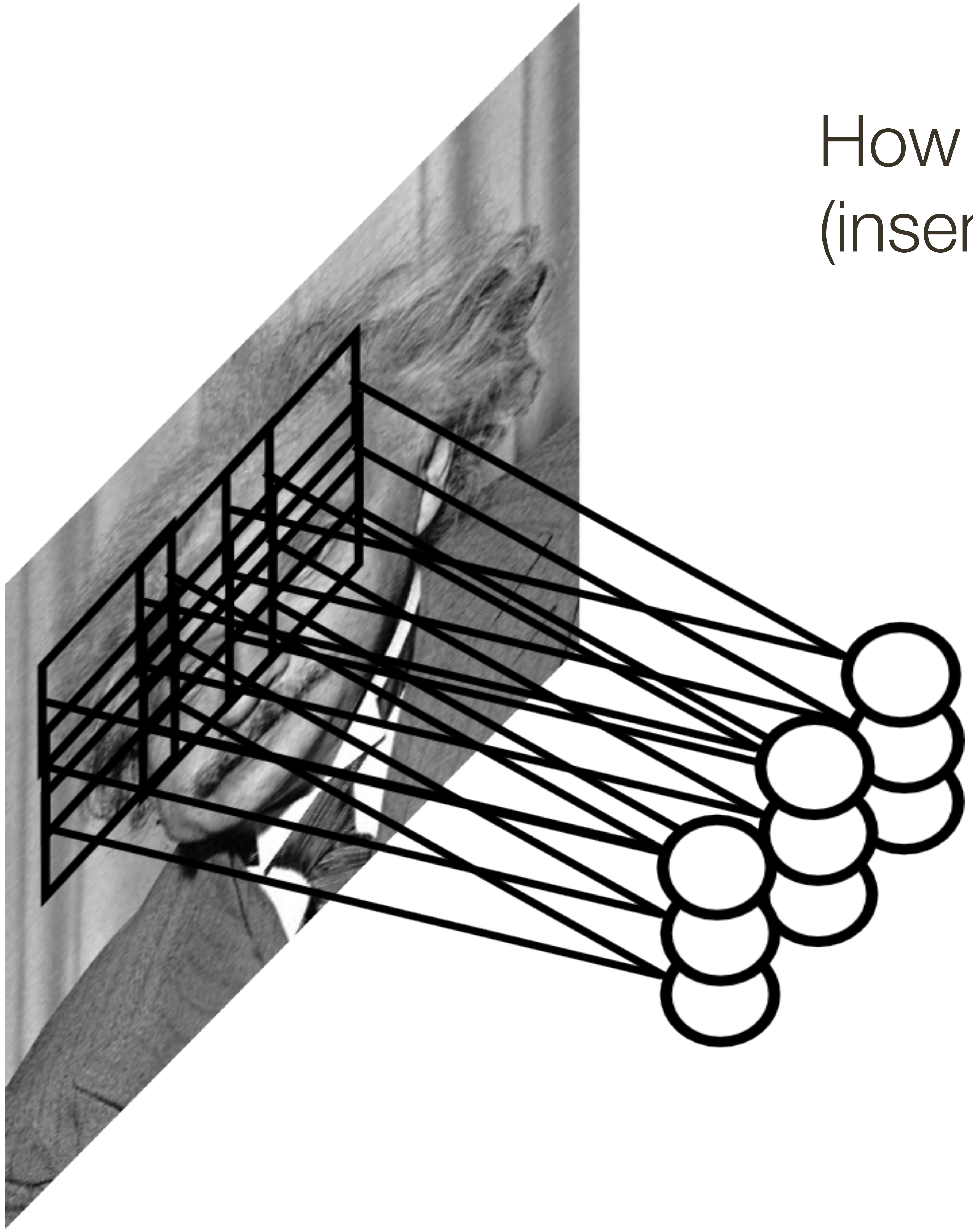


Pooling Layer

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)



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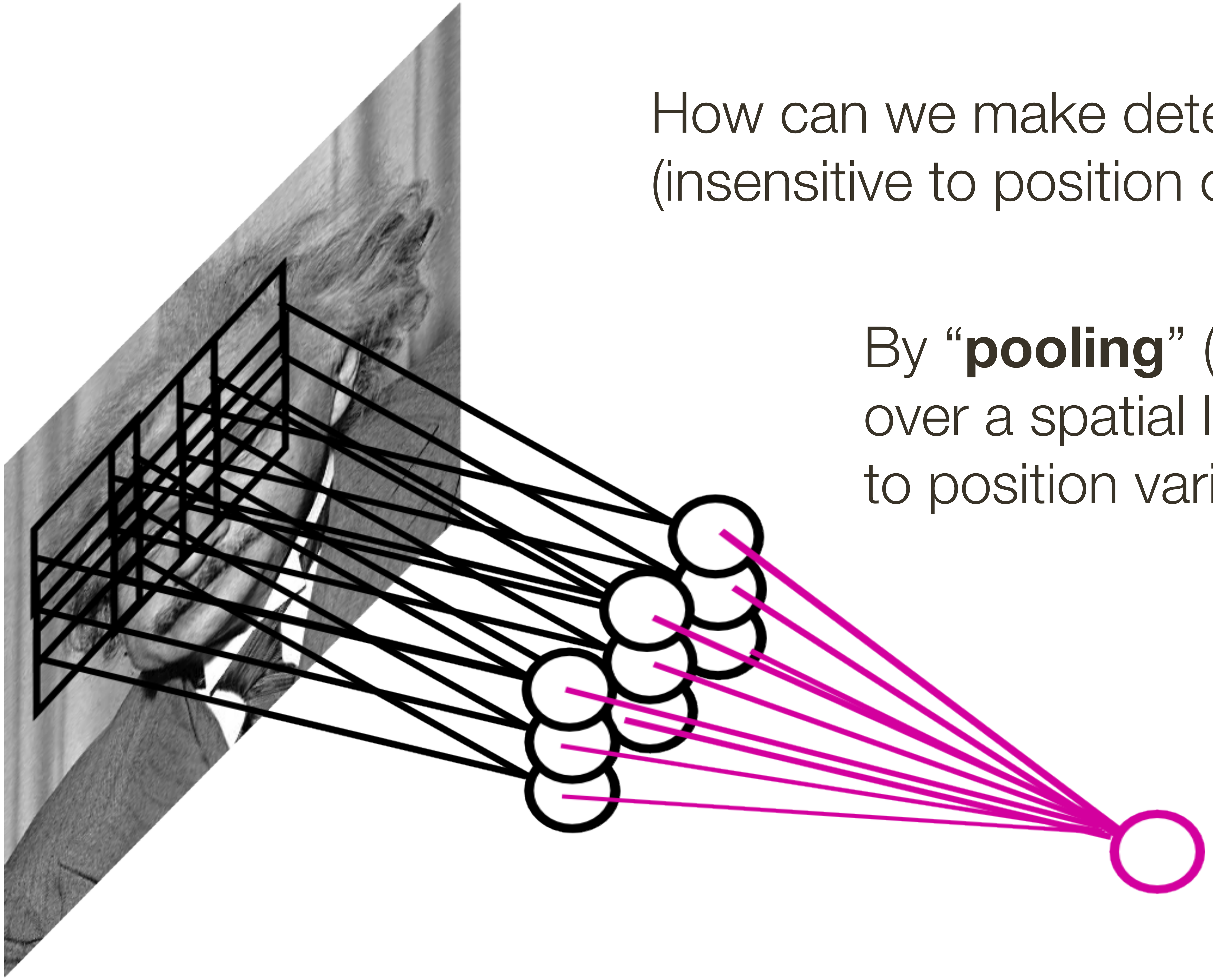
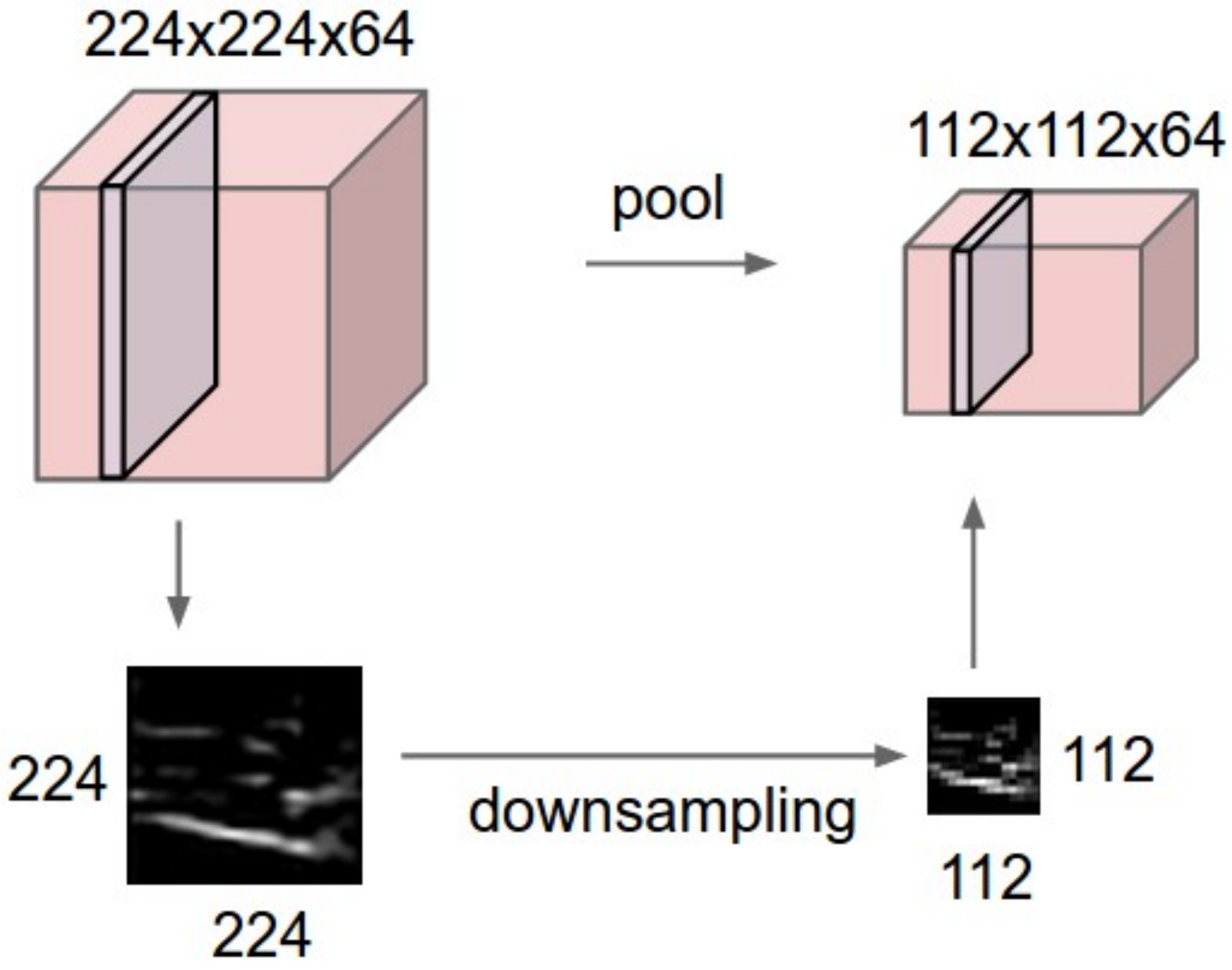


By “**pooling**” (e.g., taking a max) response over a spatial locations we gain robustness to position variations

* slide from Marc’Aurelio Renzato

Pooling Layer

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



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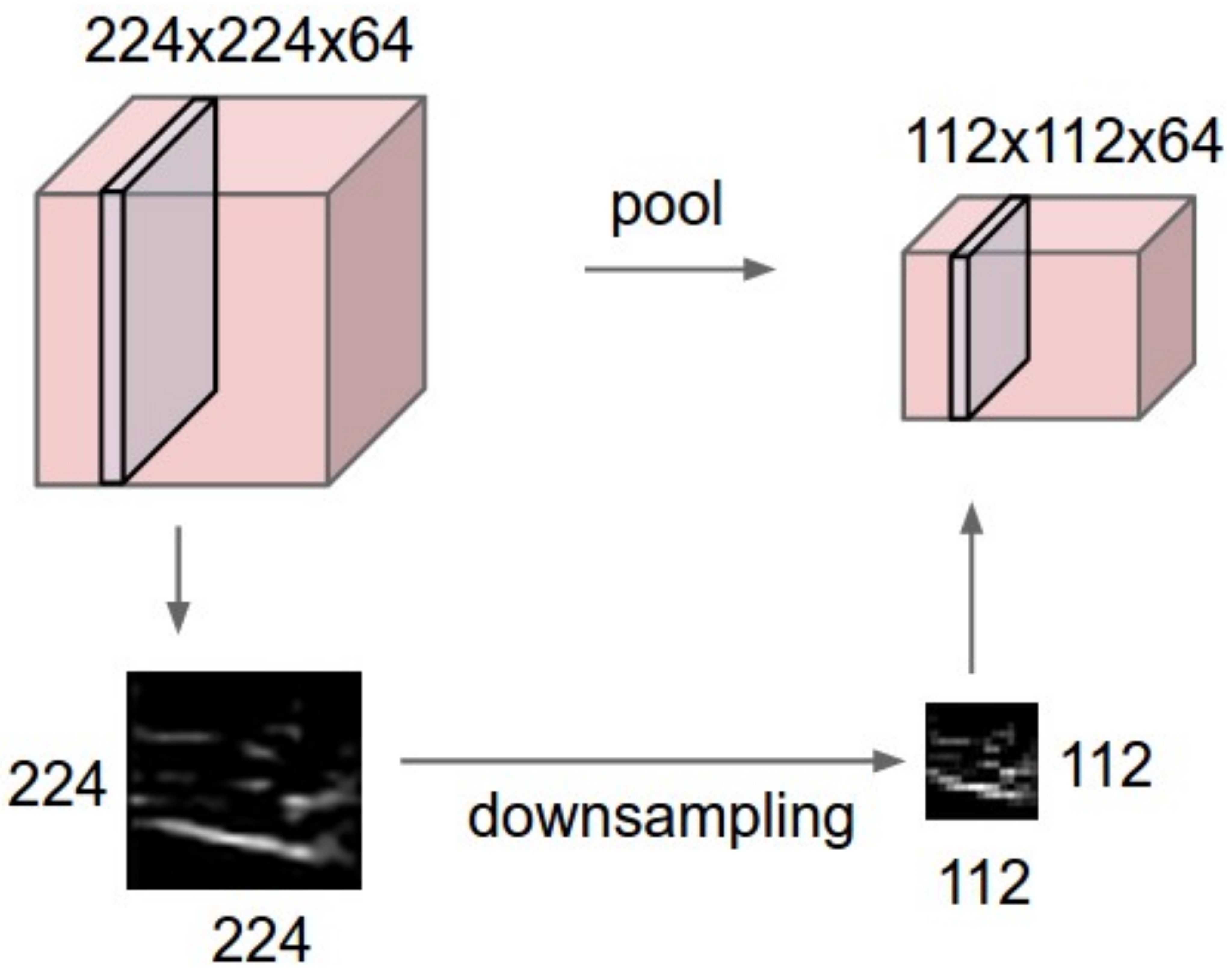

How many **parameters**?

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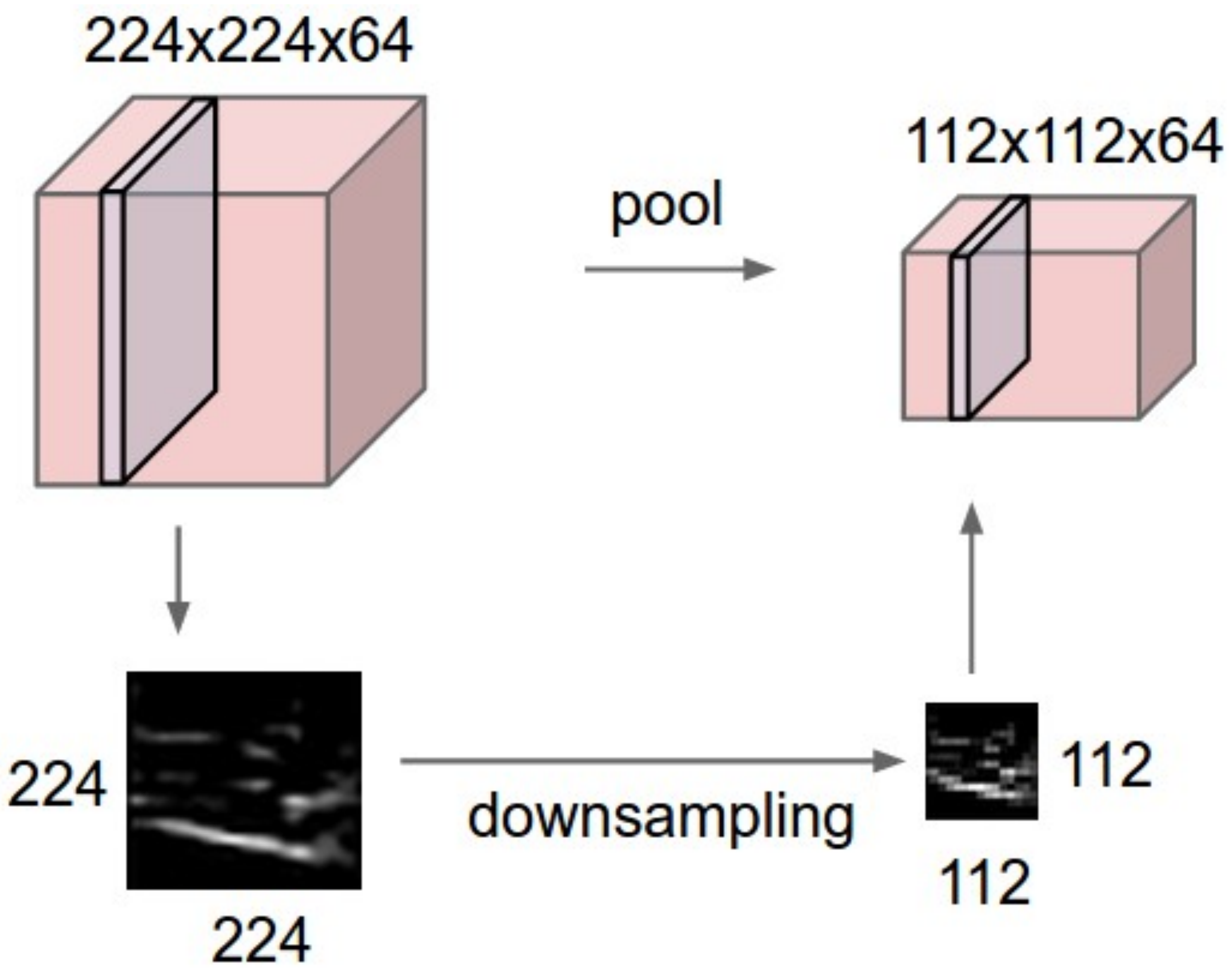

How many **parameters**?

None!

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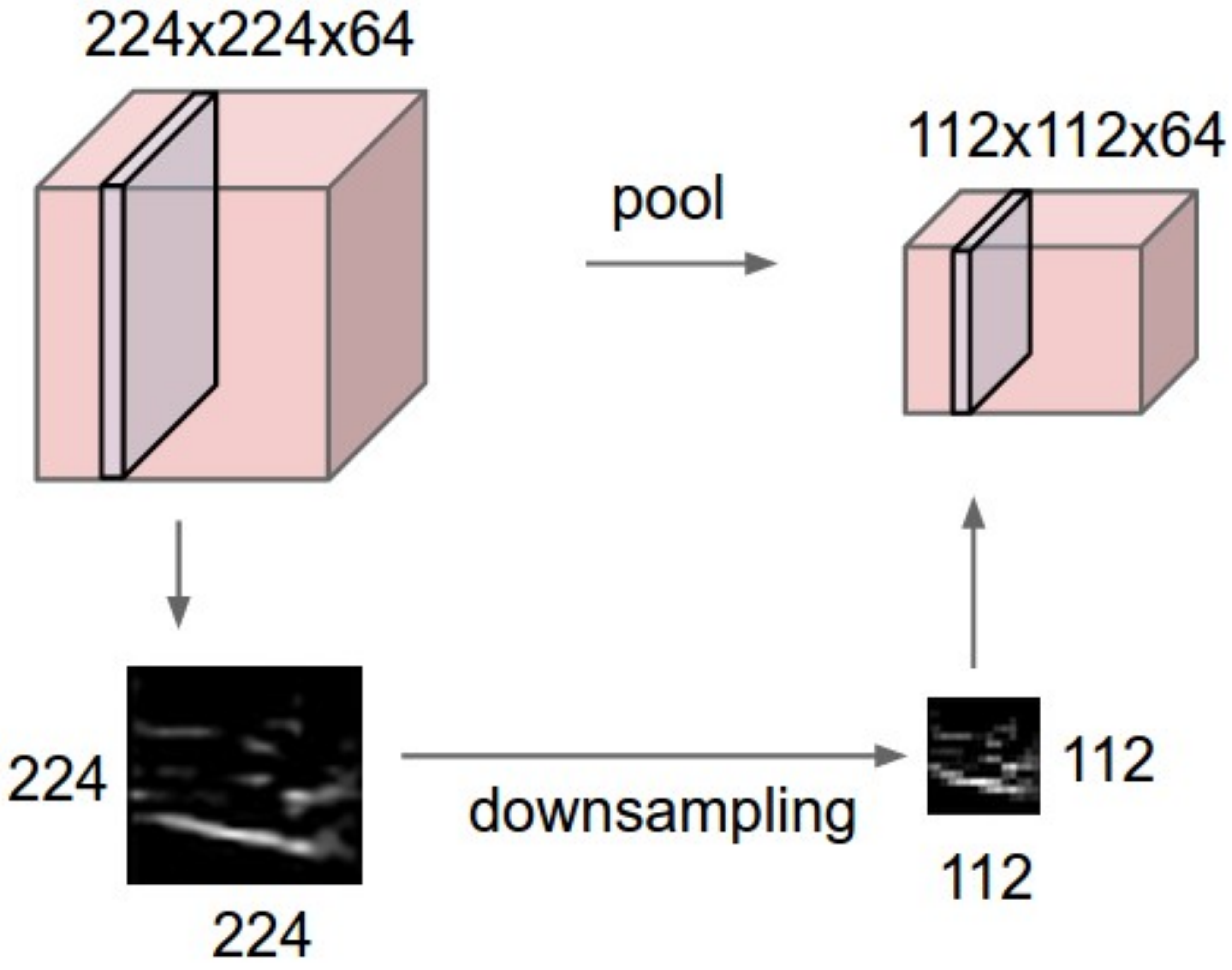

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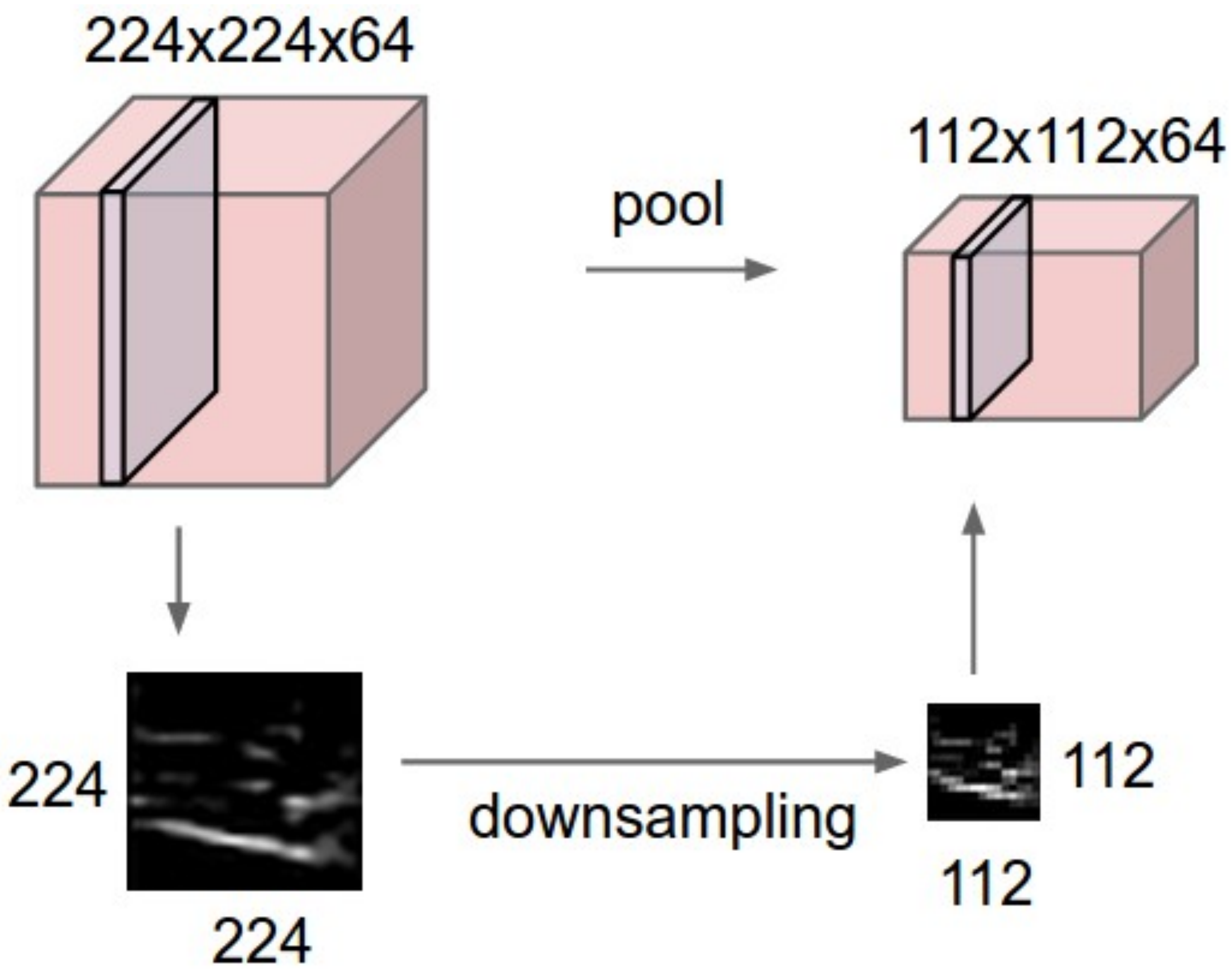
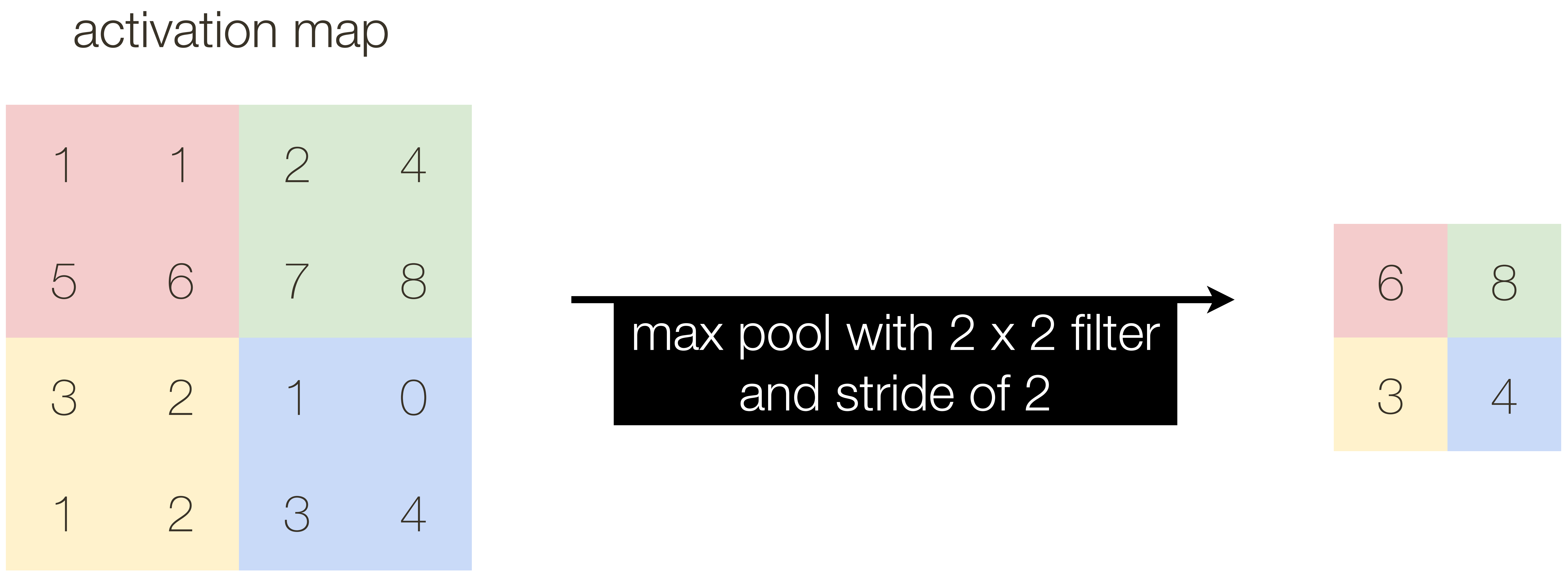


How do we implement that in a **computation graph**?

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

Max **Pooling**



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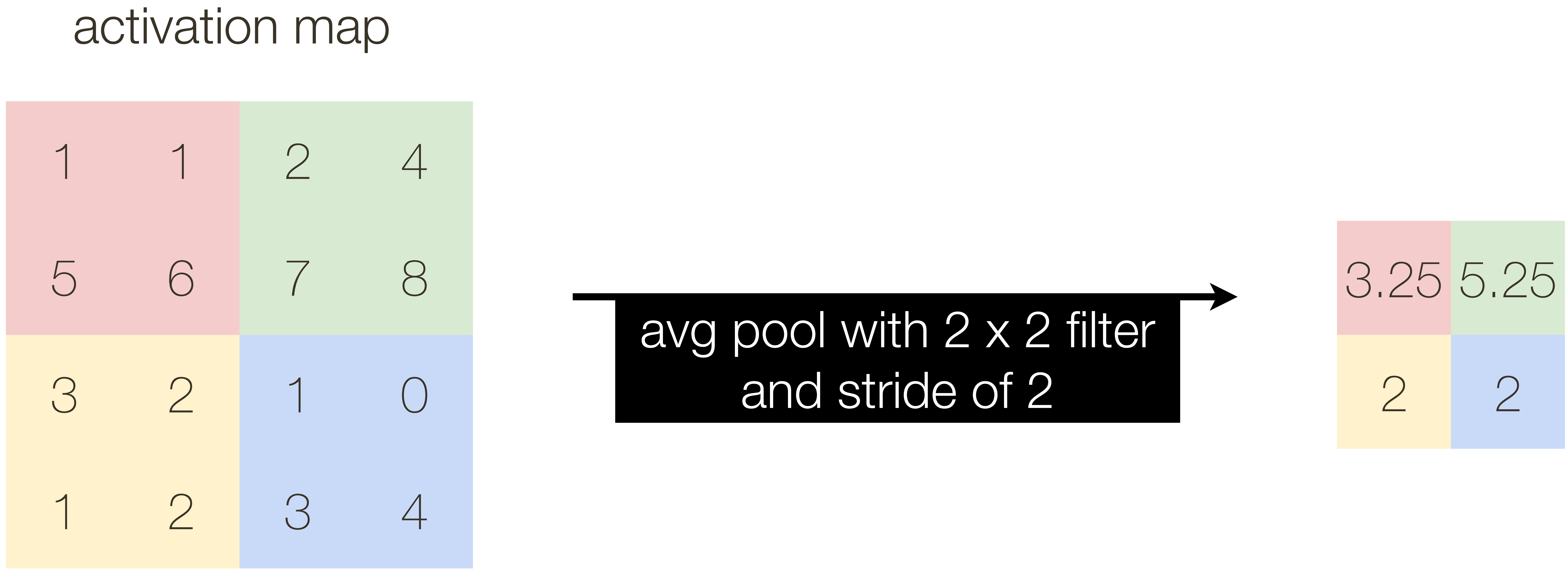
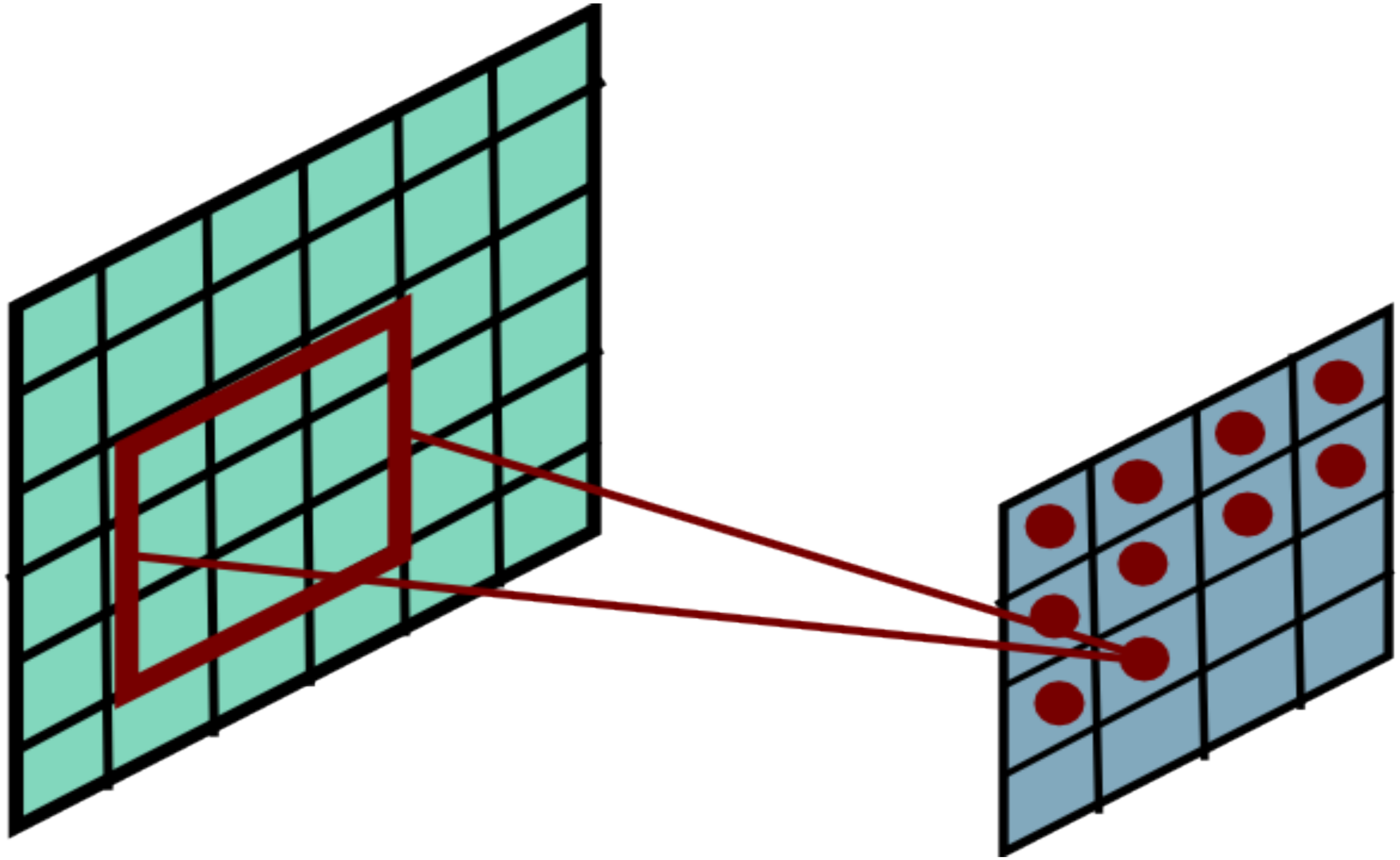
Average **Pooling**



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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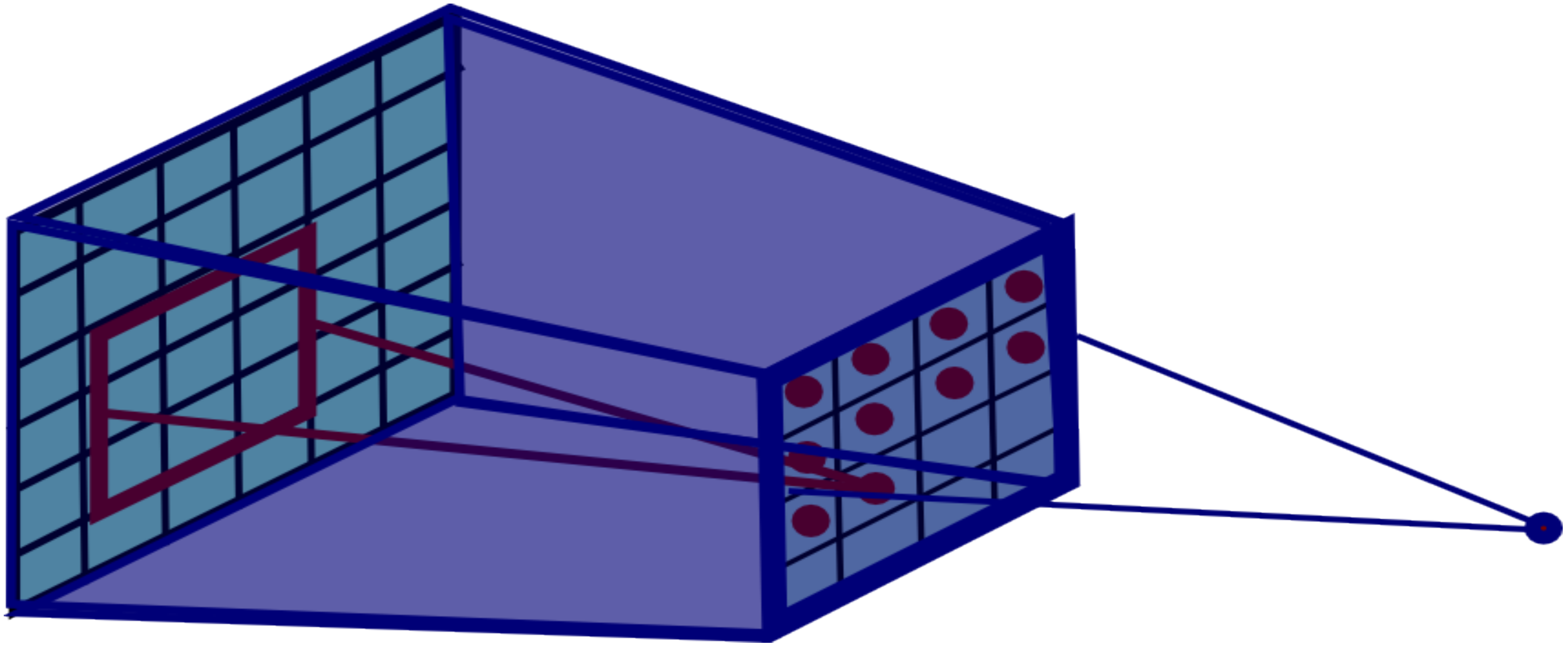


* slide from Marc'Aurelio Renzato

Pooling Layer **Summary**

Accepts a volume of size: $W_i \times H_i \times D_i$

Requires hyperparameters:

- Spatial extent of filters: K
- Stride of application: F

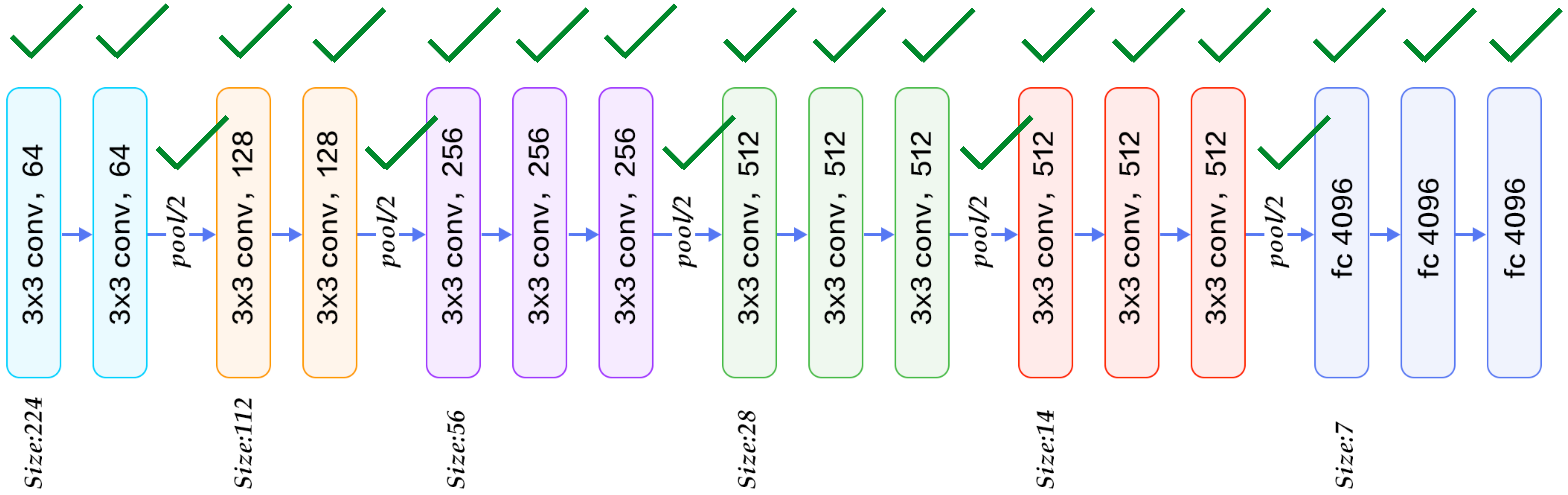
Produces a volume of size: $W_o \times H_o \times D_o$

$W_o = W_i/F$ $\quad$ $H_o = H_i/F$ $\quad$ $D_o = D_i$

Number of total learnable parameters: 0

(you can do padding, but it's a bit trickier)

Convolutional Neural Networks



VGG-16 Network

Improving **Single Model**

Regularization

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

Improving **Single Model**

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- L2, L1
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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**

Regularization

- L2, L1
- Dropout / Inverted Dropout
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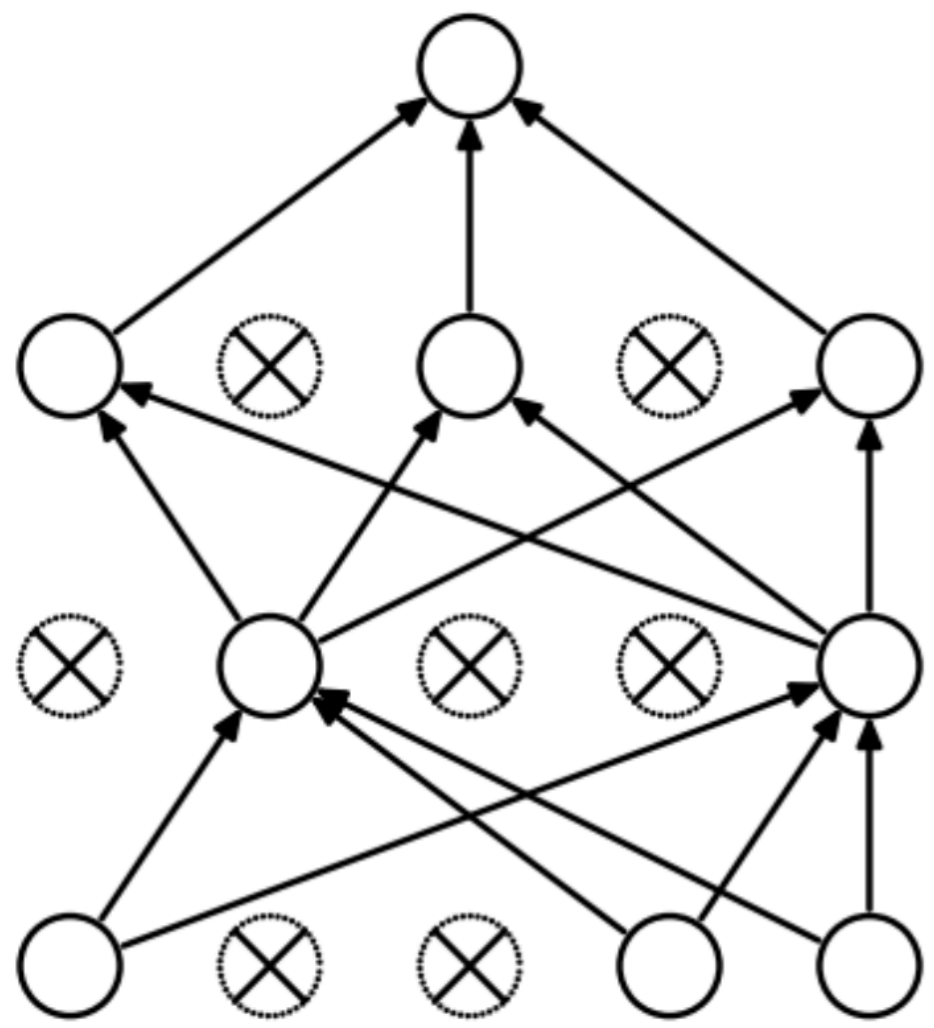

Dropout

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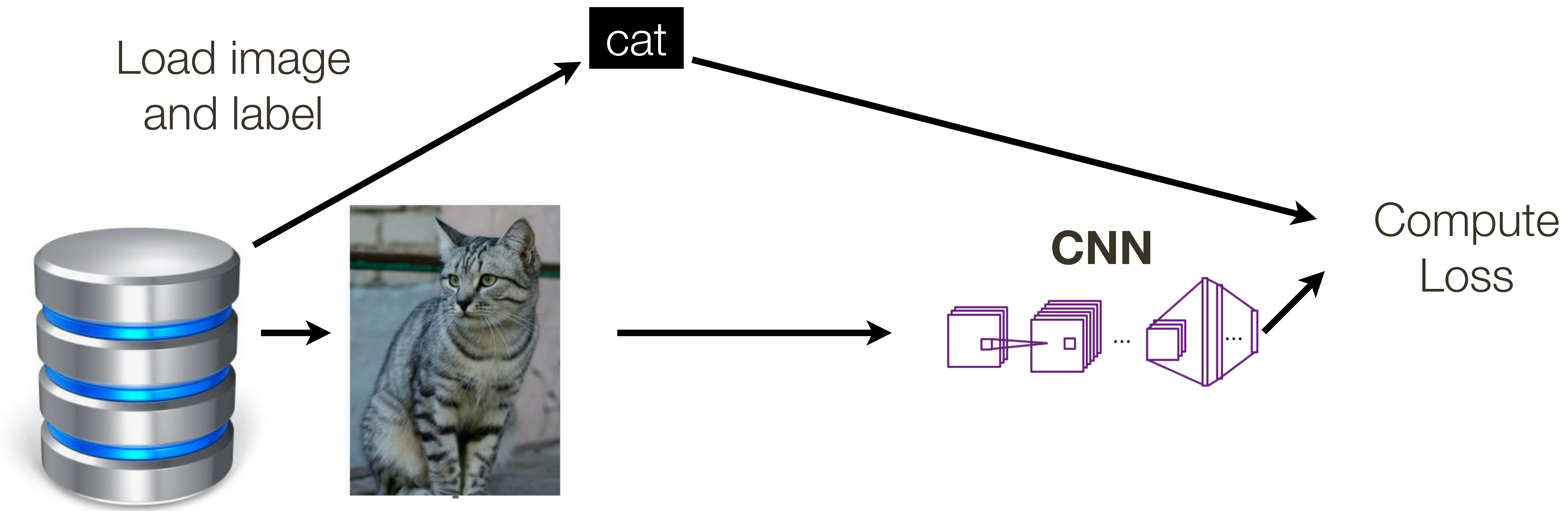
Regularization: Data Augmentation



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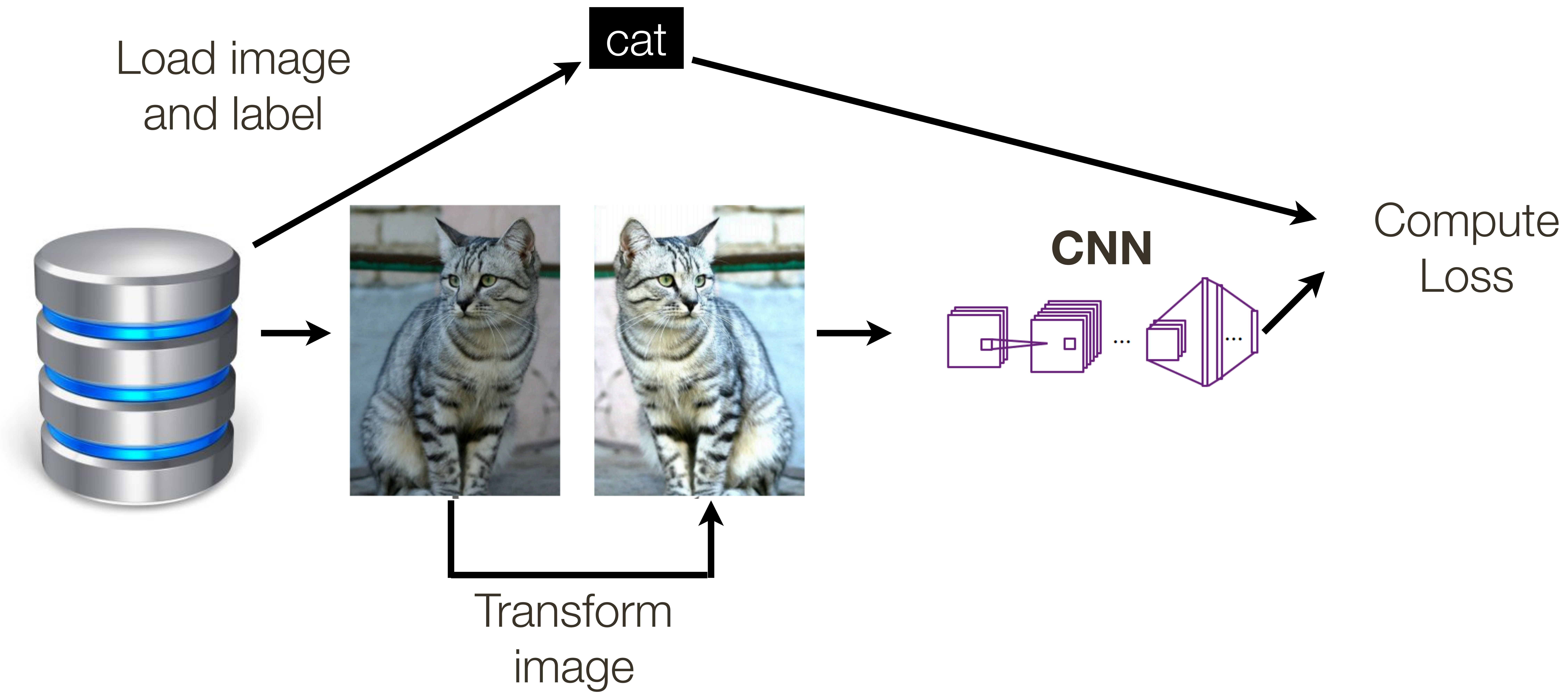

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Regularization: Data Augmentation

Horizontal flips

Random crops & scales

Color Jitter

Regularization: Data Augmentation

Horizontal flips | Random crops & scales | Color Jitter

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Regularization: Data Augmentation

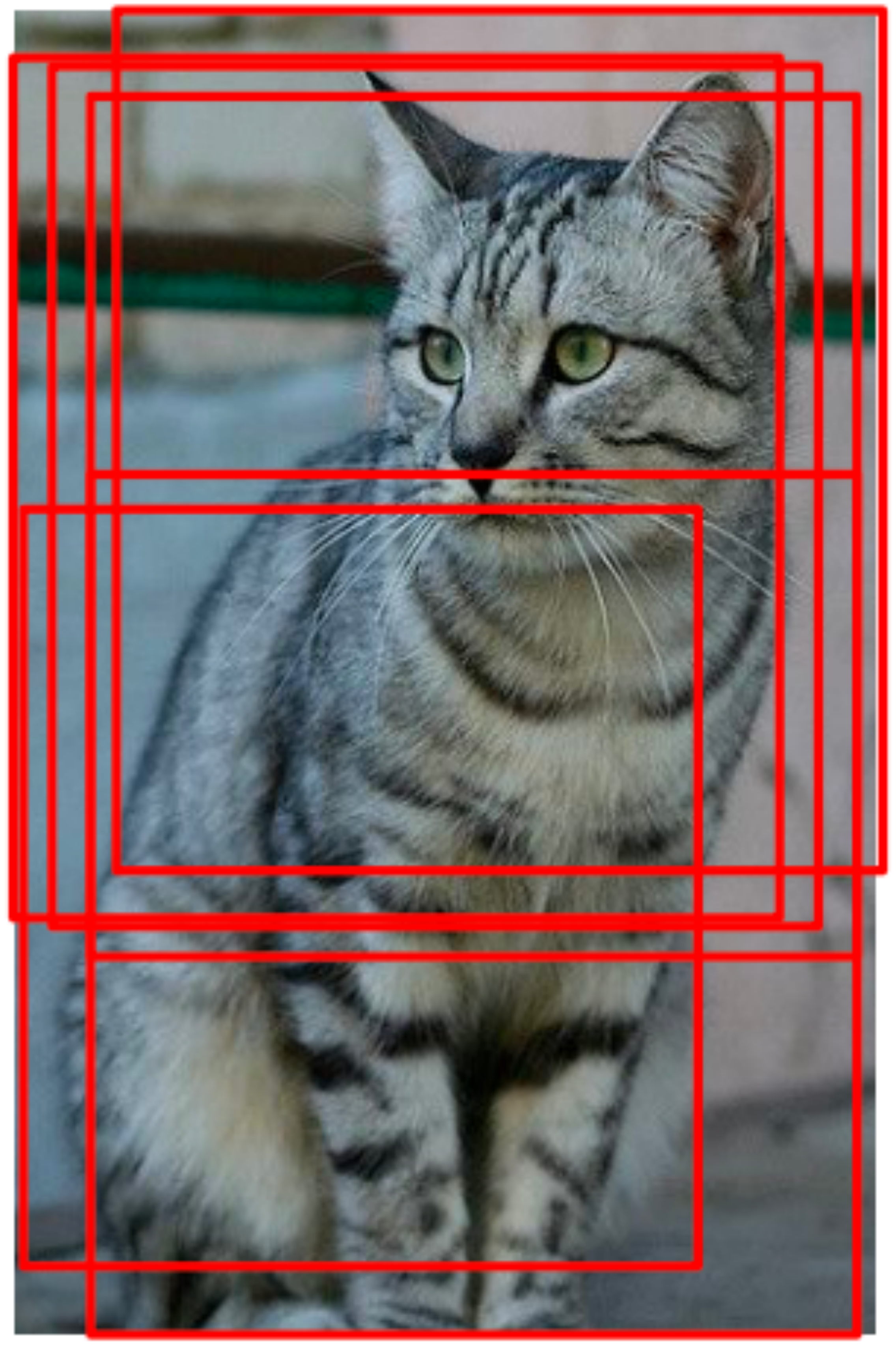
Horizontal flips | **Random crops & scales** | Color Jitter

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



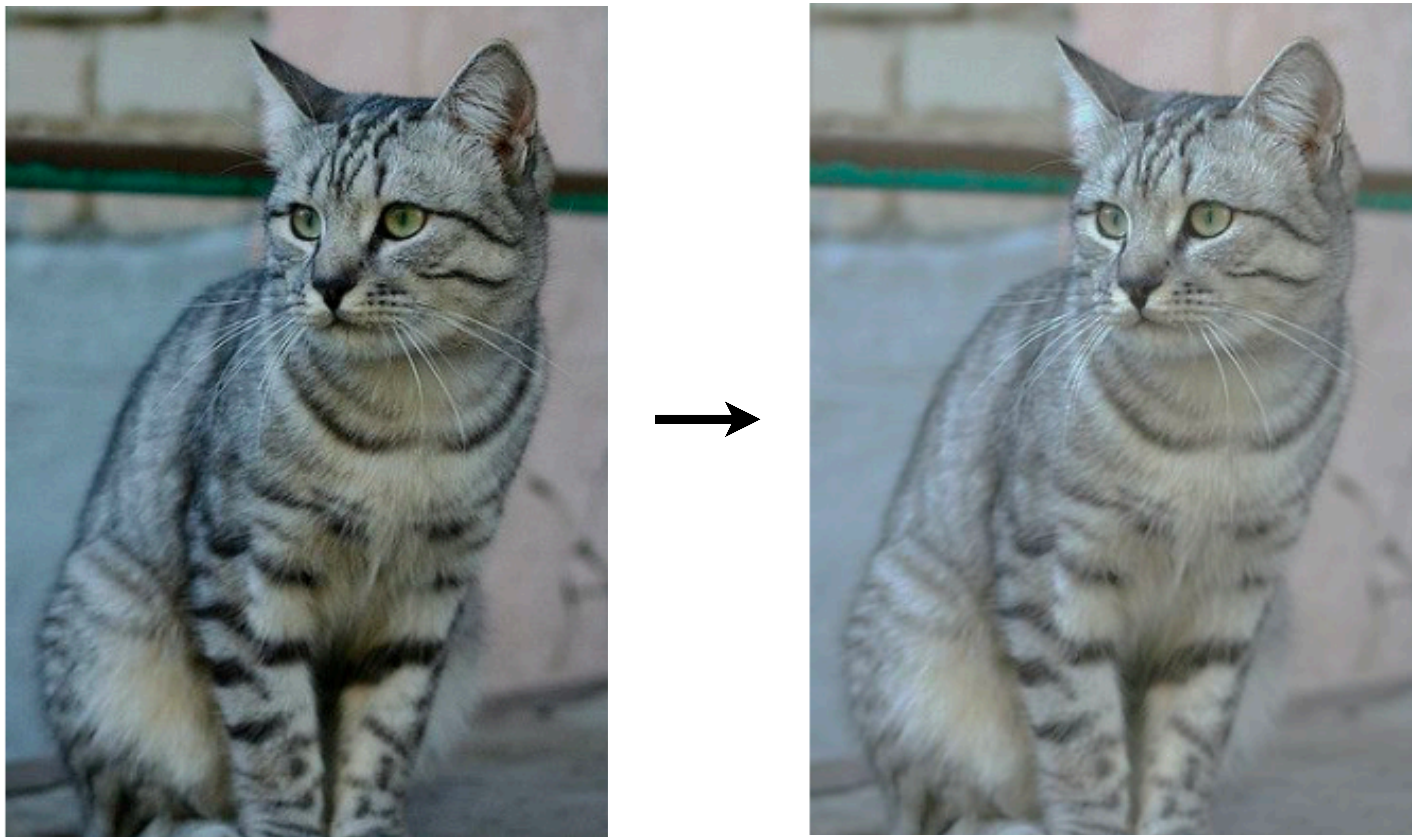
Regularization: Data Augmentation

Horizontal flips

Random crops & scales

Color Jitter

Random perturbations in contrast and brightness



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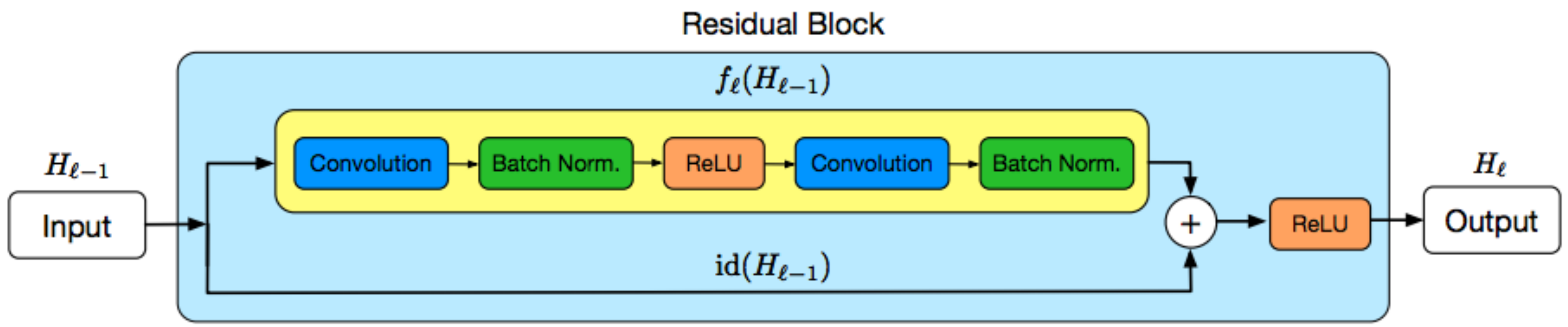
Regularization: Stochastic Depth

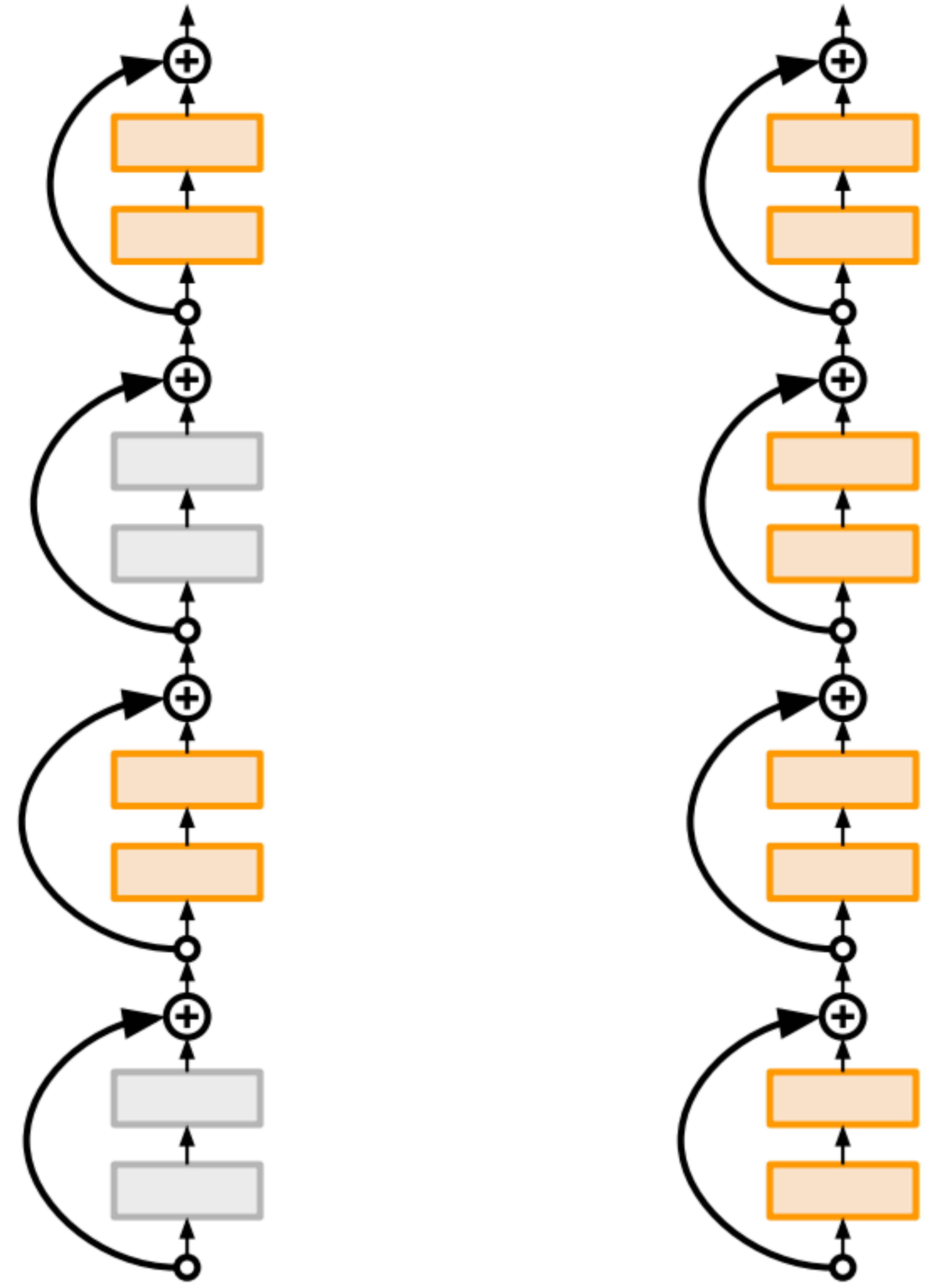
[Huang et al., ECCV 2016]

Effectively "dropout" but for layers

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

Effectively trains a collection of neural networks





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Transfer Learning with CNNs

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

Transfer Learning with CNNs

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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

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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

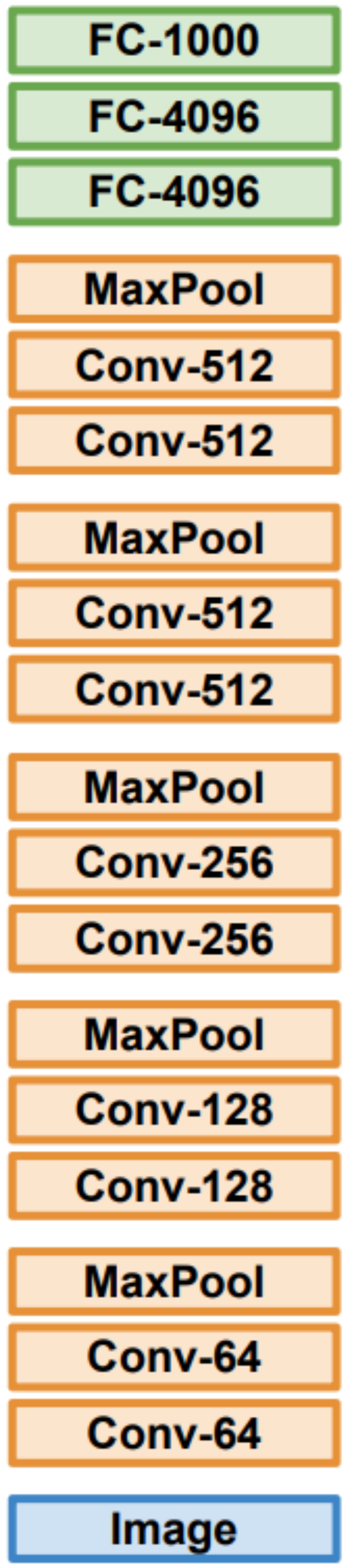
This strategy is PERVASIVE.

* 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**



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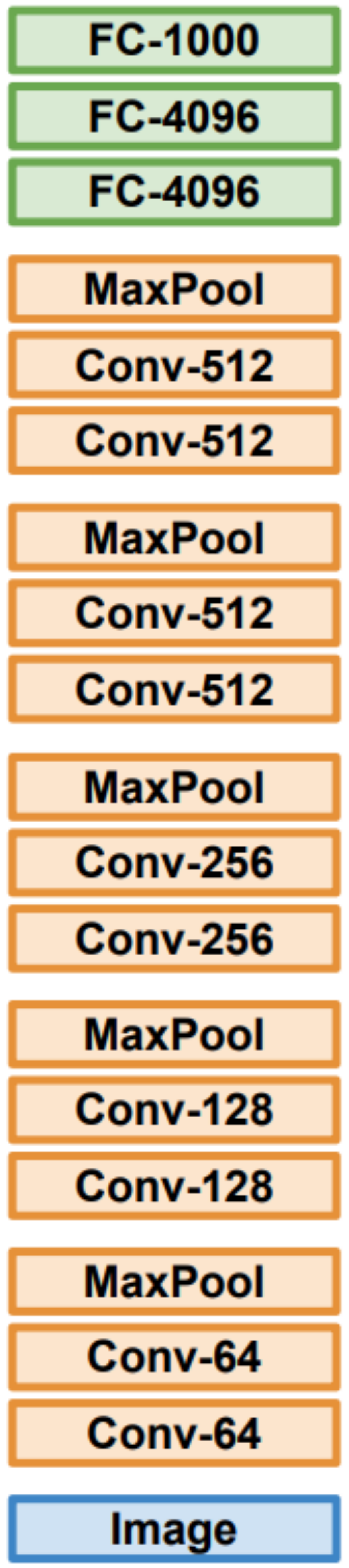

Why on **ImageNet**?

Transfer Learning with CNNs

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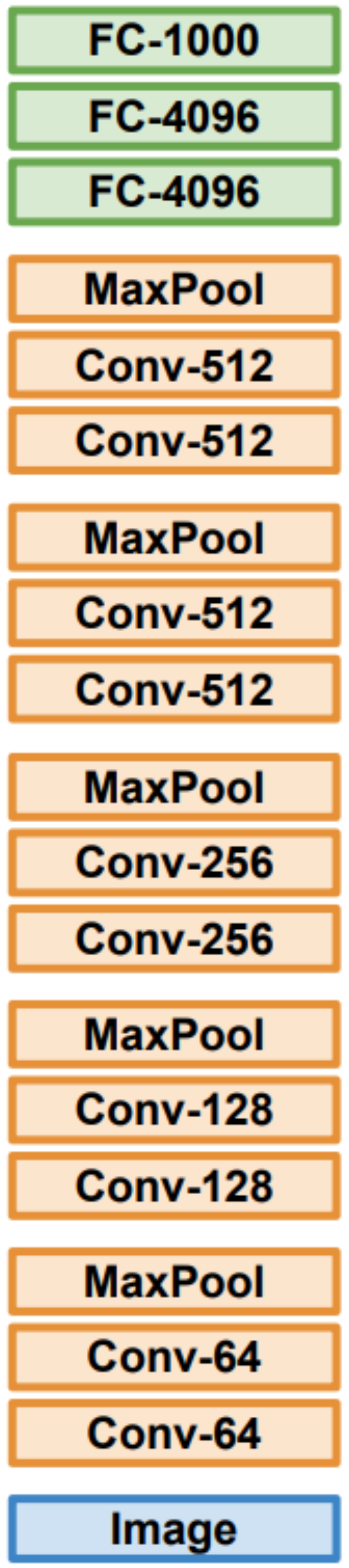

Why on **ImageNet**?

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

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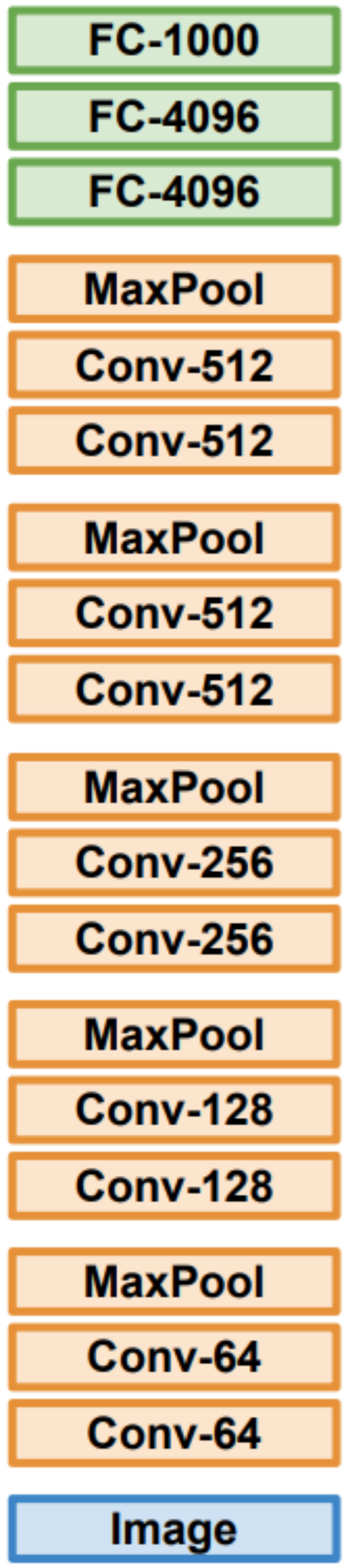

Why on **ImageNet**?

- 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)

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

Transfer Learning with CNNs

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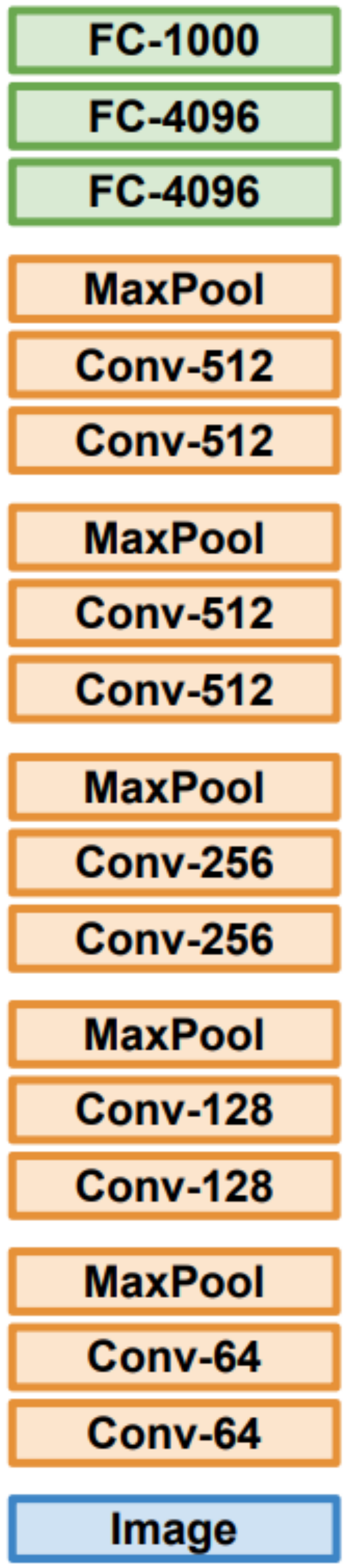

Small dataset with C classes

Transfer Learning with CNNs

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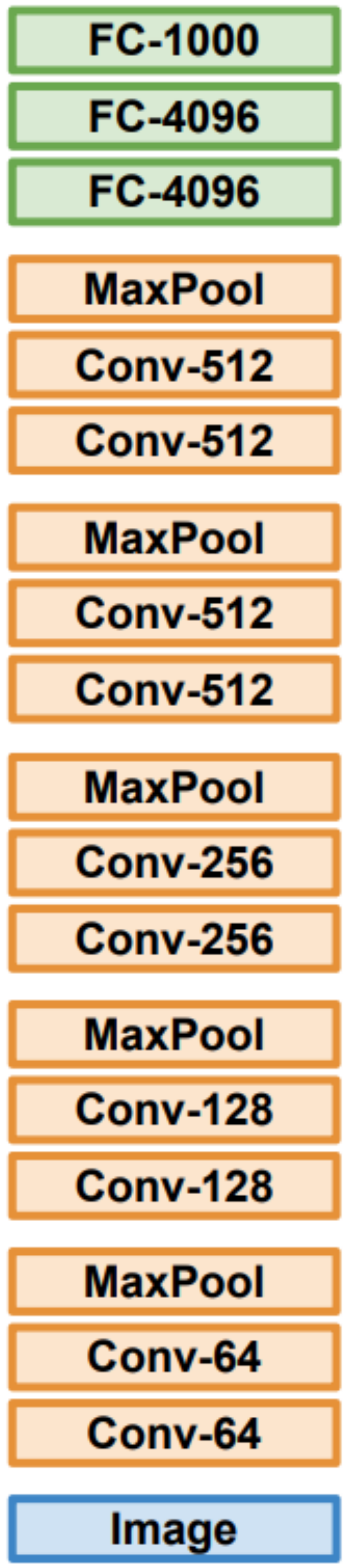

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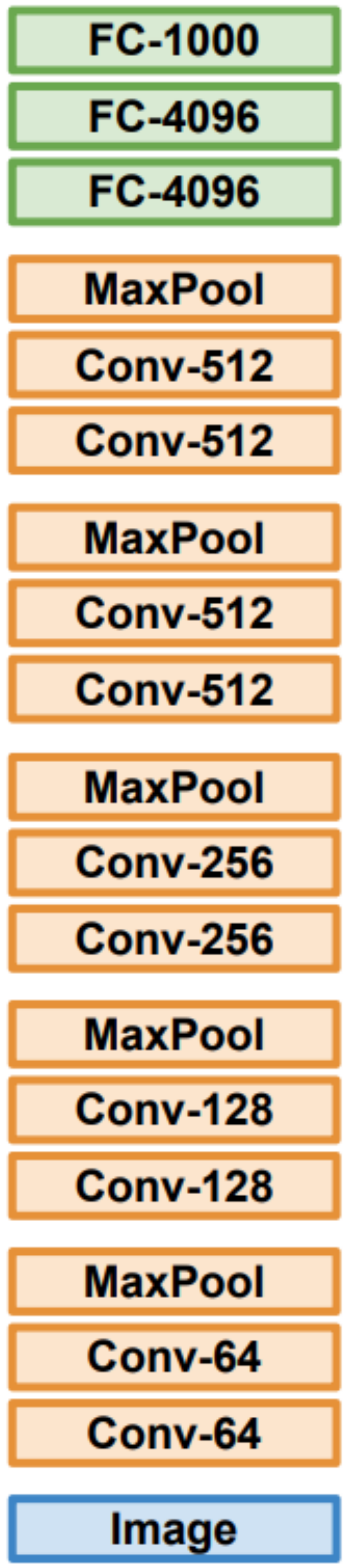

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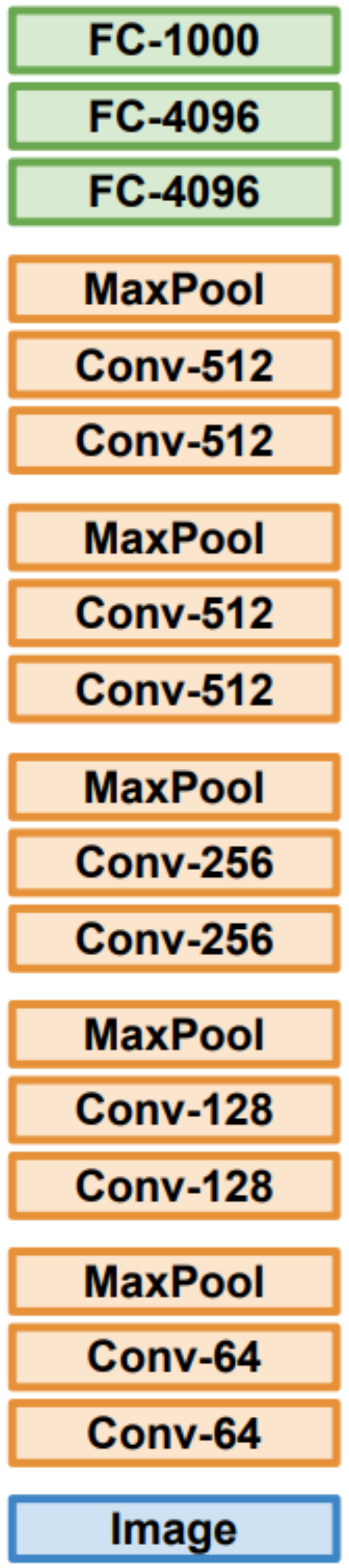

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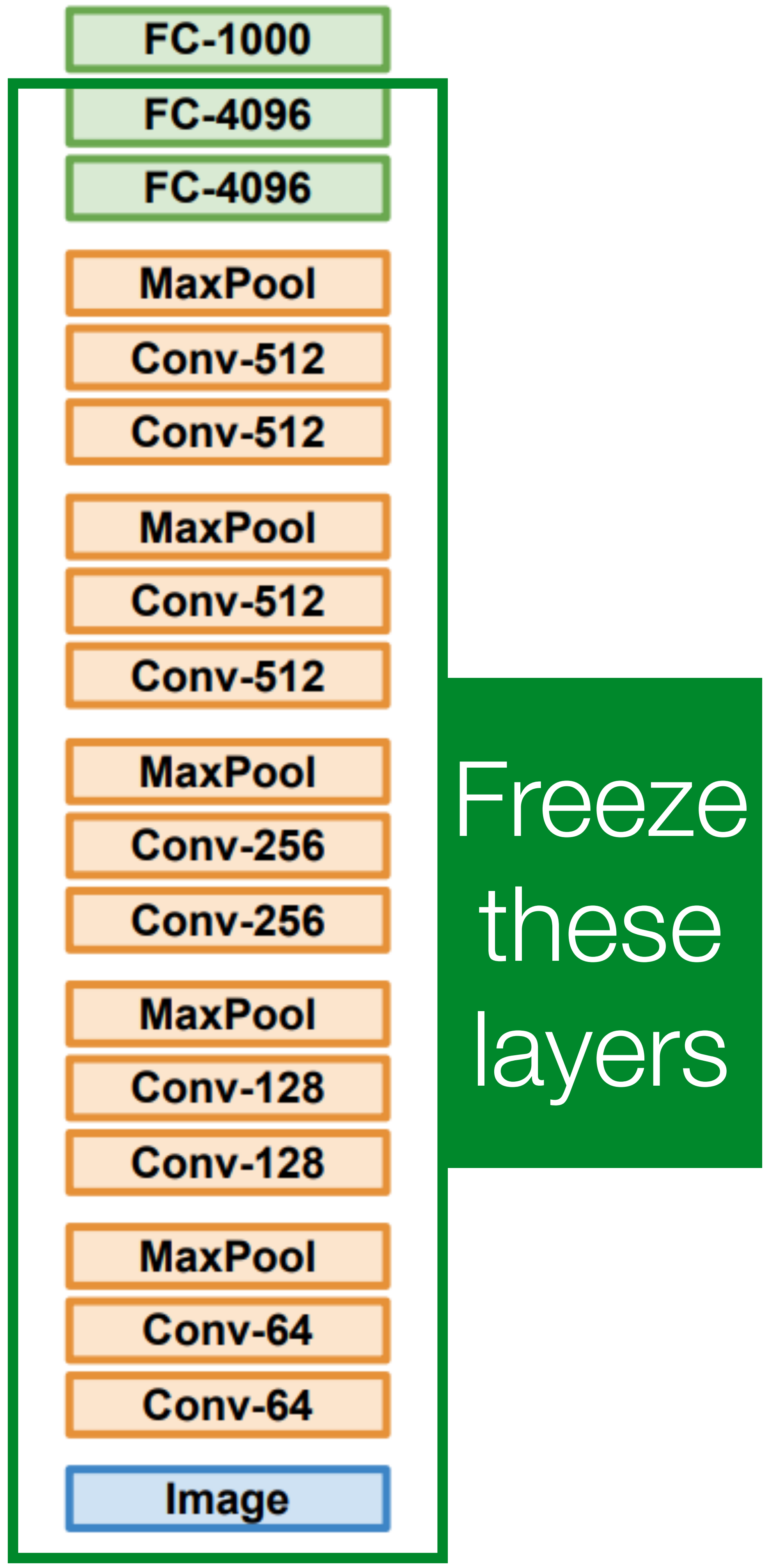

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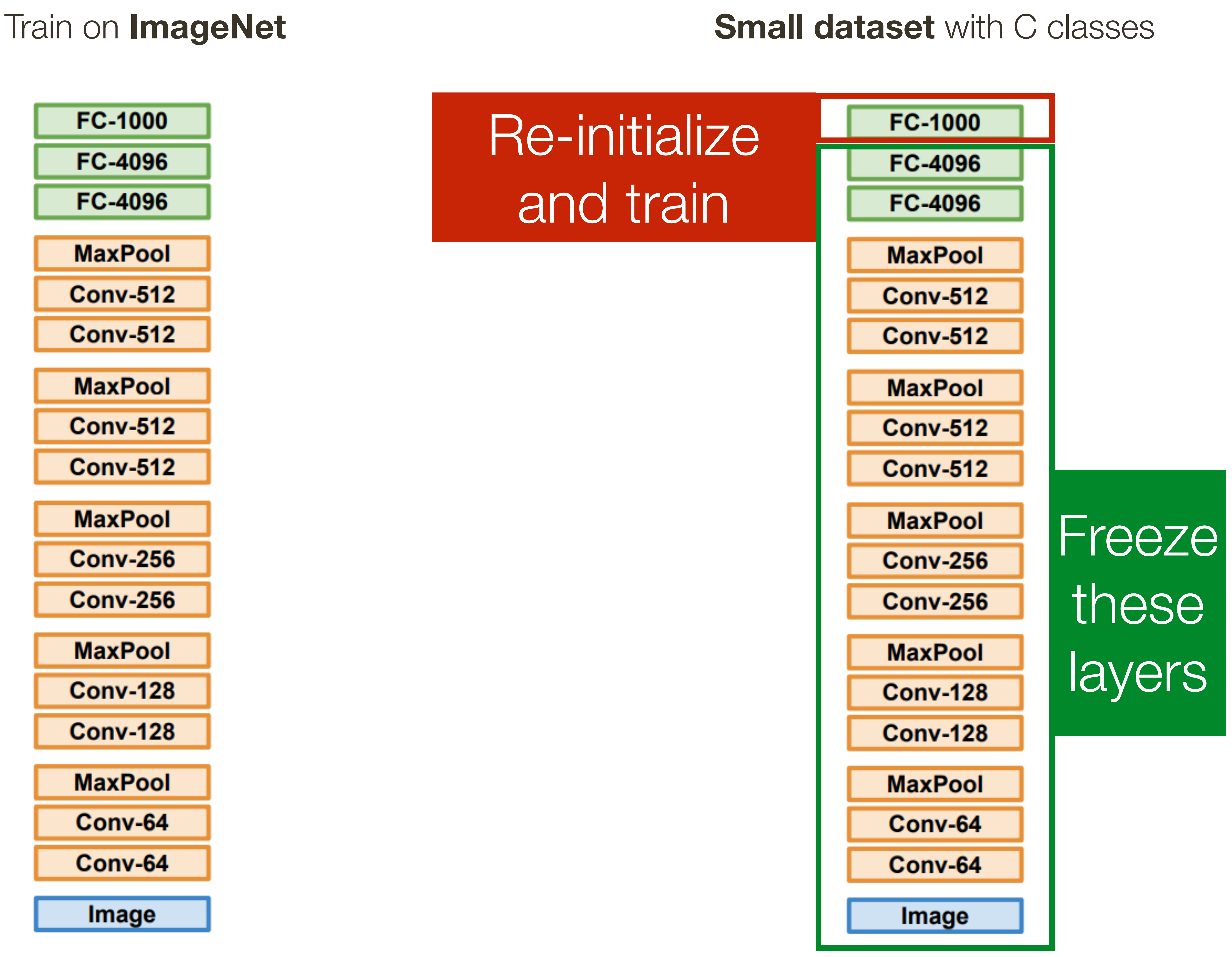

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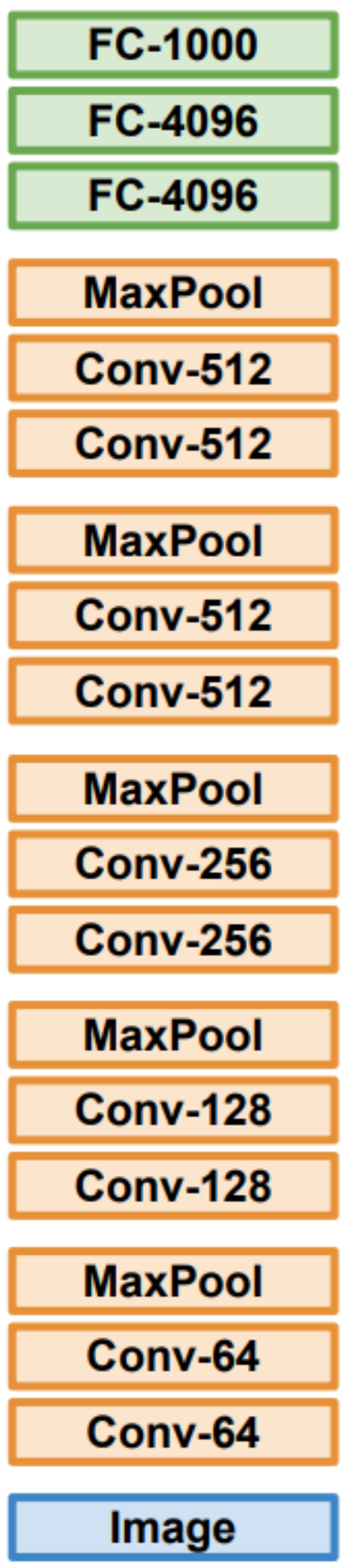

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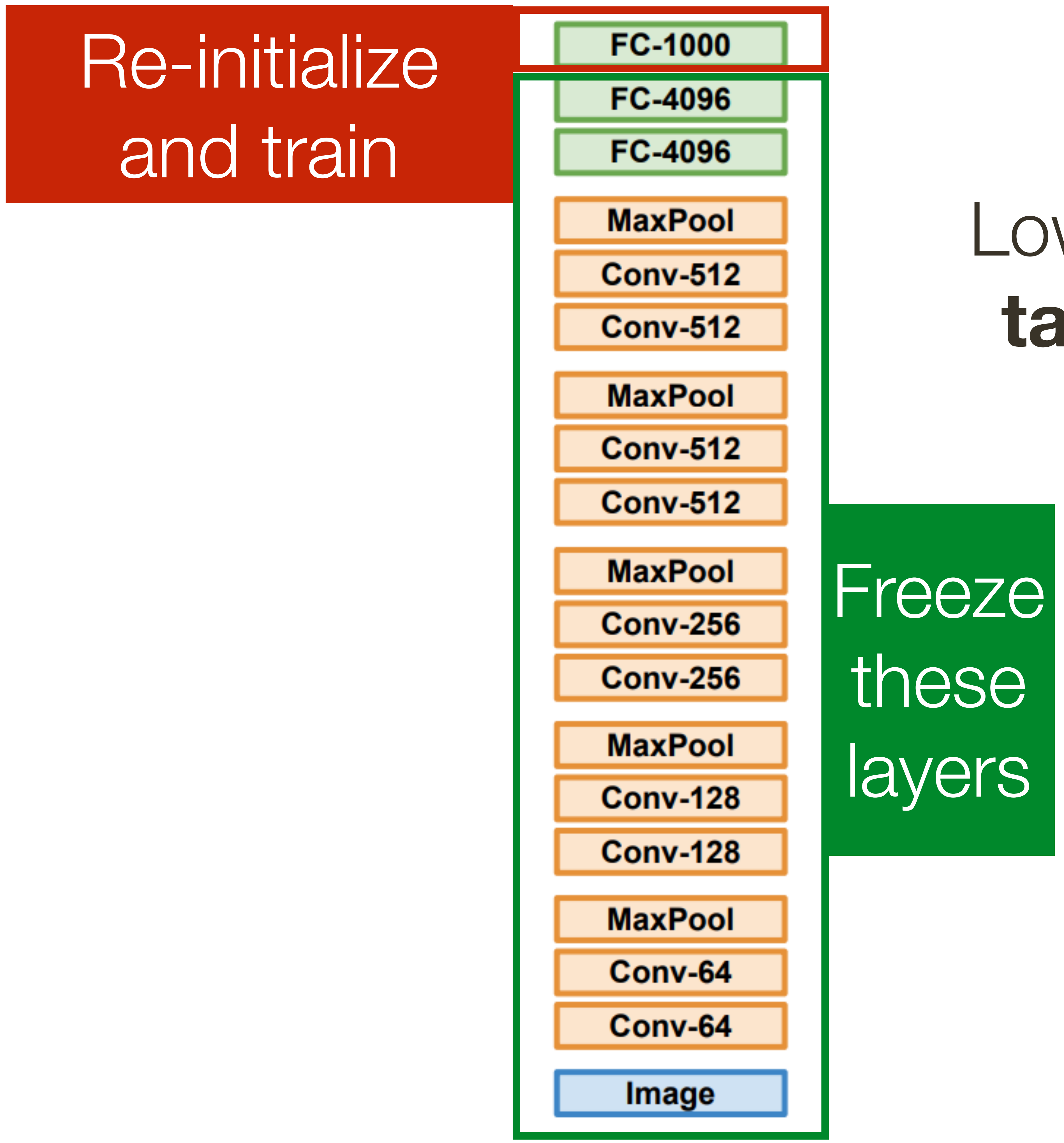

Lower levels of the CNN are at **task independent** anyways

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

Transfer Learning with CNNs

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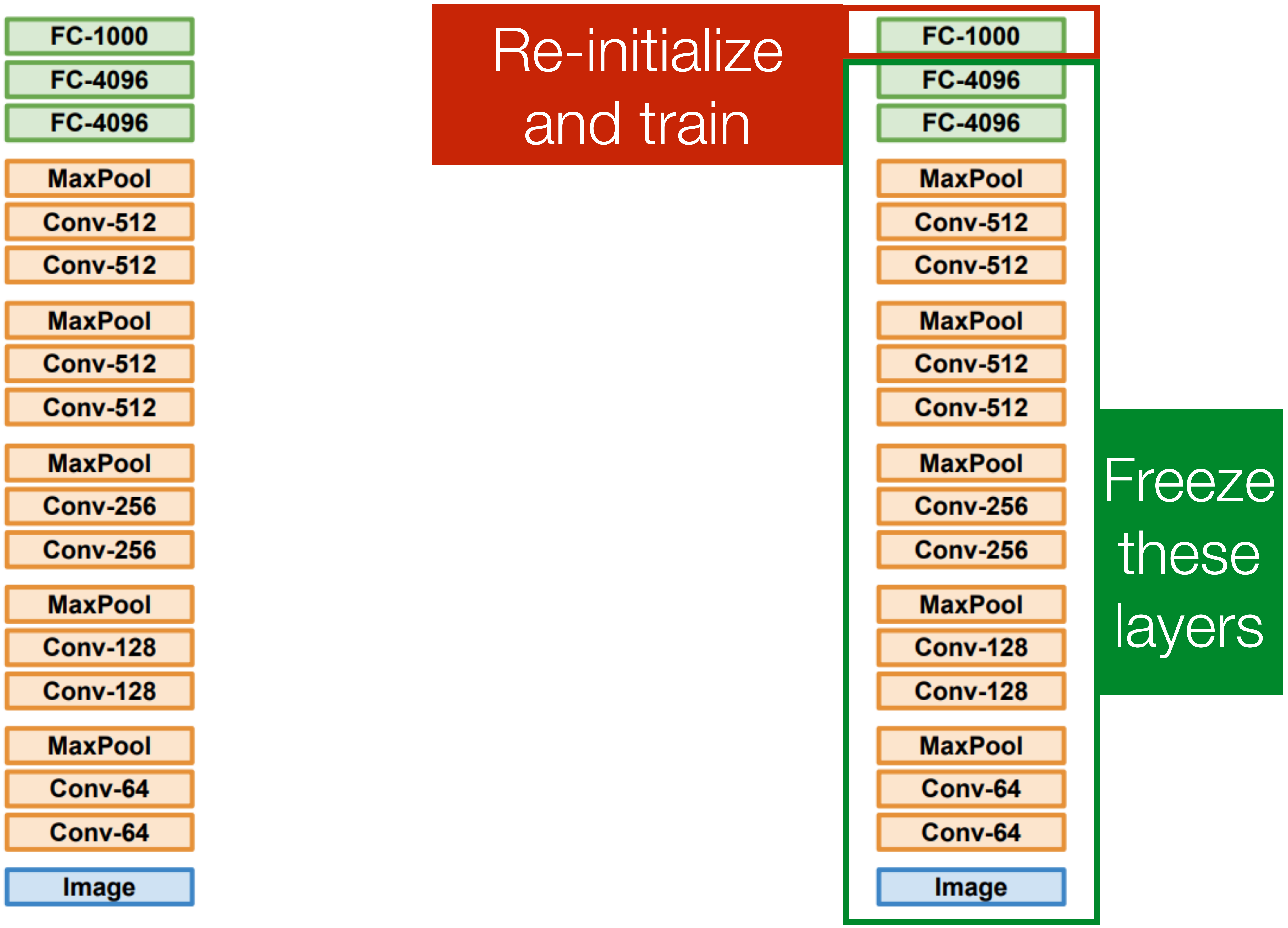
Train on **ImageNet** | **Small dataset** with C classes | **Larger dataset**



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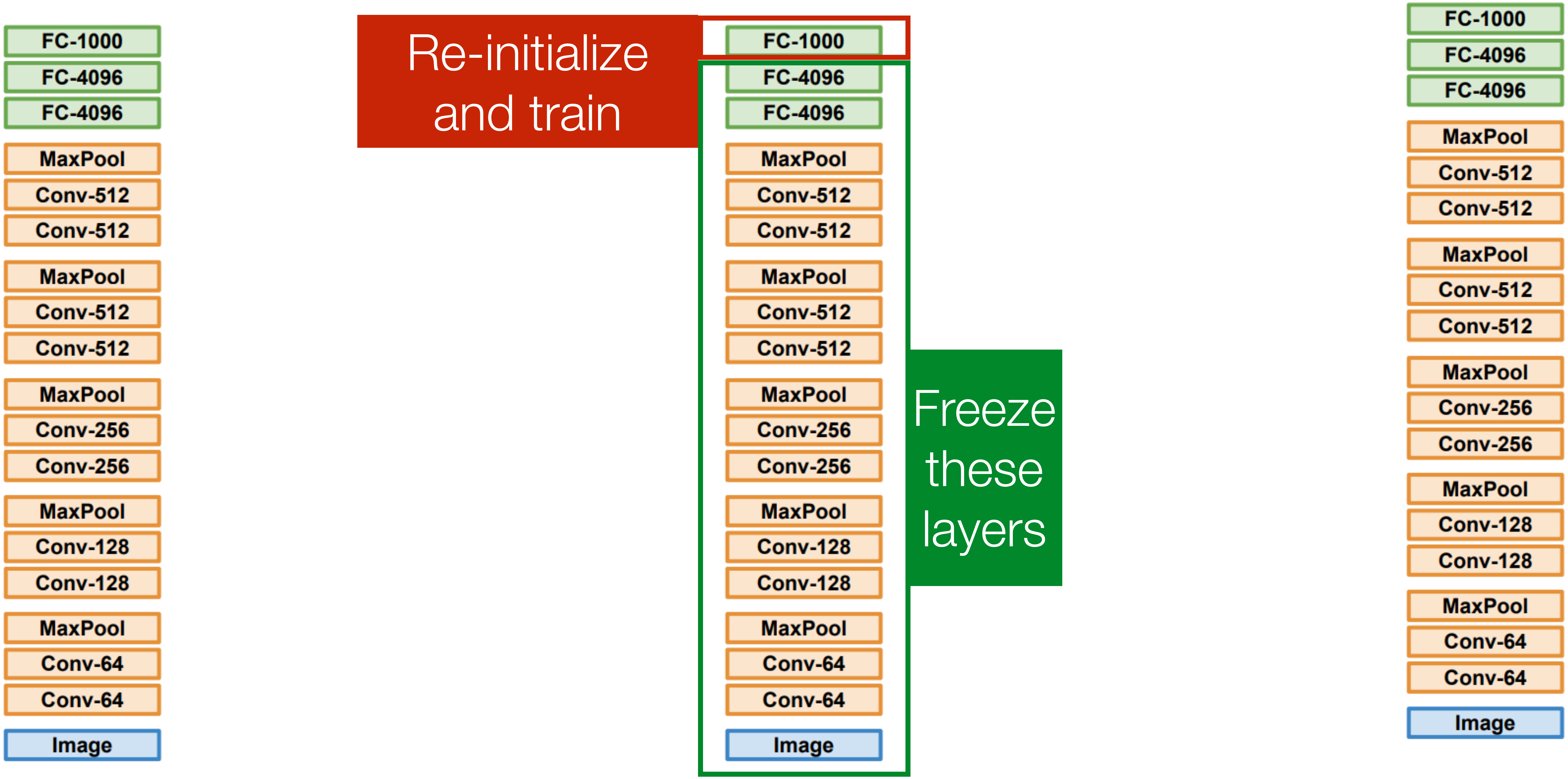

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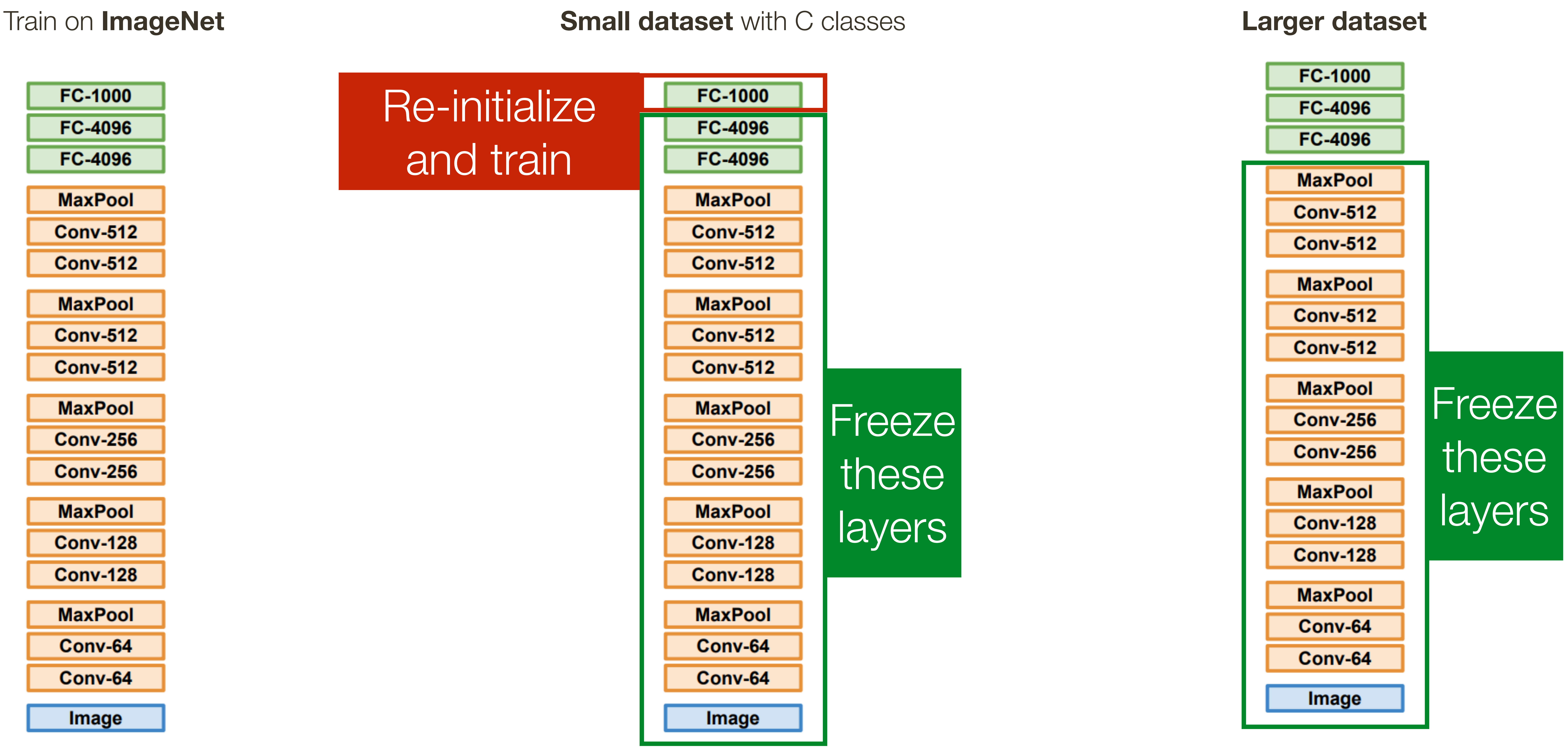

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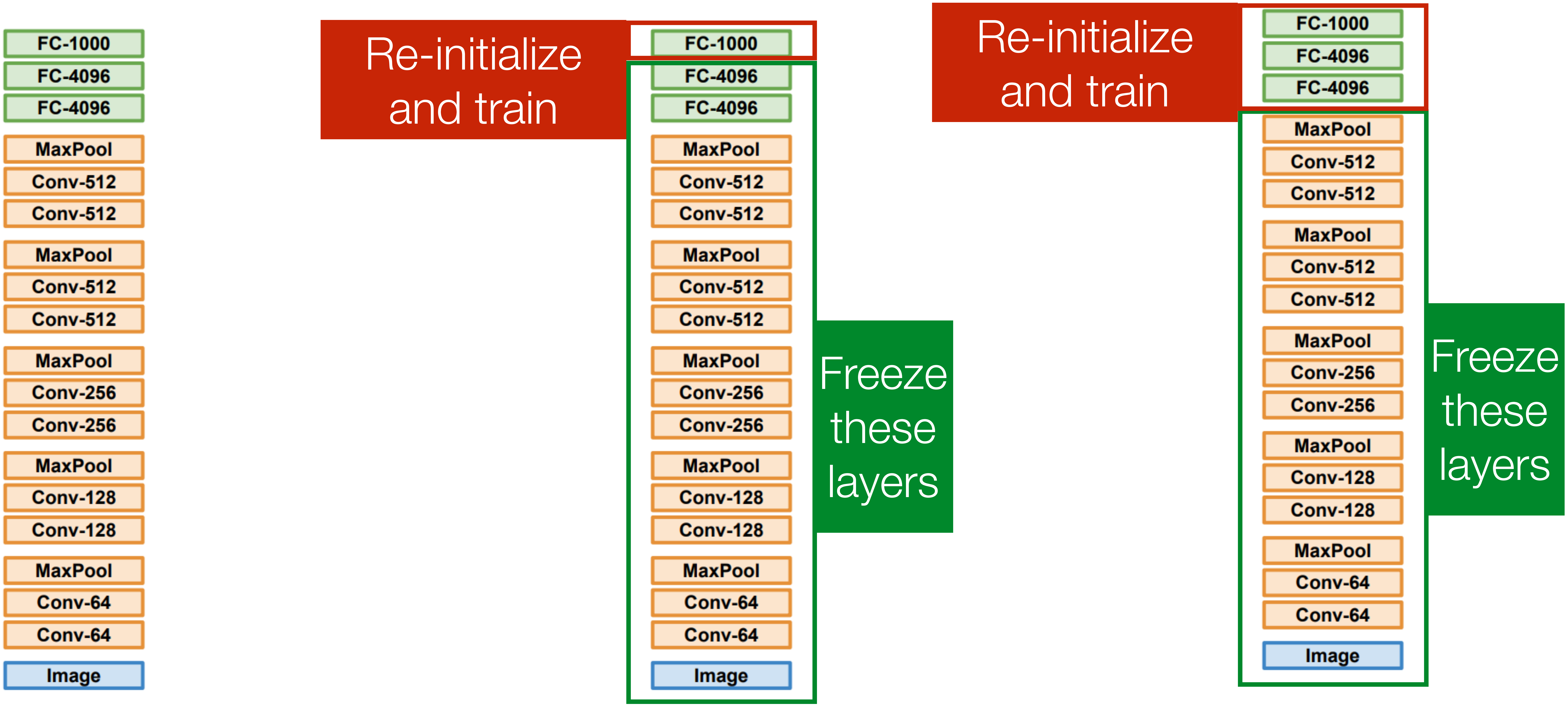

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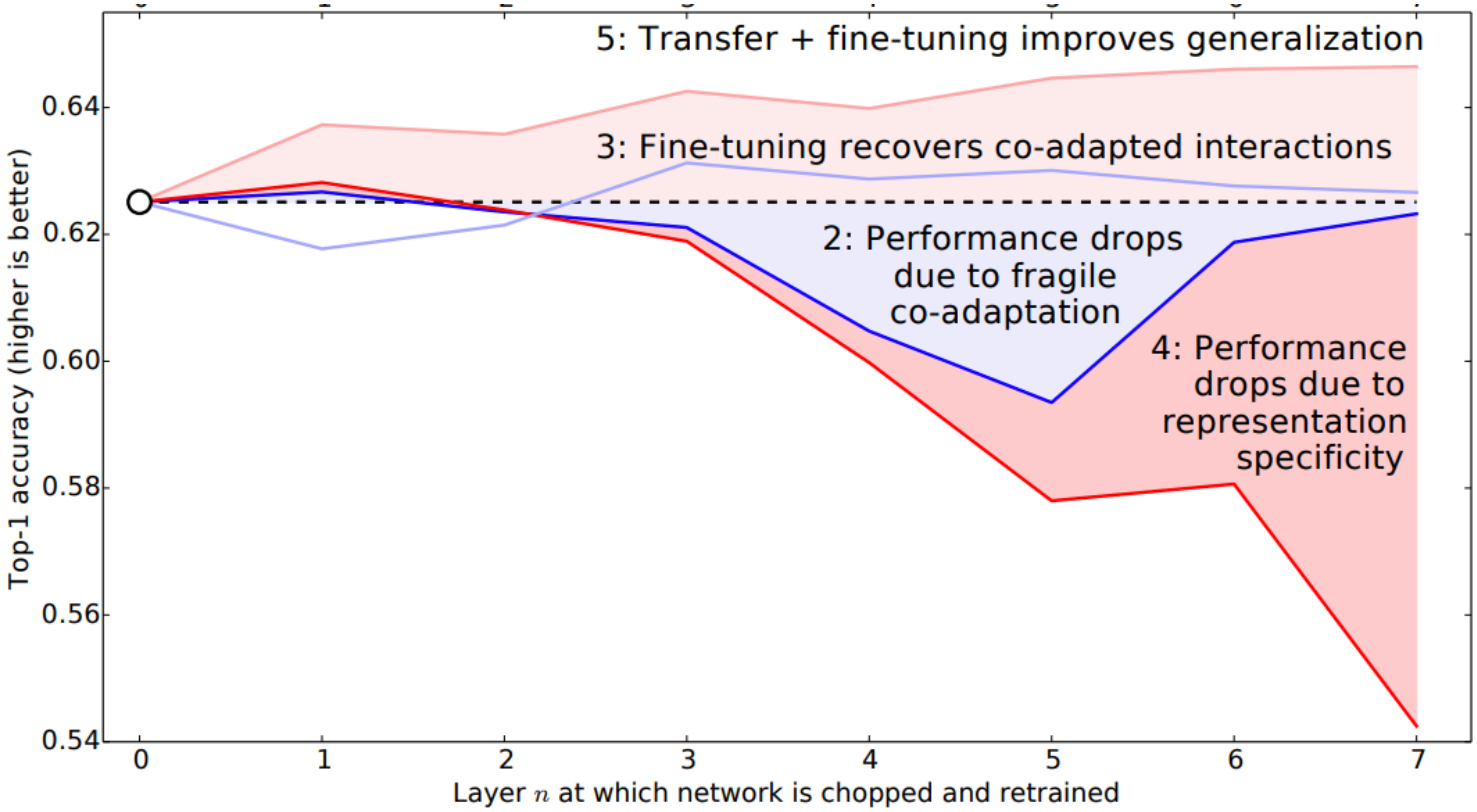
Transfer Learning with CNNs

Dataset A: 500 classes



Layers fine-tuned

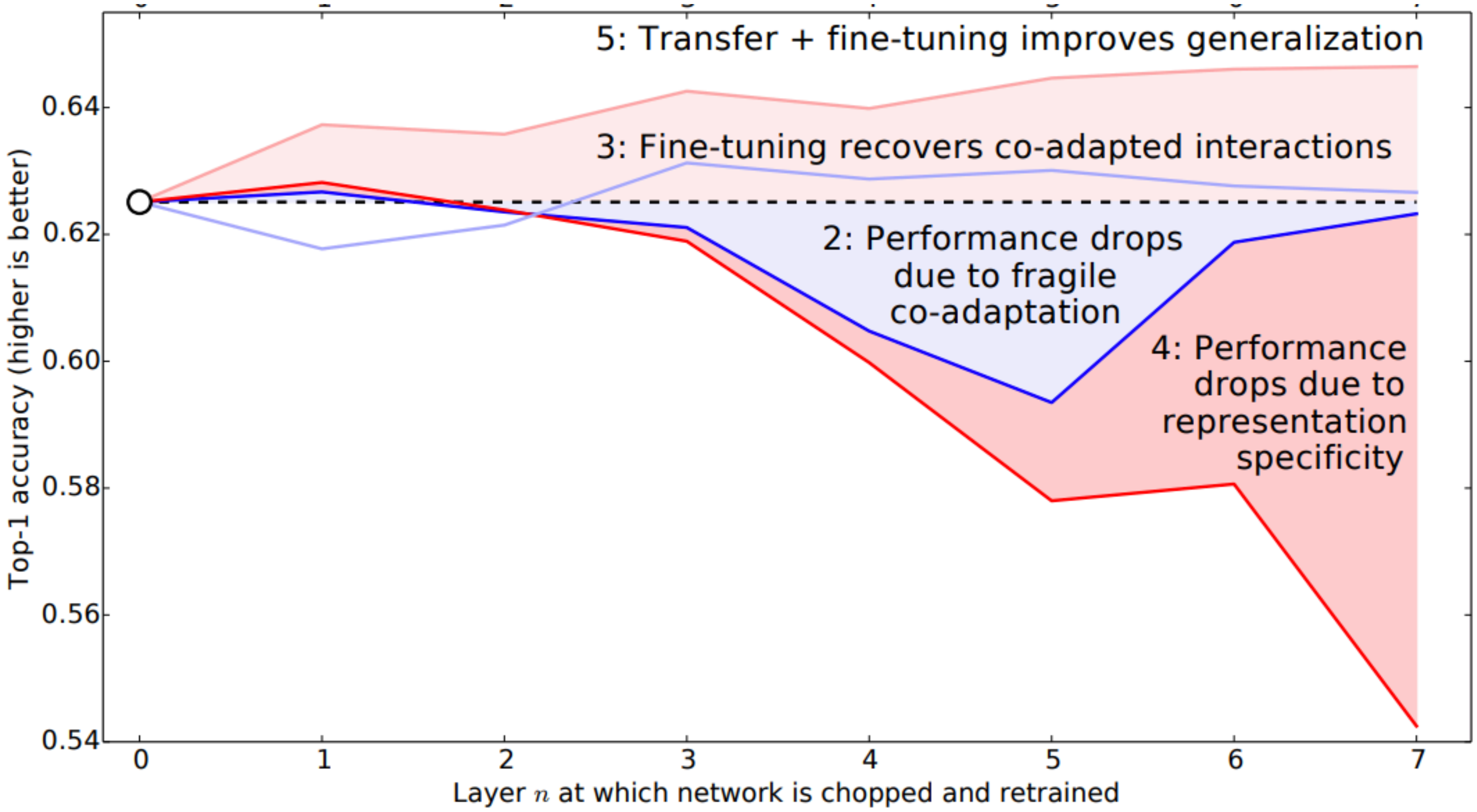
Layers fixed

[Yosinski et al., NIPS 2014]

Transfer Learning with CNNs

Dataset A: 500 classes

Dataset B: (different) 500 classes



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Layers fixed

[Yosinski et al., NIPS 2014]

Layers fine-tuned

Layers fixed

Model **Ensemble**

Training: Train multiple independent models

Test: Average their results

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~ 2% improved performance in practice

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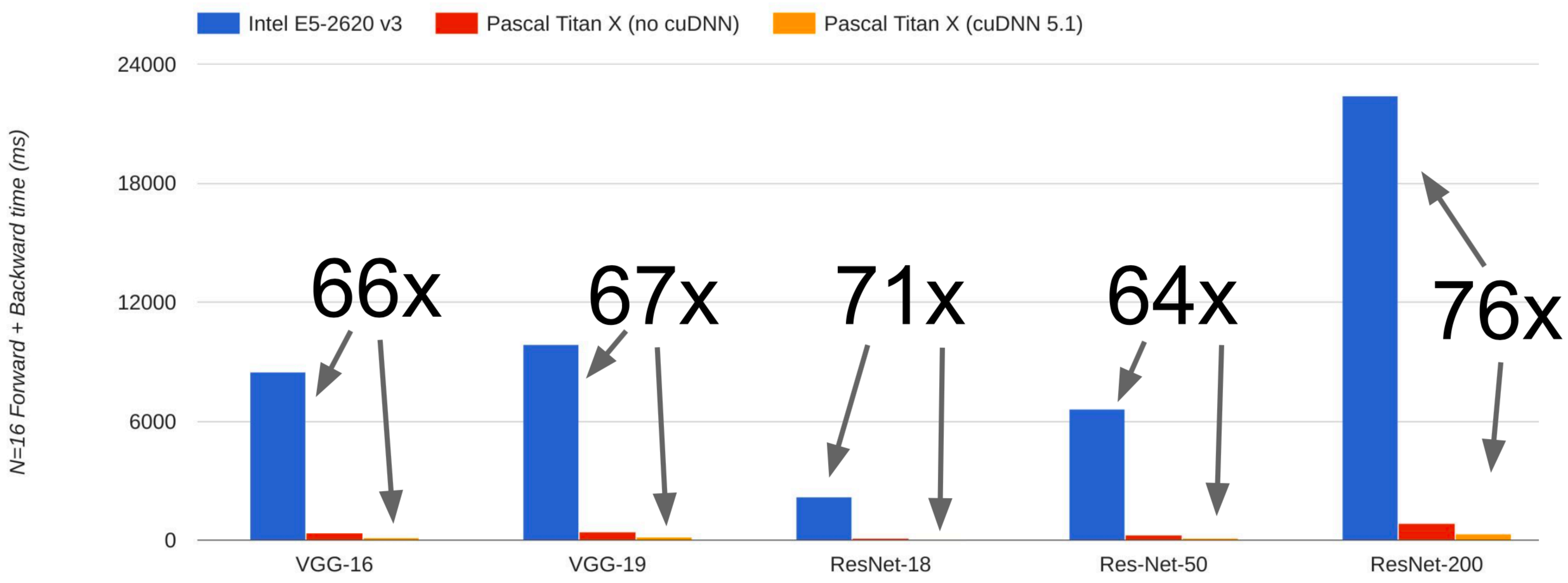
Alternative: Multiple snapshots of the single model during training!

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

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.)

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

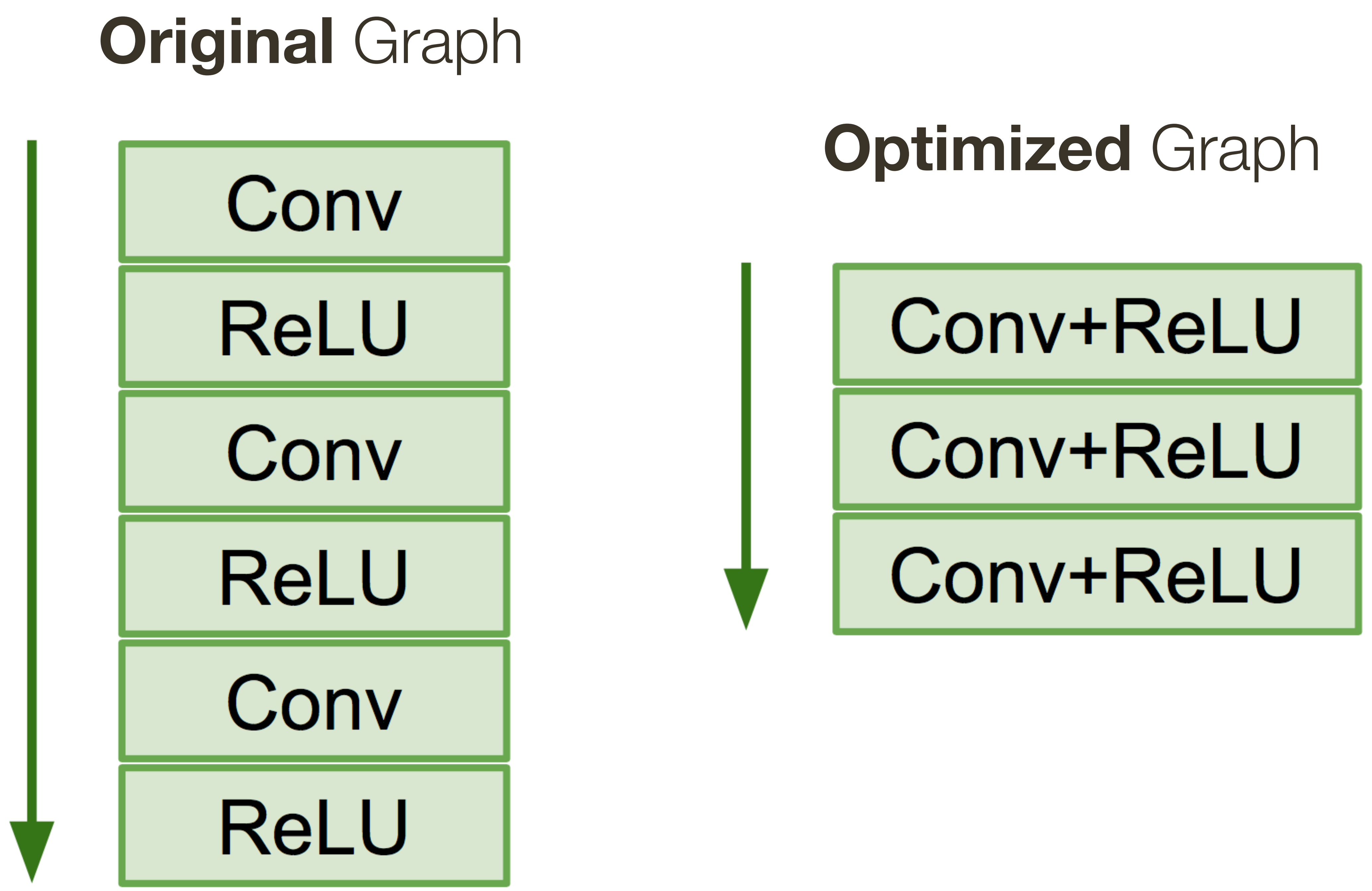
Frameworks: PyTorch vs. TensorFlow (v1)

Dynamic vs. Static computational graphs

Frameworks: PyTorch vs. TensorFlow (v1)

Dynamic vs. **Static** computational graphs

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



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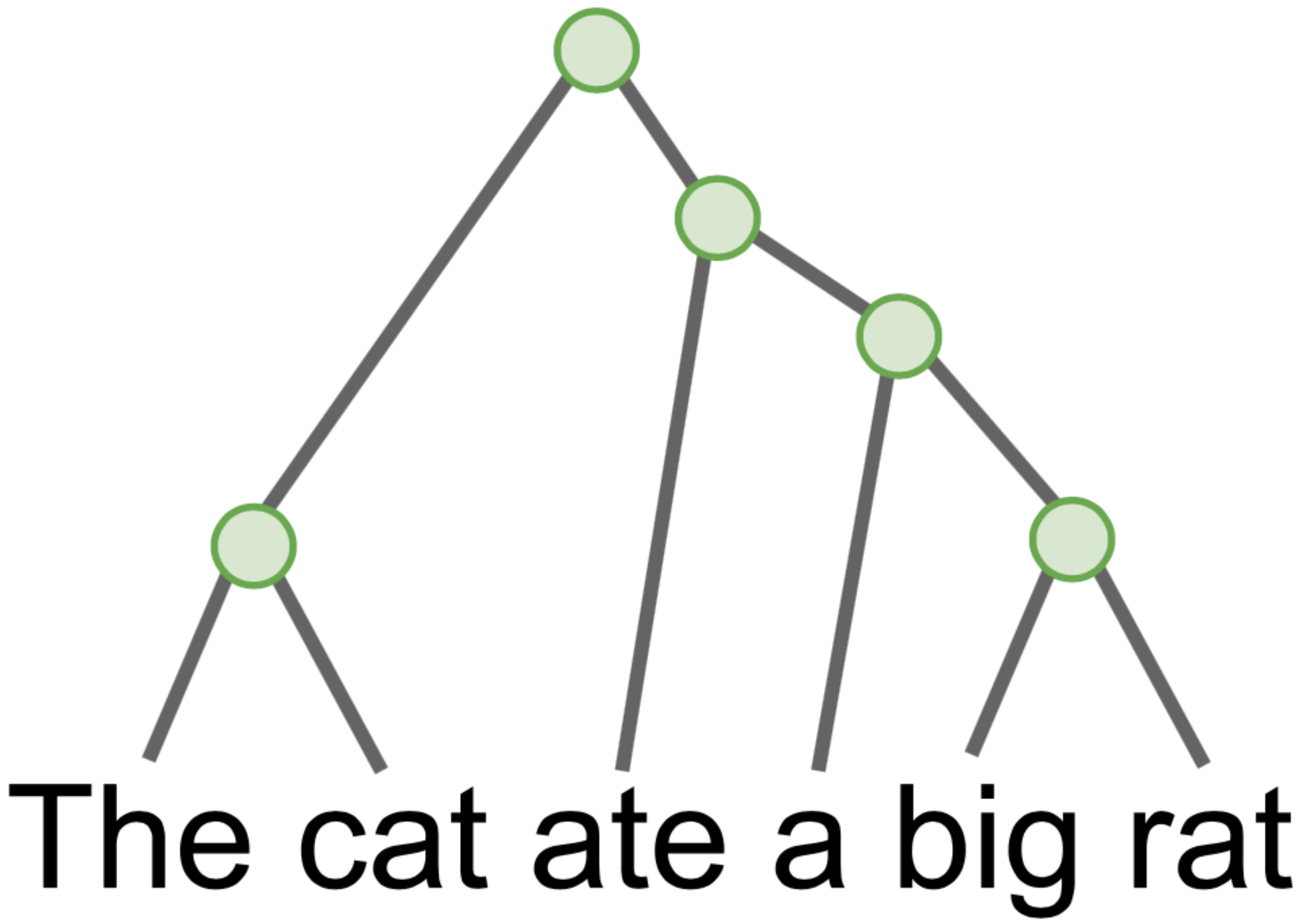
Frameworks: PyTorch vs. TensorFlow (v1)

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